The Orchestration of Computer-Supported Collaboration Scripts with Learning Analytics

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To my parents
(Ananda Amarasinghe & Sepalika Mallikarachchi)
&
To my husband
(Roshan Sedar)

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Abstract

Computer-supported collaborative learning (CSCL) creates avenues for productive collaboration between students. In CSCL, collaborative learning flow patterns (CLFPs) provide pedagogical rationale and constraints for structuring the collaboration process. While structured collaboration facilitates the design of favourable learning conditions, orchestration of collaboration becomes an important factor, as learner participation and real-world constraints can create deviations in real time. On the one hand, limited research has examined the orchestration challenges related to collaborative learning situations scripted according to CLFPs in authentic educational contexts to resolve collaboration at different scales. On the other hand, learning analytics (LA) can be used to provide proper technological tooling, infrastructure and support to orchestrate collaboration. To this end, this dissertation addresses the following research question: *How can LA support orchestration mechanisms for scripted CSCL?* To address this question, this dissertation first focuses on studying the orchestration challenges associated with scripted CSCL situations on small scales (in the classroom learning context) and large scales (in the distance learning context, specifically in massive open online courses [MOOCs]). In the classroom learning context, lack of teacher access to activity regulation mechanisms constituted a key challenge. In MOOCs, sustained student participation in multiple phases of the script was a primary challenge. The dissertation also focuses on studying the design of LA interventions that might address the orchestration challenges under examination. The proposed LA interventions range from human-in-control to machine-in-control in nature given the feasibility and regulation needs of the learning contexts under investigation. Following a design-based research (DBR) methodology, evaluation studies were conducted in naturalistic classrooms and in MOOCs to evaluate the effects of the proposed LA interventions and to understand the conditions for their successful implementation. The results of the evaluation studies conducted in the classroom context shed light on how teachers interpret LA data and how they action the resulting knowledge in authentic collaborative learning sit-

uations. In the distance learning context, the proposed interventions were critical in sustaining continuous flows of collaboration. The practical benefits and limitations of deploying LA solutions in real-world settings, as well as future research directions, are outlined.

Resumen

El aprendizaje colaborativo asistido por ordenador (CSCL) ofrece oportunidades para la colaboración productiva entre estudiantes. En CSCL, los patrones de flujo de aprendizaje colaborativo (CLFP) proporcionan un fundamento pedagógico y restricciones para estructurar el proceso de colaboración. Si bien la colaboración estructurada facilita el diseño de condiciones de aprendizaje favorables, la orquestación de dicha colaboración estructurada se convierte en un factor importante, ya que la participación del alumno y los condicionantes del mundo real pueden crear desviaciones en el momento de su realización. Por un lado, existe una investigación limitada sobre los desafíos de la orquestación de aprendizaje colaborativo guiado según los CLFP en contextos educativos auténticos a diferentes escalas. Por otro lado, la analítica del aprendizaje (LA) se puede utilizar para proporcionar las herramientas tecnológicas, la infraestructura y el apoyo adecuados para orquestar la colaboración. Con este fin, esta tesis doctoral plantea la siguiente pregunta de investigación: ¿Cómo puede LA apoyar los mecanismos de orquestación de guiones de CSCL? Para abordar esta pregunta, la tesis doctoral se centra, primero, en estudiar los desafíos de la orquestación en situaciones CSCL guiadas a pequeña escala (en el contexto del aula) y a gran escala (en el contexto de aprendizaje a distancia, específicamente en cursos masivos abiertos en línea [MOOC]). En el contexto del aula, un reto imporante es la falta de acceso de los docentes a los mecanismos de regulación de la actividad. En los MOOC, el reto principal es sostener la participación de los estudiantes a lo largo de las diversas fases del guión. La tesis doctoral también se centra en estudiar el diseño de intervenciones de LA que podrían abordar los retos de orquestación detectados. Dadas las necesidades de viabilidad y regulación de los contextos de aprendizaje investigados, las intervenciones de LA propuestas van desde acciones automáticas donde la "máquina está en control" a intervenciones que implican "control por humanos". Siguiendo una metodología de investigación basada en el diseño (DBR), se han realizado estudios en aulas y en MOOCs para evaluar los efectos de las intervenciones de LA propuestas y comprender las condi-

ciones para su buena implementación. Los resultados de la evaluación realizada en el contexto del aula arrojan luz sobre cómo los profesores interpretan los datos de LA y cómo actúan en consecuencia en situaciones auténticas de aprendizaje colaborativo. En el contexto de la educación a distancia, las intervenciones propuestas fueron fundamentales para mantener flujos continuos de colaboración. La tesis docotral describe los beneficios prácticos y las limitaciones a la hora de implementar soluciones de LA en entornos reales, así como las direcciones de investigación futuras.

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Chapter 1

INTRODUCTION

This chapter provides an overview of the research conducted in this dissertation. First, we introduce the dissertation's general context. Second, we provide the dissertation objectives and the design-based research (DBR) methodology followed to achieve the defined objectives. Next, we summarise the overall contributions of the dissertation and of the evaluation studies conducted in naturalistic learning environments. Finally, we state the primary limitations of our work, the conclusions we derived and further research directions. The chapter concludes with an outline of the dissertation.

1.1 Introduction

Collaborative learning is concerned with how coordinated efforts can co-construct and sustain a shared conception of a given problem so the resulting social interactions can lead to learning outcomes (Dillenbourg, 2002; Roschelle & Teasley, 1995). Achieving fruitful learning in collaborative contexts depends on not only activity participation, but also the intensity of the continuous, conscious and productive interactions between peers during collaboration (Kobbe et al., 2007; Roschelle & Teasley, 1995). Collaborative interactions may also be subject to change depending on numerous conditions, such as group composition, task features and communication mechanisms (Dillenbourg, 2002). Understanding the optimal balance between the aforementioned conditions to facilitate effective collaboration is difficult and requires careful planning, coordination, pedagogy and technology (Stahl, Koschmann, & Suthers, 2006).

In the field of technology-enhanced learning (TEL), **computer-supported collaborative learning (CSCL)** brings computer support to peer interactions and serves to realise the benefits of collaboration (Roschelle & Teasley, 1995). In CSCL, the potential to connect peers provides exciting and innovative avenues for productive social interactions (Stahl et al., 2006). Thanks to technologically mediated peer interactions, **CSCL is possible across different contexts and scales**: synchronously at small scales within traditional face-to-face classroom learning contexts, and asynchronously at large scales in distance learning contexts, such as in massive open online courses (MOOCs) (Stahl et al., 2006). Understanding how social interactions occur at different scales in different spaces is challenging, but understanding how students participate in group learning activities and maintain productive interactions is critical to achieve learning gains and benefit from collaboration (Soller, Martınez, Jermann, & Muehlenbrock, 2005).

In CSCL, group learning can be structured pre-emptively using **collaboration scripts** (Dillenbourg, 2002). By proposing an activity sequence and allocating roles to students with specific duties and responsibilities, scripts aim to trigger certain types of beneficial collaborative learning interactions between students (Kobbe et al., 2007). Several studies have reported the effectiveness of using scripts to achieve productive learning outcomes in collaboration (Rummel & Spada, 2005; Radkowitsch, Vogel, & Fischer, 2020).

Macro scripts and micro scripts differ based on the granularity of their prescribed actions (Dillenbourg & Hong, 2008; Kobbe et al., 2007). **Micro scripts** propose strategies to scaffold learning, often at the individual student level, e.g., by using question prompts and sentence starters. Conversely, **macro scripts** describe general learning flows and emphasize the regulatory requirements of collaboration (Hernández-Leo, Villasclaras-Fernández, Asensio-Pérez, Dimitriadis, & Symeon, 2006; Kobbe et al., 2007).

An example of a macro script is the ArgueGraph script. As the name implies, this script provides a structure for collaboration that favours argumentation among peers. The activity sequence of the ArgueGraph script consists of four phases: the survey phase, the conflict phase, the elaboration phase and the reflection phase (Kobbe et al., 2007). Within the script, collaboration starts when students provide individual answers to a multiple-choice questionnaire and provide arguments for their answers *(survey phase)*. A graph is then generated that positions students based on the dissimilarity of their responses. The teacher or system can then formulate groups (usually pairs) such that the dissimilarity between students' answers are maximised *(conflict phase)*. In these groups, students answer the same questionnaires together and provide argumentation for their choices. Teachers can then conduct a debriefing session to account for the different arguments proposed at the individual and group levels, relating them all to the course material *(elaboration phase)*. At the end of the activity, students are asked to synthesise all arguments collected throughout the script while considering the theoretical framework introduced by the teacher *(reflection phase)*. Micro script features, particularly in terms of dialogue models, can also be introduced within different ArgueGraph script phases to scaffold learners with detailed instructions, e.g., question prompts that help students build their arguments.

Collaborative learning flow patterns (CLFPs) are examples of structures for macro scripts and refer to broadly accepted expert practices (Hernández-Leo et al., 2005). CLFPs can also be described as templates that capture expert teaching practices in achieving educational objectives during CSCL situations (Hernández-Leo et al., 2006). These readily available templates can be used by novice teachers to structure collaboration; CLFPs are thus efficient, as they eliminate the need for teachers to design their own activities from scratch (Hernández-Leo et al., 2006). Some of the well-known examples of CLFPs include Pyramid, Jigsaw, Think-Pair-Share (TPS) and Thinking Aloud Pair Problem Solving (TAPPS) (Hernández-Leo et al., 2006).

The collaborative structures within CLFPs are shaped by the pedagogical rationale and constraints defined by CLFPs themselves (Manathunga & Hernández-Leo, 2018). For instance, the **Pyramid CLFP** helps groups reach a consensus following a sequence of phases that follow one another in a pyramid structure (Hernández-Leo et al., 2006). The pattern integrates activities occurring at multiple social planes, i.e., individual, group and class-wide levels, as described below. First, learners solve a given problem individually. Then they join small groups, usually in pairs, to share their solutions and agree on common solutions before formulating increasingly larger groups as the flow advances. The Pyramid CLFP thus provides opportunities for learners to share solutions, discuss them with peers and reflect on each other's ideas. To attain fruitful collaboration, it is necessary for each individual to contribute to and participate in the consensus-building process in several phases of the pyramid structure from beginning to end. Jigsaw is another example of a CLFP that provides a structure in which each student works on a given sub-problem individually. Students who worked on the same sub-problem are then grouped, thereby forming 'expert' groups in which individuals share ideas and resolve doubts related to the allocated sub-problem to become experts on that topic. Later, Jigsaw groups are formulated such that each group consists of at least one group member from each expert group. Within Jigsaw groups, the expertise of all members is used to come up with a collaborative solution to the given problem (see Appendix A).

On the one hand, the aforementioned scripts share commonalities at a macro level. Consider the ArgueGraph script and the Pyramid script. A common feature of both scripts is the integration of activities occurring at individual, group and class levels. On the other hand, differences can be found in the scripts' design rationales. The ArgueGraph script aims to generate conflicts first and then engage students in resolving them (Kobbe et al., 2007), while the Pyramid script helps learners resolve complex problems (which do not usually have a specific solution) and to reach a consensus in increasingly large group structures (Hernández-Leo et al., 2006). That said, CLFPs can be combined to formulate CLFP hierarchies (Hernández-Leo et al., 2006). For instance, to favour argumentation, the conflict phase of the ArgueGraph script can be used as team-forming criteria within the group formation phases of the Pyramid script.

Software tools and techniques have been implemented to support teachers in conceptualising, designing and deploying collaborative learning activities. Web Collage is one such online tool that enables the configuration and implementation of several CLFPs in a virtual learning environment (Villasclaras-Fernández, Hernández-Leo, Asensio-Pérez, & Dimitriadis, 2013). FROG (Fabricating and Running Orchestration Graphs) is another platform that facilitates the design, execution and monitoring of activity designs (Håklev, Faucon, Olsen, & Dillenbourg, 2019). (Harrer, Malzahn, & Wichmann, 2008) proposed the *remote control approach*, an architecture for integrating and controlling existing collaborative learning applications by humans or pedagogical agents. In this dissertation, **PyramidApp**, a tool developed by the TIDE research group, was used to design and deploy collaborative learning activities in both classroom and distance learning contexts (Manathunga & Hernández-Leo, 2018). The tool was developed using the macro-script structure employed by the Pyramid CLFP (Manathunga & Hernández-Leo, 2018). We chose this tool not only given our familiarity with and access to the related code, but because both the Pyramid CLFP and its implementation in PyramidApp is complex enough in its scripting mechanisms and enactment challenges to approach our research questions. The following paragraph provides details of the tool.

PyramidApp is a web-based tool that provides an activity design space for teachers and an enactment space for students. The tool's activity design space is built into the Integrated Learning Design Environment (ILDE) (Hernández-Leo et al., 2018). When designing a Pyramid activity, teachers must input questions to be answered by the students and configure the following parameters: 1) class size, 2) group size, 3) the number of Pyramid levels, 4) minimum number of students per pyramid, 5) duration for answer submission and 6) duration for collaboration at the group levels. Upon finishing the activity design, teachers can generate a public URL to the activity that can be shared with students for activity enactment. Figure 1.1 shows the activity authoring graphical user interface (GUI) of the PyramidApp (Appendix B provides an overview of how teachers used PyramidApp to deploy collaborative learning activities in their classrooms).

In PyramidApp, students are guided in collaboration across a number of phases (Manathunga & Hernández-Leo, 2018). First, within the individual answer submission phase, students are expected to submit answers to problems individually. At the end of this phase, students are allocated into small groups and later into larger random groups following a pyramid structure. Within the tool, collaboration between students at group levels are facilitated using a voting mechanism and an integrated chat system (see Figure 1.2). At each group level, students are shown the answers to a given problem as suggested by group members. Each answer can be voted individually so that the best answer is promoted to the next pyramid level for further evaluation. At the end of the activity, students are presented with top-rated answers, either for their own reflection or to be debriefed by teachers. PyramidApp provides a collaborative learning space in which each individual student can actively contribute to a given task, be exposed to their peers' contributions and reflect upon and contrast different contributions across a number of group phases, including small group and large group levels. The pyramid pattern promotes individual accountability and positive interdependence among students.

CLFPs provide useful and interesting pedagogical rationale for deploying structured collaboration in both classroom and distance learning contexts. Within the **classroom learning context**, the implementation of scripted CSCL scenarios helps learners achieve fruitful learning outcomes by providing guidance and structure, creating opportunities to share knowledge and encouraging productive argumentation (Kobbe et al., 2007). Computer-supported tools and techniques can provide a range of technological possibilities for teachers to implement scripted collaborative learning situations repeatedly (Kobbe et al., 2007).

In the **distance learning context**, MOOCs are growing in popularity and seek to promote equity in education, enhancing access to learning resources from prestigious educational institutes to a wider audience of learners regardless of social, economic and geographic boundaries (Deng, Benckendorff, & Gannaway, 2019; Littlejohn & Hood, 2018). MOOCs

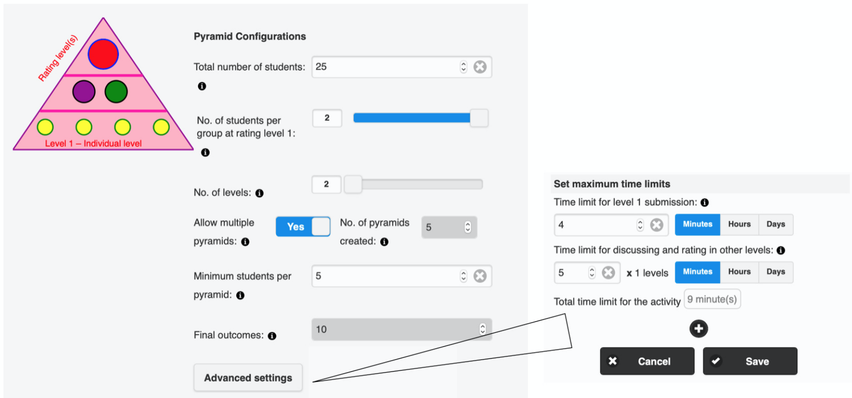

Figure 1.1: Activity authoring GUI of the PyramidApp.

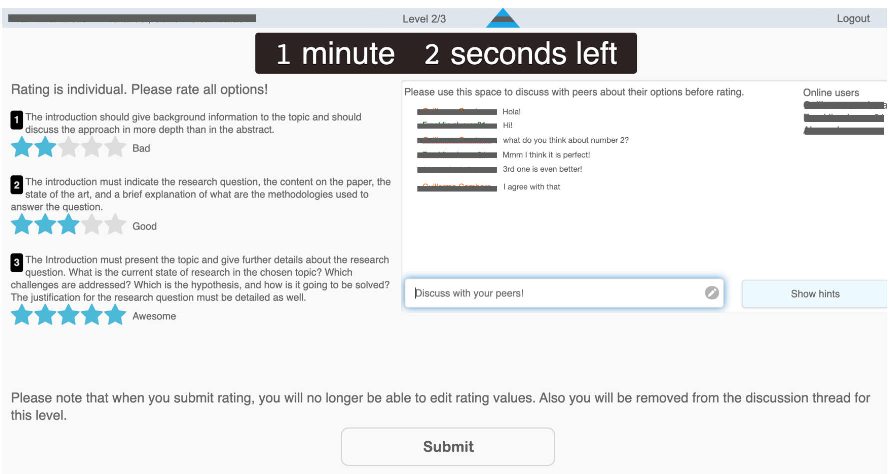

Figure 1.2: GUI of the PyramidApp, voting space (left), discussion space (right).

provide spaces to innovate in educational activities, as well as in teaching and learning practices (Zawacki-Richter, Bozkurt, Alturki, & Aldraiweesh, 2018). Implementing social learning activities in MOOCs can bring together diverse student populations to share thoughts and ideas and solve problems collaboratively (Zawacki-Richter et al., 2018). The deployment of structured collaborative learning activities that follow the pedagogical rationale of CLFPs can create impactful collaborative learning opportunities for MOOC participants (Manathunga, Hernández-Leo, & Sharples, 2017; Hecking, Chounta, & Hoppe, 2017). The existing social learning spaces of MOOCs, such as forum threads, do not provide adequate opportunities to harness the social learning benefits of structured collaboration. Instead, they have been shown to have potentially negative effects on learners, e.g., decreased engagement and motivation (Caballé & Conesa, 2018).

Monitoring group dynamics to detect where students face problems and propose supporting strategies/interventions to overcome those problems is considered in the concept of **adaptive collaboration support**. In the context of CSCL, adaptive scripted collaboration has been defined as the 'idea of tailoring the support offered by the scripts during the run time according to the characteristics of the individuals, groups and the learning situations' (Demetriadis & Karakostas, 2008). Adaptive collaboration support aims to enhance the pedagogical effectiveness of scripts and has been shown to create positive effects on student learning (Magnisalis, Demetriadis, & Karakostas, 2011). Adaptive collaboration support can be offered in different forms. For instance, collaborative groups can be formulated based on individual student attributes, e.g., individual preferences and domain knowledge, (Magnisalis et al., 2011) to create beneficial initial conditions (Dillenbourg, 1999). Adaptive support can also be provided in the form of peer interaction support. In peer interaction support, systems monitor collaboration and take different actions to encourage student participation and the acquisition of collaborative learning skills, thus creating opportunities for meaningful collaboration (Magnisalis et al., 2011; Evans, Davis, & Wobbrock, 2019).

For instance, software agent technologies can be used to provide peer interaction support in which the agents analyse group behaviours by detecting deviations as compared to an ideal scenario (Caballé & Conesa, 2018). The detected deviations are then used to trigger agent interventions. Different types of agents, e.g., conversational agents and teachable agents, can be employed by collaborative learning systems (Kumar, Rosé, Wang, Joshi, & Robinson, 2007; Biswas, Jeong, Kinnebrew, Sulcer, & Roscoe, 2010). The agents can be designed to remediate problem in the learning process, including off-topic conversations, passive student attitudes and learning difficulties (Vizcaíno, 2005). An adaptation mechanism can be activated automatically, e.g., using intelligent agents, (Kumar et al., 2007) or semi-automatically, e.g., by notifying teachers when action is required.

Learning Analytics (LA) constitute an emerging research area that supports the implementation of adaptive learning technologies. LA is defined as the 'measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs' (Siemens & Gašević, 2012). LA is often referred to as a *bricolage* field (Gašević, Dawson, & Siemens, 2015) influenced by a wide range of disciplines, including, but not limited to, the learning sciences, machine learning, data mining, information visualisation and psychology (Sclater, Peasgood, & Mullan, 2016).

With the increased digitisation of education, educational institutes now collect data containing rich information about how learning occurs in different learning spaces (Mangaroska & Giannakos, 2019; Wise, Zhao, & Hausknecht, 2013). Using different LA techniques, the analysis of these digital traces (log data) can support well-informed and data-driven decisions to propose adaptive interventions to enhance learning (Gašević et al., 2015). LA draws on a number of analytics mechanisms that can be used to analyse data for many purposes. For instance, machine learning techniques, such as predictive analytics, can be used to predict at-risk students and help them improve retention (Arnold & Pistilli, 2012). Social network analytics and discourse analysis techniques can be used to understand behavioural patterns within social networks and detect misunderstandings in online discussions (Poquet, Jovanovic, & Dawson, 2020). As LA intervention tools, intelligent agent technologies can be used to analyse group dynamics within CSCL environments to trigger productive peer interactions (Caballé & Conesa, 2018).

On the one hand, LA can heighten students' awareness of their own learning outcomes and regulate their progress (Arnold & Pistilli, 2012). Providing information to students about their own learning patterns can help them comprehend their successes and deficiencies alike, as in knowledge retention or course failure (Arnold & Pistilli, 2012; Sclater et al., 2016). Despite the student learning benefits of LA, the constant collection and analysis of learner data has raised ethical issues and privacy concerns. Transparency about the purpose of data collection and analysis, the anonymisation procedure and data sharing terms and conditions might remove barriers and help learners actively engage with LA services (Tsai, Whitelock-Wainwright, & Gašević, 2020).

On the other hand, LA provides opportunities to enhance teaching practices. For instance, LA can facilitate teachers to make informed decisions and provide personalised and proactive feedback to students by 'closing the loop', thereby improving the teaching and learning processes (Siemens & de Baker, 2012; Clow, 2012; Gašević et al., 2015). Moreover, by aligning LA with learning designs and by identifying the learning patterns to be observed in the data using different analytics beforehand, e.g., *checkpoint* and *process analytics*, and visualisations, e.g., *exploratory* and *explanatory* visualisations, teachers can discern how learning unfolds with reference to pedagogical intentions and goals dictated by the learning design, which encourages pedagogical action and intervention (Lockyer, Heathcote, & Dawson, 2013; Echeverria et al., 2018; Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015; Hernández-Leo, Martinez-Maldonado, Pardo, Muñoz-Cristóbal, & Rodríguez-Triana, 2019).

Because the ultimate goal of analysing learner trace data is to produce actionable knowledge that can facilitate student learning, the **actionability of LA** has garnered attention recently (Gašević et al., 2015). The term 'actionable analytics' can be understood as analytics concerned with the potential for practical action rather than theoretical description or mere reporting (Cooper, 2012). In the context of CSCL, the actionable knowledge that can be produced using LA can facilitate teachers in regulating collaborative learning activities in real time.

In TEL, the **orchestration** metaphor conveys the idea of managing real-time learning activities in multi-constrained learning situations (Dillenbourg & Jermann, 2010). Unlike approaches concerned with facilitating the design of favourable learning conditions, orchestration is concerned with activity regulation, which becomes important in real-time interactions (Dillenbourg & Jermann, 2010; Soller et al., 2005). The deviations between actual and targeted interactions, which often result in challenging group work and other constraints naturally arise from learning environments (such as curriculum, assessment, time, energy, space and safety constraints) demand regulated collaboration and space for relaxed script constraints on the fly (Dillenbourg & Tchounikine, 2007; Dillenbourg & Jermann, 2010; Pérez-Sanagustín, Burgos, Hernández-Leo, & Blat, 2011).

Although structuring and orchestrating collaboration is essential to create fruitful learning situations, limited research has studied the orchestration challenges related to collaborative learning situations scripted according to CLFPs in authentic educational contexts at various scales. While flexible orchestration mechanisms are often regarded as a way of addressing orchestration issues in collaboration, studies that focus on the application of such flexible strategies in naturalistic scripted collaborative learning situations are scarce (Manathunga & Hernández-Leo, 2019).

Previous studies have shown that in classroom contexts, teachers often face challenges in orchestrating CSCL activities (van Leeuwen, Janssen, Erkens, & Brekelmans, 2014; Martínez Maldonado, Kay, Yacef, Edbauer, & Dimitriadis, 2013). Despite the number of existing tools and technologies to support teachers in orchestrating collaboration (van Leeuwen & Rummel, 2019), such as teacher-facing LA dashboards, how teachers decode the information presented within such tools to take relevant pedagogical actions in authentic contexts is not yet fully understood (Wise & Jung, 2019; Echeverria et al., 2018); moreover, the regulatory requirements associated with implementing Pyramid pattern-based CSCL in classroom learning contexts have not yet been studied in detail.

As described in (Dillenbourg, 2013), the pedagogical flavour of orchestration is concerned with empowering practitioners in their classroom practice. Recent research has shown that teachers are not adequately facilitated to handle orchestration issues and support groups in naturalistic collaborative learning situations (Lawrence & Mercier, 2019; Martinez-Maldonado et al., 2020). Orchestration technology that disregards teachers' pedagogical intentions, goals and needs have been criticised for introducing an additional orchestration load for teachers instead of supporting and simplifying activity regulation (Sharples, 2013).

Previous research has provided evidence to suggest that adaptive support systems enhance collaboration on a small scale (Kumar & Rose, 2011; Evans et al., 2019; H.-C. Wang, Rosé, & Chang, 2011). However, when considering CSCL activities deployed at different scales, it is difficult to postulate that scripting and regulation mechanisms that work in conventional classroom settings will produce the same effects when deployed at a large scale, e.g., within a MOOC, given the many differences between the two learning contexts (Fidalgo-Blanco, Sein-Echaluce, & García-Peñalvo, 2015). Appropriate script adaptation mechanisms, close monitoring and guidance that support dynamic learner behaviours in MOOCs may help realise the benefits of scripted CSCL activities in large collaborative learning spaces. Various real-time script adaptations and activity regulation requirements in CSCL activities deployed in naturalistic settings can influence collaboration at different scales. Although a number of research studies have used LA to study how students' learning engagement in MOOCs varies across different dimensions (Hecking et al., 2017; Poquet et al., 2020), limited studies have examined structured collaboration in MOOCs to assess group dynamics and participation rates within such collaborative learning spaces, and few propose adaptive support and regulation mechanisms (Manathunga & Hernández-Leo, 2019). This highlights the need to study and identify appropriate orchestration and adaptation mechanisms that could facilitate group learning in MOOCs.

On the one hand, the multifaceted nature, flows of information across diverse learning spaces at different scales (Dillenbourg, 2013) and interplay among a number of different elements, particularly the *activities* that orchestration entails, [the] *actors* that perform these activities and [the] *background* that shapes the way orchestration is performed (Prieto, Dimitriadis, Asensio-Pérez, & Looi, 2015), all complicate the notion of orchestration. On the other hand, LA can be used to provide proper technological tooling, infrastructure and support to orchestrate collaboration not only in physical and digital learning environments, but also in cross-context (across-spaces) learning situations. Proposing suitable LA interventions that support the adaptive orchestration of CSCL at different scales becomes a challenging yet intriguing task that requires consideration of the aforementioned aspects.

This opens up a variety of interesting research questions and opportunities for innovative research to address diverse challenges related to scripted CSCL. To this end, in this dissertation, we explore how to provide LA support for orchestrating scripted CSCL activities. Accordingly, the central research question is: *'How can LA support orchestration mechanisms for scripted CSCL?'*

1.2 Dissertation Objectives

Given the aforementioned research context and considering the central research question, we have defined three dissertation objectives.

1. [**OBJ_1**] **To study the orchestration challenges of scripted collaboration in distance and classroom learning contexts**

   In this dissertation, we focus on scripted collaborative learning activities. A tool called *PyramidApp* (see section 1.1) was used to deploy Pyramid pattern-based CSCL activities in authentic classroom and distance learning contexts (Manathunga & Hernández-Leo, 2018). As previously mentioned, our decision to use PyramidApp to deploy collaboration was influenced by a number of factors. First, this tool implements a particularisation of the Pyramid

CLFP that enables deploying collaborative learning scenarios using non-trivial scripting mechanisms in different learning contexts. Second, the tool was developed within the context of a previous PhD thesis in the TIDE research group (Manathunga, 2017), which made it possible for us to access the full application for our research purposes. Third, the tool provides scalability features, which act as a 'means of elastically accommodating growing numbers of learners while being pedagogically effective' (Manathunga, 2017); such features create an opportunity to deploy scalable social learning activities at different scales.

As explored in the above-mentioned PhD dissertation, it has been shown that the technological infrastructure provided by the PyramidApp tool can be used to deploy scalable Pyramid pattern-based CSCL activities. However, the orchestration challenges teachers face when regulating Pyramid pattern-based CSCL activities in classroom learning contexts, in addition to the variance of peer interactions and participation in collaborative PyramidApp learning activities at various scales, have not been studied in detail. Analysis of log data collected from the PyramidApp tool, observations from real-world learning scenarios concerned with teacher and student behaviours when using the tool and interviews with different stakeholder groups (such as teachers, students and researchers who have previously used it) can reveal the orchestration challenges associated with implementing Pyramid pattern-based CSCL activities in classroom and distance learning contexts. Studying the orchestration challenges associated with this specific scripted collaboration scenario creates opportunities to propose appropriate LA interventions that enhance peer interactions and productivity within CSCL activities deployed at different scales.

2. [**OBJ_2**] **To propose LA interventions to orchestrate scripted collaboration in the distance learning context**

   Given the limited innovative pedagogical practices adopted in MOOCs, growing research interest in incorporating social learning opportunities into MOOCs has recently been observed (Zawacki-Richter et al., 2018; Caballé & Conesa, 2018). Studies have shown that since learning is often solitary within such distance learning environments, students value the incorporation of peer interaction activities into MOOCs (Caballé & Conesa, 2018; Brinton et al., 2014; Deng et al., 2019). Coursera's student meetups and learning hubs, as well as the content-wide and course-wide cohorts introduced on the edX platform, are examples of such initiatives (Manathunga et al., 2017). It has been also shown that the deployment of scripted collaborative learning activities in MOOCs can be beneficial; collaboration within such spaces is essentially pre-structured and guided, which can facilitate positive social learning atmospheres (Manathunga et al., 2017).

Despite the benefits that such social learning opportunities may create, engaging learners in fruitful social learning activities in MOOCs is challenging for various reasons. For instance, the asynchronous nature of collaboration, lack of educator influence and differences in learners' interests, expectations, attitudes, goals and motivations, may affect continuous participation in social learning activities (Fidalgo-Blanco et al., 2015; Hecking et al., 2017; Ferguson & Clow, 2015; Poquet et al., 2020). However, sufficient student participation is required to sustain the meaningful flow of collaborative learning activities and for social learning activities to be productive (Rosé & Ferschke, 2016). Consider the deployment of Pyramid pattern-based scripted CSCL activities in MOOCs. The pattern entails a number of phases that occur consecutively, and failure to maintain continuous activity participation in different phases of the script adversely affects meaningful activity progression. For instance, inactive groups may delay the progress of active groups in reaching a consensus, resulting in unsuccessful learning experiences. Achieving success within scripted collaborative learning situations relies heavily on students' active and continuous participation throughout all script phases. Moreover, the learning design and underlying technology used to implement such learning activities may also impact student participation in such activities (Daradoumis, Bassi, Xhafa, & Caballé, 2013).

Several studies have shown that the pedagogical effectiveness of MOOCs can be improved by incorporating adaptive and intelligent techniques into course activities (Sonwalkar, 2013; Ferschke et al., 2015). LA can be used to model learners' behaviours in MOOCs and to propose adaptive and intelligent techniques that can help students achieve course objectives. Within the context of collaborative learning, techniques like adaptive group formation strategies that tailor group formation according to activity participation or agent techniques that support peer interaction (e.g., pedagogical and conversational agents that monitor behaviours, analyse information and engage students in collaborative learning activities) are expected to boost student participation in MOOC group learning activities and minimise attrition (Bassi, Daradoumis, Xhafa, Caballé, & Sula, 2014; Caballé & Conesa, 2018). However, the implementation of collaborative learning spaces alongside adaptive support and orchestration services in MOOCs is an emerging area of research (Karakostas, Nikolaidis, Demetriadis, Vrochidis, & Kompatsiaris, 2020), and few such technologies have been deployed and studied for their impact within real MOOC learning contexts (Karakostas et al., 2020; Rosé & Ferschke, 2016). A lack of focus on implementing CSCL activities scripted according to CLFPs has been observed.

To this end, in the second objective of the dissertation we focus on proposing and evaluating the application of carefully designed LA-informed interventions to facilitate and promote participation and to regulate Pyramid pattern-based scripted CSCL flows in MOOC learning contexts.

3. [**OBJ_3**] **To propose LA interventions to orchestrate scripted collaboration in the classroom learning context**

   The use of LA to model and visualise student participation in CSCL activities is equally important to consider in the classroom learning context. On the one hand, as described in OBJ_2, adaptive group formation strategies that model and formulate groups adhering to participant profiles may create opportunities to deploy fruitful collaborative learning activities not only in MOOCs, but also in classroom learning contexts. On the other hand, access to summarised information, e.g., visualisations, that provide glimpses of student participation rates can help teachers manage classroom collaboration.

In the context of scripted CSCL situations, monitoring and regulating collaboration becomes challenging because teachers must divide their attention across different social planes (Dillenbourg, 2015). For instance, when a collaborative learning script like the Pyramid CLFP is deployed, multiple groups advance activity flow at different degrees and develop different solutions. While a given activity may only last for a few minutes, a large amount of data about the students' participation in the collaborative activity is created. The manual rapid capture and real-time processing of this information by teachers, which is intended to identify potential problems in groups, requires the constant distribution of their attention across different social planes (i.e., individuals, groups, and the class as a whole). Without the proper technological supports and tools, such a task is challenging and oftentimes infeasible. LA can support teachers in monitoring collaboration by summarising relevant information about students' activity participation, script progression and other pertinent data. It can also elucidate the required interventions, e.g., on-the-fly adaptations of script parameters and assistance for low-performing groups (van Leeuwen, Rummel, & Van Gog, 2019; Rodríguez-Triana et al., 2015; Martínez Maldonado et al., 2013).

Recently, a heightened research interest in teacher-facing dashboards as tools for teachers to orchestrate collaboration has been observed (Martinez-Maldonado, 2019; Do-Lenh, Jermann, Legge, Zufferey, & Dillenbourg, 2012; Charleer, Moere, Klerkx, Verbert, & De Laet, 2018; Gutiérrez et al., 2020; Ez-Zaouia, Tabard, &

Lavoué, 2020; Wise & Jung, 2019). Despite the increased number of research attempts to deploy LA dashboards for teachers, recent reviews conducted in the field have demonstrated a number of limitations associated with said research. For instance, the lack of involvement of end users in the design process, to capture needs and expectations that often creates disparity between users and designers, a lack of focus on employing evaluation studies in authentic situations and a lack of grounding in established learning theories are to name a few (Schwendimann et al., 2017; Prieto, Rodríguez-Triana, Martínez-Maldonado, Dimitriadis, & Gašević, 2019; Echeverria et al., 2018; Wiley, Dimitriadis, Bradford, & Linn, 2020). Moreover, detailed analyses of how teachers use LA dashboards to make sense of the information presented and subsequently enact relevant pedagogy in authentic contexts have not been fully explored (Martinez-Maldonado, 2019; Wise & Jung, 2019).

Understanding how teachers interpret information on LA dashboards and how they translate their knowledge into actions considering the epistemic and social aspects of authentic collaborative learning situations can provide insight towards the affordances of LA dashboards in teaching practice (Martinez-Maldonado, 2019).

The gap between the interesting and actionable analytics that inform teaching practices is relatively under-explored, but bridging this gap can help teachers incorporate LA into their practice (Wise & Jung, 2019). Engaging teachers in the design process through co-design sessions to identify their technical requirements and support needs (Holstein, McLaren, & Aleven, 2017; Soller et al., 2005) can facilitate the creation of tools that cater to teacher needs while considering their cognitive loads. Finally, understanding the relationship between teachers' pedagogical actions and students' CSCL participation could realise beneficial interventions. The third objective of the thesis concerns the aforementioned aspects.

Figure 1.3 presents the overview of the research context, research question and objectives of the dissertation.

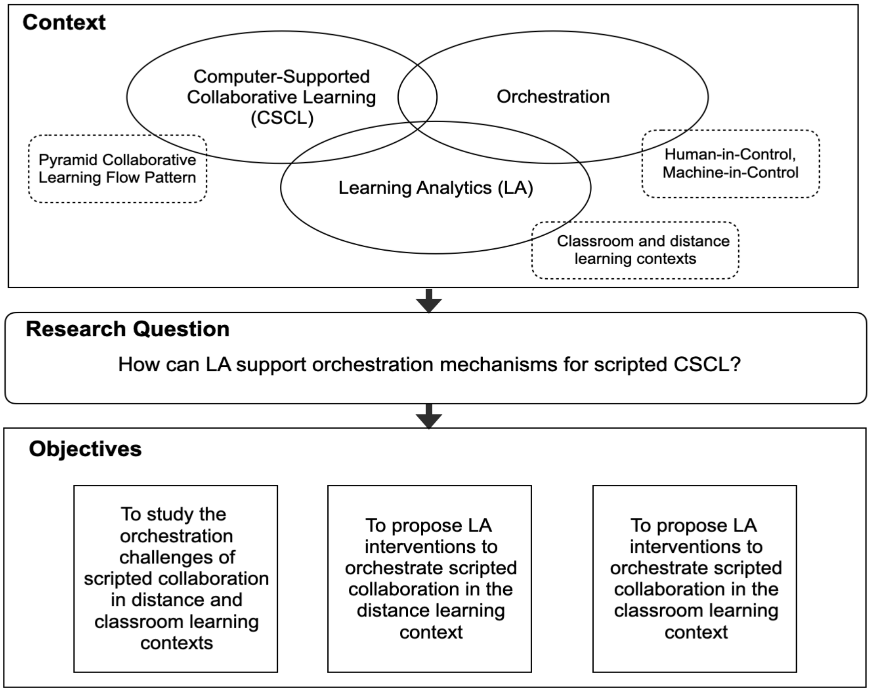

Figure 1.3: An overview of the research context, global research question and specific research objectives of the dissertation.

1.3 Research Methodology

This dissertation focuses on studying orchestration challenges and proposes LA interventions to orchestrate scripted collaboration in classroom and distance learning contexts. Given that we focus on investigating the role of technology in a naturalistic educational context using progressive refinement strategies aimed at building connections between research and real-world educational problems, DBR methodology was selected as an appropriate research methodology (Collins, 1992; Amiel & Reeves, 2008). DBR has been acknowledged as a pragmatic methodology in the learning sciences and is widely used in TEL environments in particular (Barab & Squire, 2004; F. Wang & Hannafin, 2005).

DBR is defined as 'a series of approaches, with the intent of producing new theories, artifacts and practices that account for and potentially impact learning and teaching in naturalistic settings' (Barab & Squire, 2004). DBR accounts for the unpredictability and constraints of real-world contexts and emphasises the importance of conducting educational research in naturalistic learning environments, given that the detachment of research from practice would obfuscate learning issues and the potential success of educational interventions (Collective, 2003). Unlike in traditional psychological methods in which research participants are considered 'subjects', DBR instead recognises 'subjects' as 'co-participants', for instance in collaboration with researchers. This alternate classification encourages research participants to bring their expertise into the research, design and progressive refinement of interventions, the analysis of which fosters educational innovations that can genuinely address participant concerns (Barab & Squire, 2004; F. Wang & Hannafin, 2005).

By linking educational research with participants and real-world problems and by systematically and iteratively refining innovation, DBR facilitates the investigation of innovation adoption proposals in reference to theory, designed artifacts and practices, yielding design principles of practical importance to other designers and generating new theories (after long-term research and a number of design investigations) without limiting the evaluations of existing ones (Amiel & Reeves, 2008; Collective, 2003; Barab & Squire, 2004; F. Wang & Hannafin, 2005). However, as described in (Barab & Squire, 2004) the systemic constraints associated with naturalistic learning contexts, the effects of confounding situational variables challenge the development of DBR theories. Hence, the challenge in DBR is to identify and generate design principles and develop adaptive theories that will likely remain robust and effective even in new local contexts that encompass changing situational variables (Barab & Squire, 2004; F. Wang & Hannafin, 2005).

The emphasis of DBR on the practical impacts of educational research (Anderson & Shattuck, 2012) places DBR on the fourth quadrant of Pasteur's quadrant (Stokes, 1997), within which interventions are constructed and progress is made to understand human learning while solving real-world educational problems. This emphasis leads to the continuous improvement of proposed interventions and innovations in educational technology and makes 'connections to theoretical assertions and claims that transcend the local context' (Barab & Squire, 2004).

DBR acknowledges the importance of collaboration and communication between multiple stakeholders, including but not limited to researchers, practitioners, subject matter experts and designers, to bring educational innovation into practice. The DBR methodology shares similarities with other research methodologies applied in information systems research, such as the design science research methodology, in which the central focus is to create demonstrably practical design innovations (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007).

Figure 1.4 provides a visual representation of the DBR model adopted from (Amiel & Reeves, 2008), which consists of four iterative stages. As shown in Figure 1.4, DBR entails multiple cycles of testing in-situ of the proposed intervention. It starts with the initial analysis of the practical problems within a particular educational context. The assessment of the problem gives rise to the development of the solution(s) informed by theories. The implemented solutions are then evaluated in a series of iterative cycles (design-reflection-design cycles) that improve the design of the proposed solution. The knowledge generated from iterative solution refinement is then reflected upon to further enhance solutions and produce usable knowledge for others in similar research contexts (Amiel & Reeves, 2008).

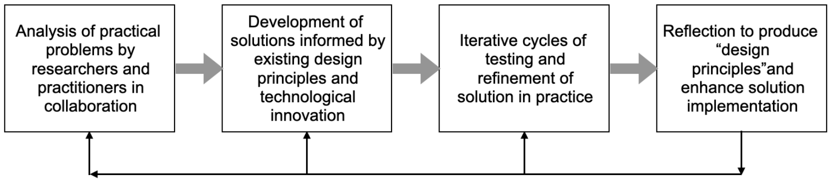

Figure 1.4: Design-Based Research Methodology (Amiel & Reeves, 2008)

(Reimann, 2016) describes that DBR fits naturally into the general learning sciences and LA research, since both DBR and LA shares the goal of addressing real-world educational problems and generating solutions grounded in educational learning theory. The application of LA solutions to solve practical problems in education using LA, as well as the iterative improvement of these solutions to build theories over time, both constitute the variety of progressive refinement proposed within DBR (Reimann, 2016).

In the context of this dissertation, during the analysis phase of each DBR cycle we conducted, we focused on understanding the challenges of scripted collaborative learning at different scales, i.e., classroom and distance learning contexts, to propose LA interventions that address identified orchestration challenges. This gave rise to the formulation of initial research questions that were revised in later iterations of the DBR methodology. We applied the DBR model proposed by (Amiel & Reeves, 2008) described above and conducted three DBR cycles as shown in Figure 1.5, to address the objectives proposed in this dissertation. Table. 1.1 provides an overview of the main research question and the specific research questions addressed within each cycle of the DBR methodology.

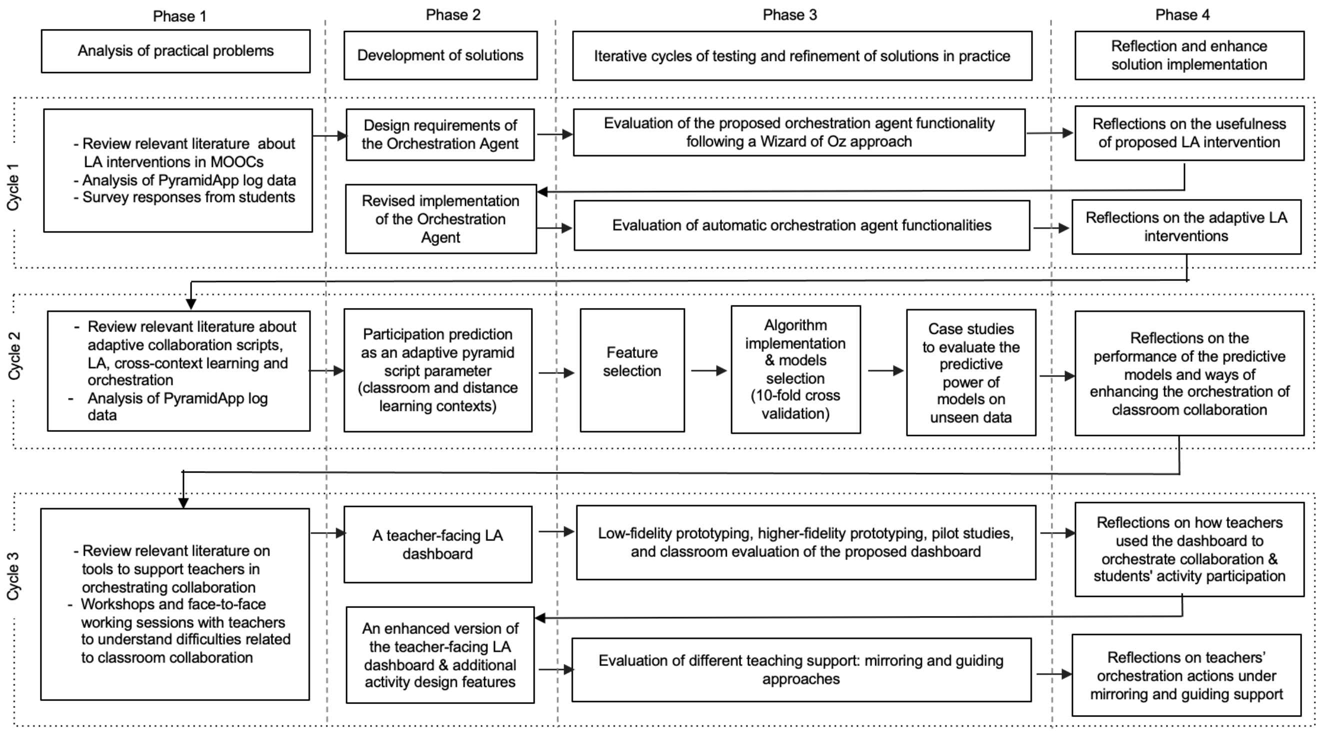

Figure 1.5: Design-Based Research process of the dissertation.

Table 1.1: Research questions addressed in this dissertation.

Main Research Question
How can LA support orchestration mechanisms for scripted CSCL?
Specific Research Questions
[RQ1] What are the challenges in conducting scripted collaborative learning activities at different scales? (related to [OBJ_1]). [RQ1a]: How do individual students' activity participation differences affect Pyramid pattern-based scripted CSCL activities deployed in MOOC contexts? [RQ1b]: What challenges do teachers face in conducting collaborative learning activities in general, and Pyramid pattern-based scripted CSCL activities specifically, in classroom learning contexts?
[RQ2] How can continuous flows of scripted collaboration be sustained? (related to [OBJ_2] and [OBJ_3]). [RQ2a]: How can adaptive intervention strategies be used to sustain collaboration in MOOCs? [RQ2b]: Can participation prediction be used to inform decisions for adaptive collaborative scripts in across-spaces learning situations?
[RQ3] How can technology support teachers in orchestrating scripted classroom collaborative learning situations? (related to [OBJ_3]). [RQ3a]: How did teachers use the dashboard to orchestrate collaboration? [RQ3b]: Do teachers' orchestration actions affect students' participation in activities? [RQ3c]: How do mirroring and guiding supports influence the orchestration actions of the teachers?

In the following paragraphs, we describe the three DBR cycles carried out in this dissertation.

1. **Cycle 1**

   At the inception of the first DBR cycle, within the analysis phase, we focused on eliciting the orchestration challenges accompanied by the scripted collaborative learning activities deployed in MOOCs **(related to [RQ1a])**. To understand these challenges, we conducted an exploratory study in which Pyramid pattern-based CSCL activities were deployed in a MOOC. Log data collected from the PyramidApp was analysed to understand students participation within the scripted collaborative learning space. Students' overall opinions about the activity were collected using an online survey. Related literature has also been reviewed to understand the potential orchestration challenges associated with scripted collaboration in MOOCs and how LA solutions have been proposed to address similar challenges. A mixed-method approach was used to contextualise and triangulate the quantitative and qualitative data collected and to produce study findings related to orchestration challenges.

   The findings of the exploratory study and the work already done in the field suggested that the incorporation of LA interventions, e.g., intelligent agents, into MOOCs can result in added advantages. While such agents can monitor and intervene during collaboration (based on predefined rules) while performing regulatory actions, they can also be discussion partners as conversational agents (Kumar et al., 2007; Tegos, Demetriadis, Papadopoulos, & Weinberger, 2016). The findings of our analysis and the directions proposed in related work led us to design different agent interventions to regulate Pyramid pattern-based collaborative learning flows deployed within MOOCs **(related to [RQ2a])**.

   To this end, we proposed the design of an LA intervention that we referred to as an *orchestration agent* implementing different intervention strategies that adapt to the activity participation differences of students observed within scripted collaboration spaces in MOOCs. We conducted two iterations of testing and refining the orchestration agent's functionalities and features. In the first iteration, the proposed agent functionalities were evaluated in a real MOOC via a Wizard of Oz (WoZ) approach, which is recommended to avoid the high costs associated with actual design requirements for such interventions (Maulsby, Greenberg, & Mander, 1993). In the WoZ approach, the researcher simulated agent functionalities. In the second iteration, a revised implementation of the proposed orchestration agent functionalities was built into the PyramidApp architecture to perform automatic interventions. The revised agent functionalities were later evaluated in another MOOC. Chapter 2 provides details about the work carried out during this cycle.

2. **Cycle 2**

   The reflections and findings of the first DBR cycle showed that not only a fully automatic agent approach, but also the implementation of other LA interventions (such as adaptive group formation policies) facilitate the orchestration of group learning, thereby encouraging fruitful collaboration. Group formation is a central topic in CSCL and is concerned with how to distribute learners into groups to maximise productivity within group learning activities (Tsovaltzi et al., 2019).

   During cycle 2, in the analysis phase, we studied how a group formation strategy that adapts to students' individual degrees of activity may provide an alternative solution for sustaining fruitful collaborative flows in Pyramid scripts in both distance and classroom learning contexts **(related to [RQ2b])**. In each learning context, we collected log data that reflected students' learning activity participation in different learning spaces. Then, for a given student's past history, we attempted to predict whether said student would participate in a future group learning activity using supervised machine learning techniques. We implemented three machine learning classifiers, namely Support Vector Machines (SVMs), Neural Networks

(NNs) and Random Forests (RFs) for prediction purposes. Feature selection and model evaluation was conducted iteratively to obtain high classification accuracy.

The proposed adaptive group formation strategy organised groups such that students predicted to participate in activities were mixed in real time with those not predicted to participate. It was important for this group formation policy to be implemented within the Pyramid script for minimising the number of non-participating groups which would deter collaboration and break the continuous flow of learning.

The findings of the case studies revealed how data collected from across-spaces learning situations can inform the formulation of adaptive collaborative learning groups using predictive analytics and elucidate the practical challenges associated with deploying such LA interventions. Chapter 3 of the dissertation elaborates on the work carried out during this cycle.

3. **Cycle 3**

   On the one hand, the findings of the adaptive group formation strategy proposed in the second DBR cycle provided insight about the requirements of additional monitoring and collaborative activity regulation capabilities for teachers in classrooms. On the other hand, teacher-training workshops and face-to-face working sessions conducted with secondary school and higher education teachers emphasized the importance of enhancing teachers' access to collaboration regulation mechanisms **(related to [RQ1b])**. These requirements led us to design a teacher-facing LA dashboard to facilitate the orchestration of Pyramid pattern-based scripted collaborative learning situations in the classroom learning context within the third DBR cycle.

   The Learning Awareness Tools - User eXperience (LATUX) workflow (Martínez Maldonado et al., 2015) was followed during the design, deployment and evaluation of the proposed dashboard. The

LATUX workflow is an iterative workflow that has been specifically proposed for projects looking to design and deploy tools that improve instructors' awareness of students' learning activities in the classroom (Martínez Maldonado et al., 2015). The LATUX workflow comprises the following steps: problem definition, low-fidelity prototyping, higher-fidelity prototyping, pilot studies and classroom use (or validation 'in the wild'). In the following, we describe how these workflow phases were adhered to while accommodating teacher input during the design (Buckingham Shum, Ferguson, & Martinez-Maldonado, 2019)..

First, within the problem identification phase, we explored the difficulties teachers face when conducting collaborative learning activities in classrooms in general and how they might handle problems when conducting PyramidApp-based scripted collaborative learning activities specifically. A literature review also informed a number of limitations associated with current LA dashboard research.

We then designed low-fidelity prototypes to represent the intended design of a teacher-facing dashboard that would provide a technological means for teachers to regulate Pyramid pattern-based scripted collaborative learning situations. Following the LATUX workflow, we then conducted higher-fidelity prototyping, pilot studies and validation studies in naturalistic settings.

We triangulated quantitative and qualitative data collected from the experiments conducted in naturalistic classroom sessions, using mixed methods to interpret how teachers acted upon the dashboard's information **(related to [RQ3a])** and how teachers' orchestration actions affected students' activity participation **(related to [RQ3b])**.

The findings from the first dashboard iteration resulted in an improved version in the second iteration in which not only features and functionalities were improved, but also the activity authoring space of the PyramidApp to configure dashboard elements. The improved dashboard was then used to orchestrate Pyramid scripts in real classroom settings. We evaluated how different types of dashboard support, e.g., mirroring support and guiding support (Soller et al., 2005), informed teachers in taking relevant pedagogical actions **(related to [RQ3c])**. Chapters 4 and 5 of this dissertation provide details about the research cycles and their resulting findings.

Table 1.2 provides an overview of the data collection conducted using different strategies. Mixed-method research (Johnson & Onwuegbuzie, 2004; Creswell, 2014) that incorporates the complementary strengths of quantitative and qualitative research, as well as the triangulation of data, was used in most iterations of the DBR cycles. The data collection instruments used in the cycles varied according to the research questions and experimental designs at hand (F. Wang & Hannafin, 2005).

In Cycle 1, in the MOOC context, we collected quantitative data (e.g., log data) from PyramidApp to analyse individual students' activity participation. This helped us investigate participation differences across the many phases of the Pyramid script. Students' opinions regarding the collaborative learning activities in MOOCs were collected using online surveys. In Cycle 2, we used a quantitative approach as we analysed how the proposed adaptive LA intervention strategies (e.g., agents and predictive analytics for group formation) affected student participation, as well as the accuracy of the prediction models. In Cycle 3, the difficulties teachers faced when conducting collaborative learning sessions in classrooms and how they handled problems were captured via brainstorming sessions and guided questions. During the evaluation studies, we collected both qualitative data (e.g., screen-captured data from the dashboard tablet (audio and video), observation notes, video recordings and post-activity questionnaire responses) and quantitative data (e.g., log data) that reflected teachers' observable behaviours and perceived cognitive load in authentic classroom-based trials. Student participation during the sessions was collected and analysed using log data. A post-activity questionnaire with Likert-scale items was also used to capture students' perceived learning and satisfaction regarding collaboration.

Table 1.2: Main data sources and data collection techniques.

Technique	**Description**	**Purpose**
Questionnaires (Students)	Online questionnaires that include different types of questions: open-ended, closed-ended questions with Likert scale and multiple-choice questions	To understand students' perceptions on the collaborative learning experience and their satisfaction rates with reference to control-experimental groups
System Logs (Students)	Automatic registration of students' interactions with PyramidApp	To identify student participation rates, areas of improvement, and any changes during and after the interventions
Questionnaires (Teachers)	Online questionnaires that include different types of questions: open-ended, closed-ended questions with Likert scale and multiple-choice questions	To understand teachers' expectations of orchestrable technologies, what works and what must be improved upon with respect to LA interventions

Continued on next page

Table 1.2 – *Continued from previous page*

Technique	**Description**	**Purpose**
Brainstorming sessions and interviews (Teachers)	Spoken and written responses about problems teachers face when conducting collaborative learning activities and how to handle them	To understand problems, expectations and perspectives on tools and technologies that can aid teachers in orchestrating collaboration
System Logs (Teachers)	Automatic registration of teachers' interactions with LA dashboards	To capture teachers' actions while using the dashboard and to understand what must be improved
Observations (Teachers)	Notes, screen recordings of the LA dashboard and video recordings of classroom collaboration sessions	To capture teachers' actions during classroom collaborative learning sessions

1.4 Main Contributions

This section provides a summary of the dissertation's main contributions alongside details of the evaluation studies it encompassed. It also provides a list of publications derived from the research carried out for this dissertation and several research projects in which the research is framed.

As mentioned earlier, in this dissertation we focus on scripted CSCL activities deployed at different scales. In the following, we provide an overview of this dissertation and position its contributions considering the elements illustrated in the orchestrating learning analytics (OrLA) conceptual framework: *background, actors* and *activities* (Prieto et al., 2015).

The research *background* lies in the context of CSCL with a focus on providing support for orchestrating scripted collaborative learning activities. We have considered the orchestration challenges associated with scripted collaborative learning activities deployed within two different learning contexts: 1) the classroom learning context and 2) the distance learning context.

In terms of *actors*, we collaborated mainly with researchers and teachers from secondary schools and a public university in Spain. In the distance learning and classroom learning contexts, respectively, students registered for particular MOOCs and in-class learners participated in our CSCL activities voluntarily.

When considering *activities*, the scripted CSCL activities were designed and deployed using PyramidApp (Manathunga & Hernández-Leo, 2018). To address the identified orchestration challenges associated with the specific scripted collaborative learning situations of interest, we proposed different LA interventions. Based on different agents in control of taking orchestration actions, the LA interventions can be described as either 'machine-in-control' or 'human-in-control'. Due to the nature of activity distribution in time and lack of instructor involvement in MOOCs, automatic LA intervention agents took over collaboration regulation and were characterised as machine-in-control, which was more suitable and feasible. In human-in-control intervention, teachers have complete agency to make decisions related to orchestration (*Ethics guidelines for trustworthy AI*, 2019). In the classroom learning context, LA interventions in the form of teacher-facing dashboards supported teachers in regulating collaboration.

The dashboard implemented two different types of support: mirroring and guiding. In mirroring support, the interpretation of information and dashboard use were decided by the teachers without additional guidance, whereas in guiding support teachers were guided to take action via an alert mechanism that flagged critical moments in collaboration. Mirroring support thus scaffolds human-in-control sense-making and orchestration actions, whereas in guiding support, automatic machine-generated alerts suggest orchestration actions and offload teachers' decision-making responsibilities to some extent, all the while amplifying their actionability and respecting their agency. This can be characterised as a hybrid human-machine approach. Another LA intervention, which formulates adaptive collaborative groups using inputs from prediction algorithms (considering students' activity participation observed within across-spaces learning situations) and incorporates them into the Pyramid activity flow, has also been proposed and evaluated in both classroom and MOOC learning settings. This intervention can be positioned under machine-in-control, as it automatically generates group formation policies based on predictions.

The proposed LA interventions were designed to increase *awareness*, support *adaptation* and encourage *management* (Prieto et al., 2015) of scripted collaboration at different scales. Figure 1.6 shows an overview of the proposed LA interventions that characterise the contributions of the dissertation (details are provided in section 1.4.1). Figure 1.7 shows how each contribution is mapped with the objectives of the thesis and the evaluation studies conducted.

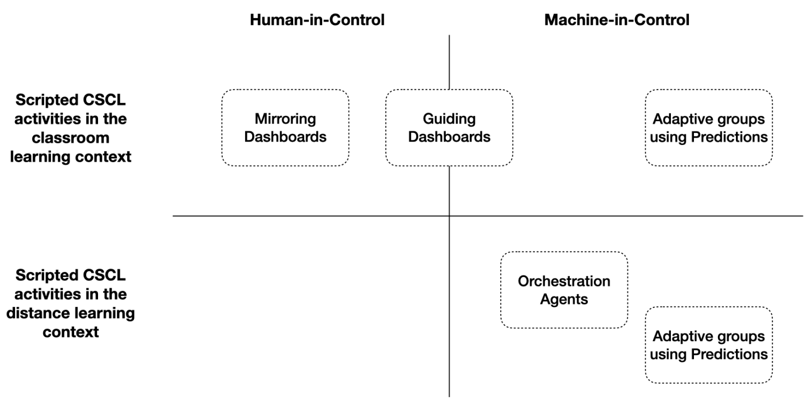

Figure 1.6: An overview of the proposed LA interventions.

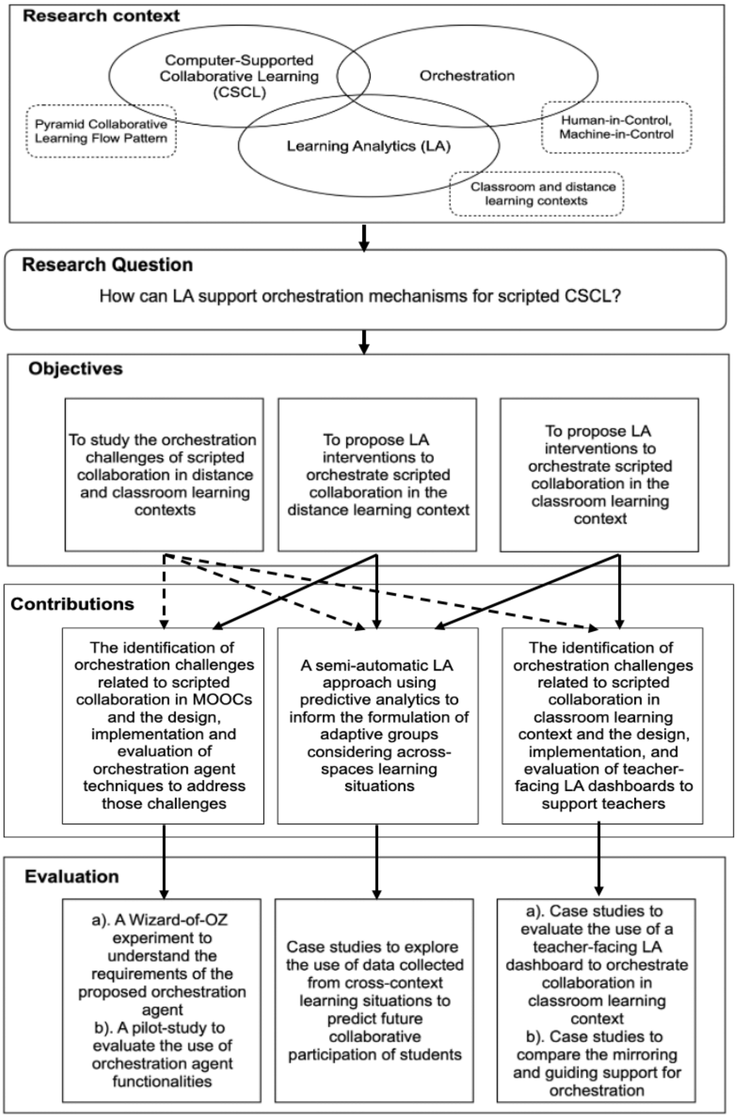

Figure 1.7: Schema of the research context, global research question, specific research objectives, contributions and evaluation studies.

1.4.1 Contributions

1. **The identification of orchestration challenges related to scripted collaboration in MOOCs and the design, implementation and evaluation of orchestration agent techniques to address those challenges**

   Previous studies have shown that incorporating different types of agents, e.g., pedagogical and conversational, facilitate fruitful collaborative learning activities in educational contexts (Bendou, Megder, & Cherkaoui, 2017; Bassi et al., 2014). However, other recent studies have demonstrated that adaptive and intelligent technologies have not yet been fully leveraged within MOOC contexts, and empirical studies on learning and teaching in MOOCs are scarce (Deng et al., 2019; Fauvel & Yu, 2016; Bassi et al., 2014; Rosé & Ferschke, 2016). Moreover, a number of proposals have been made for LA interventions to support social learning opportunities in MOOCs to enhance student discussion (Rosé & Ferschke, 2016), but little attention has been paid to how such technologies can be used to maintain participation along the pedagogical structures of scripts that help students gain productive learning outcomes from activities. Apart from being animated characters or conversational partners, agents can analyse data produced by MOOC platforms to provide intelligent assistance, thereby improving the design, delivery and assessment of collaboration (Bendou et al., 2017; Bassi et al., 2014). To this end, an LA intervention, which we refer to as an *orchestration agent*, to implement different strategies to handle orchestration problems related to scripted CSCL activities in MOOCs is presented.

   a. First Iteration

   A contribution related to orchestration agent interventions, first in Pyramid pattern-based collaborative learning scenarios, was deployed in MOOCs. Log data collected from the PyramidApp tool was analysed to identify how MOOC learner participation varied in different phases of the Pyramid script. The analysis revealed that the overall number of learners who participated in Pyramid activities decreased over several weeks. A detailed analysis at the individual student level showed that some students only submitted individual answers and skipped the group levels in the Pyramid script; others logged into the activities but never participated in subsequent phases of the script. The uncertainty associated with learners' continuous participation along the consecutive Pyramid script phases undermined the pedagogical benefits of the Pyramid CLFP.

Another challenge was identified with respect to rigid script design parameters. In particular, activity duration was seen as a critical determinant of uptake when deploying scripted collaboration in MOOCs. Unnecessarily long durations could result in increased waiting times for activity participants to move to the next level of the script, whereas overly brief durations provide inadequate collaboration time.

Suitable real-time management or orchestration of collaborative learning scenarios were seen vital to implement in MOOCs to create fruitful scripted collaboration spaces by addressing the orchestration challenges identified. To this end, in the first iteration, an architecture of an orchestration agent was designed to diagnose the state of interactions (by comparing the current state of learner interactions within the Pyramid script to a desired state following some added rules) to take remedial actions that could facilitate and advance the script by disregarding inactive participants and providing opportunities for active ones to reach a consensus by the end of the script. The proposed agent interventions included the following: 1) simulating fake student profiles to reach the minimum student count required to initiate a Pyramid activity, 2) automatically presenting model answers (formulated by instructors beforehand during activity design) to groups lacking answers to discuss and vote on and 3) performing automatic voting on behalf of inactive groups.

To understand how the proposed agent mechanisms must be adapted according to different learning designs, we performed evaluation studies that reflected four different learning designs based on defined activity durations: *very rapid, rapid, long* and *very long*. The results of the evaluation studies revealed that the proposed agent intervention was necessary in different phases of the Pyramid scripts, especially within group phases in all four types of learning designs, to maintain uninterrupted yet meaningful flows of collaboration.

b. Second Iteration

A second iteration focused on student participation in discourse during the Pyramid activities and augmented agent interventions by introducing automatic discussion prompts. These prompts were inserted into the PyramidApp discussion space automatically to encourage discussion participation. Two terms describe the different types of roles being built into the proposed agent architecture: simulated students and simulated teachers

The results of the evaluation studies conducted in a MOOC revealed that initiating collaboration via simulated students, which are fake student profiles, was important in the CSCL activities generated at the end of each week of the MOOC. The need for initiation increased in the second week of the course. The simulated teacher interventions to perform automatic rating interventions were also important in the same CSCL activities, but no rating interventions were required in the large group phases because students displayed satisfactory rating participation. MOOC participants also responded to the timed simulated teacher prompts in the chat, although there was variance in the number of participants who responded and the specific prompts they answered. Further, students who responded to the timed prompts in small group collaboration phases were later observed building conversations in the large group phase of the Pyramid activity. Details of the proposed agent architecture, evaluation studies and results are presented in Chapter 2 of the dissertation.

2. **A semi-automatic LA approach using predictive analytics to inform the formulation of adaptive groups considering across-spaces learning situations**

   Technological advances and the rise of online learning platforms have created a plethora of learning opportunities for students, and students now engage in numerous learning activities across diverse learning spaces (Ellis & Goodyear, 2018; Kloos, Hernández-Leo, & Asensio-Pérez, 2012; Martinez-Maldonado et al., 2016). The notion of *across-spaces learning* is used to describe such complex learning situations that go beyond the traditional physical classroom learning opportunities provided by formal educational contexts (Kloos et al., 2012).

   Scenarios implementing CSCL scripts can involve the use of multiple technology-supported learning spaces. These across-spaces scenarios are challenging (Prieto et al., 2017), but they also offer opportunities to use data tracked in different learning spaces to inform script design parameters. However, this is difficult for educators to do because it is time-consuming and requires specialised knowledge (Appendix C of the dissertation also elaborate on the related concepts). It has been shown that the advantages of using data collected from different learning spaces to propose adaptive and personalised LA interventions have not yet been explored (Martinez-Maldonado, Hernández-Leo, & Pardo, 2019) . A key contribution of this dissertation falls under this under-explored territory and proposes a data-driven LA approach that informs the formulation of adaptive collaborative learning groups considering across-spaces learning situations. The proposed group formation strategy employs predictive analytics to model students' future collaborative learning activity participation based on their past individual and collaborative learning behaviours recorded in different learning spaces. Three different supervised machine learning techniques, SVMs, NNs and RFs, were trained and tested for prediction purposes.

Based on the considerably high cross-validation accuracy scores of the trained machine learning models, it was seen that data collected from across-spaces learning scenarios are informative to automatically classify students based on differences in their activity participation. This seems to convey interesting connections that exist across different learning spaces. Such an estimated future activity participation differences of students can inform adaptive group configurations.

Evaluation studies were conducted in authentic learning situations to demonstrate whether the trained classifier outcomes could be used to inform adaptive group configurations in real time. The findings of the case studies, in which trained model outcomes were used to inform adaptive scripts in authentic learning situations, underscore the difficulties in real-world classification problems; for instance, the class imbalance of training data (i.e., large fractions of training data labels were biased to dominant labels) affected the real-time testing of the prediction models, which posed a difficult learning problem. Moreover, the classroom dynamics and timeframes in which the evaluation studies were positioned affected the accuracy of the prediction results. Details of the proposed group formation strategy and evaluation studies conducted are presented in Chapter 3 of the dissertation.

3. **The identification of orchestration challenges related to scripted collaboration in classroom learning contexts and the design, implementation and evaluation of teacher-facing LA dashboards to support teachers**

   The requirements for teachers to observe classroom dynamics, provide additional monitoring and regulate collaborative activity led to the third DBR cycle in which we focused on supporting teachers in orchestrating scripted classroom collaboration.

   a. First Iteration

   Following the iterative LATUX workflow proposed in (Martínez

Maldonado et al., 2015) during the problem identification phase, we conducted brainstorming and face-to-face working sessions with secondary school and higher education teachers to capture problems related to classroom (scripted) collaboration and ascertain their expectations of supportive technologies. Some of the main findings of these studies highlighted the teachers' desires for tools augmenting teacher-initiated actionability.

Select feedback from teachers and a literature review informed the design of low-fidelity prototypes in the following phase of the workflow. The teachers' suggested improvements regarding those prototypes led to the definition of three different types of dashboard controls, namely *timing, flow* and *participation* controls that may facilitate teachers to handle problems during collaborative learning sessions. Next, higher-fidelity prototyping and pilot study phases were developed within which the features and functionalities of the dashboard were further revised.

The results of the evaluation studies indicated that the teachers found the information presented in the dashboard to be useful in gaining awareness of student activity participation, script progression and their own observations. When considering teachers' sense-making actions, it was found that they engaged in *reading data* more often than *explaining patterns*. Considering the pedagogical responses under the experimental conditions, the most frequent actions were *whole-class scaffolding* and *targeted scaffolding*, which indicated that having access to the dashboard did not detract from teachers' attention to the class; instead, it helped them provide useful scaffolds at individual, group and class levels. However, teachers pointed out that receiving a number of warnings indicating a lack of group participation during short durations created situations in which teachers could not decide which groups to attend to, resulting in a *wait-and-see* posture. Regarding the use of dashboard controls, teachers did not often use flow and timing controls to *revise course (learning) design*. Conservative plans in the designs, reluctance to revise designs in real time at run-time and user interface limitations were identified as causes for the aforementioned behaviour. In contrast to the experimental conditions, it was found that under control conditions (in which teachers had no dashboard access), actions related to *explaining patterns, whole-class scaffolding* and *targeted scaffolding* remained low.

Teacher actions related to student activity participation were also evaluated. Log data analysis indicated that students submitted more answers and engaged in more voting and discourse under experimental conditions than control conditions, resulting in higher overall class activity in the former case. More details about this phenomenon, including teachers' suggestions for improving the dashboard user interface and a qualitative interpretation of how teacher actions positively affected student participation, are presented in Chapter 4.

b. Second Iteration

In the second iteration, we introduced design changes to visualised information, the placement of GUI elements and triggered warnings and controls based on suggestions and lessons learnt from the first dashboard iteration. For instance, we introduced a new set of warnings that conveyed critical events related to collaboration: *No Keywords*, *Answer Submission Skipped*, *More time for answer submissions* and *More time for voting submissions*. The PyramidApp authoring features were enhanced to allow teachers to configure keywords and automatic dashboard alerts.

A study of how teachers' pedagogical actions varied using different types of teaching support to orchestrate scripted collaboration, i.e., with no dashboard, with mirroring support and with guiding support, was conducted using mixed methods. An Epistemic Network Analysis (ENA) (Shaffer, Collier, & Ruis, 2016) determined that in the mirroring condition, teachers mainly focused on the epistemic facets of learning activities and missed chances to perform potentially necessary script modifications, e.g., changing the duration of a script phase to provide more time for collaboration when required. In contrast, in the guiding condition, the additional information presented in the form of dashboard warnings increased teachers' awareness of collaboration and led them to take orchestration actions. However, teachers experienced a relatively high cognitive load in the guiding support condition when compared to the mirroring condition. To disentangle the differences of the perceived cognitive load experienced by teachers under experimental conditions, we deconstructed the notion of orchestration load into different facets: *situation evaluation, goal formation* and *action-taking*. We also identified other competing load aspects, such as content-load, that may add to teacher workload during orchestration. More details on the aforementioned aspects are presented in Chapter 5.

In the following, we outline design principles for actionable dashboards to support CLFPs derived from the research:

(a) **Warn teachers of critical events concerned with the epistemic facet related to the learning task but also to the social facet affecting the collaborative learning flow mechanisms:** Enabling the flexible modification of learning scenarios during run-time is a necessary feature of orchestration technology. However, it is not sufficient if the technology does not help teachers initiate informed actions. In our study, teachers mentioned that they missed chances to react to critical events during collaboration due to their real-time concerns about the epistemic and social facets of the learning activities. By generating automatic warnings to advise of critical events, teachers can take advantage of orchestrable technology to provide instant support for students.

(b) **Offer capabilities to customise warnings:** Criteria to generate warnings may depend on teacher expectations and the task at hand. Teachers wanted to access authoring features permitting them to modify criteria for generating warnings.

(c) **Generate action-impact indicators:** Teachers indicated they want to know how their interventions or pedagogical actions impact students; for instance, whether student discussion participation increased following a group message from the instructor.

(d) **Align students' artefacts with teacher expectations:** Teachers want to rapidly evaluate whether student answers align with their expectations. Since Pyramid CLFP tasks can be of different natures and the tasks employed in this study were open-ended, this was a challenging request to support. Providing space for teachers to input keywords they wish to see in students' answers and matching of teacher's expected answers versus students' answers can facilitate a first approach for real-time content evaluation.

(e) **Avoid hidden menus:** Teachers indicated that the dashboard controls placed in a hidden menu resulted in added complexity and usability issues. They wanted all information and dashboard controls to be visible and easily accessible.

(f) **Use instructor vocabulary instead of technical terms:** Teachers requested that the tool employ language closer to their own vocabulary, as technical terms used in the dashboard were difficult to interpret in real-time.

(g) **Provide automatic action recommendations:** Teachers mentioned that having access to dashboard controls (e.g., pause, resume, etc.) is useful. However, the use of such controls during activity run-time markedly decreased, indicating a gap between teachers' subjective perception of such controls and their real-time use. This may occur due to lack of familiarity with the technology, lack of confidence in revising learning design in real time or inability to use controls while evaluating the epistemic and social characteristics of the learning scenario at hand. Generating automatic action recommendations for when to use dashboard controls, and giving instructors the flexibility to accept or reject them, would help bridge the gap between perception and technological affordances.

1.4.2 Main Evaluation Studies

This dissertation consists of pilot and case studies conducted during three DBR cycles. In the following, we describe the evaluation studies conducted within each cycle.

1. **Cycle 1**

   In this cycle, the proposed orchestration agent mechanisms were first evaluated using a WoZ approach. In this scenario, the agent role was enacted by a researcher in a MOOC. Pyramid pattern-based collaborative learning activities were deployed during the first and second week of the MOOC. Participants were informed that activity participation was voluntary.

   To understand how activity duration affects collaboration and how the proposed agent interventions had to be adapted according to different learning designs, we differentiated four activity types: *very rapid activities*, *rapid activities*, *long activities*, and *very long activities*.

   According to the log data, 28 learners participated in the very rapid activities, 22 participated in rapid activities, 37 participated in long activities and only 5 participated in very long activities. Log data was analysed and visualised using chord diagrams, which provided a compact view of learners' variant activity participation across the four activity types and of the differences in their participation within different phases of a given Pyramid script, e.g., answer submission and voting phases. Chord diagrams also visualised at which levels the interventions of the orchestration agent became necessary to maintain uninterrupted yet meaningful flows of collaboration.

   In the second iteration, a revised implementation of the proposed orchestration agent functionalities was built into the PyramidApp architecture such that interventions were automatically enabled. We evaluated the automatic interventions within pilot studies in the first and second weeks of a MOOC. Log data collected from the PyramidApp tool was analysed to report the results. The details of the learning designs deployed, proposed agent functionality and the results are presented in detail in Chapter 2.

2. **Cycle 2**

   In the second DBR cycle, we focused on the use of predictive LA to facilitate the orchestration of group learning by providing the means to form adaptive collaborative learning groups in Pyramid scripts. In this cycle, we studied how supervised machine learning techniques could be used to predict whether a given student would actively participate in a future CSCL activity given their history of student-platform interactions within different learning spaces. The objective was to inform an adaptive group formation strategy that adapts to the degree of activity of individual students considering their diverse learning behaviours in different learning spaces.

   We attempted to use supervised machine learning techniques to learn a classifier to predict individual students' future collaborative learning activity participation. The prediction problem addressed in this study was modelled as a binary classification problem, with the target variable representing whether a given student will participate or not in a given activity. Our input data was collected from heterogeneous data sources from both classroom and distance learning contexts. In the classroom learning context, we collected data from a Moodle course (164 cases). In the distance learning context, we collected data from a MOOC (230 cases). The collected data characterised students' individual learning behaviours in terms of student-platform interactions in two different digital learning environments. We also deployed Pyramid pattern-based collaborative learning activities in the classroom and distance learning contexts to collect data that characterised students' collaborative learning behaviours. We then built two data sets: 1) a data set merging PyramidApp log data with Moodle course data of a particular set of students and 2) a data set merging PyramidApp log data with MOOC data for another set of students. We used a correlation-based approach for feature selection (Yu & Liu, 2003). Based on the results of the correlation analysis in the classroom context, the input vector included seven input features; in the distance learning context, the input vector included ten input features (see details in Chapter 3 of the dissertation).

Three supervised machine learning techniques, SVMs, NNs, and RFs that have been widely used in literature for similar prediction tasks, were trained and tested for our prediction purposes. Each algorithm was trained separately in both classroom and distance learning contexts to determine the best-performing classifier. We also conducted a grid search to obtain the best hyper-parameters for each algorithm, which were then evaluated using 10-fold cross-validation, a process that the literature has demonstrated as reliable in estimating model accuracy (Cen, Ruta, Powell, Hirsch, & Ng, 2016). Based on cross-validation accuracy, SVMs were best at predicting students' future collaborative learning activity participation in the classroom learning context, whereas NNs was better at making the same predictions in distance learning contexts.

We then conducted evaluation studies in which we attempted to use the prediction outcomes of the best-performing models, i.e., SVMs for classroom learning context and NNs for distance learning contexts, to formulate adaptive groups in classrooms and MOOCs in real time. The case study findings indicated several practical problems to be accounted for when using predictive analytics for real-world classification problems in real time.

3. **Cycle 3**

   In Cycle 3, we focused on supporting teachers in orchestrating scripted collaborative classroom learning situations. Following the LATUX workflow, we conducted validation studies in a real setting using a within-subjects design. Four teachers from the engineering school of a public university in Spain participated in 16 authentic class sessions. Ideally, the four teachers would have conducted an equal number of experiments each, but this was not feasible during our study. In the experimental condition, teachers monitored and orchestrated group activities using the dashboard; and in the control condition, the dashboard was not available. First-year undergraduate students from the classes took part in the study. Students' collaboration in both conditions and teachers' dashboard actions in the experimental condition were automatically logged. In the experimental condition, teachers' dashboard actions were also recorded using screen-captured data from the dashboard tablet. A researcher also performed classroom observations during every session. At the end of the experiments, post-activity questionnaires were distributed to determine teachers' perceptions of the dashboard and students' perceived learning outcomes and satisfaction rates. Teacher actions performed during the sessions were coded using *instructors' analytics use* model (Wise & Jung, 2019). A mixed-method approach was used to contextualise and triangulate quantitative and qualitative data to produce results about the two conditions.

In the next iteration of the dashboard following a within-subjects design, six higher education teachers from the engineering school of a public university in Spain participated in our study. The objective of the study was to understand how teachers' actions vary when different supports are available (e.g., no dashboard, mirroring and guiding conditions). Each teacher conducted three different collaborative learning sessions using different support provisions. We defined a coding scheme to facilitate the coding of teachers' actions during the aforementioned activities. The differences in teachers' actions across the three conditions were disentangled using ENA techniques, and teachers' subjective responses were collected with a post-activity questionnaire. Apart from referring to the subjective responses, we also explored how orchestration load can be estimated using physiological measures, e.g., electrodermal activity

(EDA) in triangulation with subjective responses (see Appendix D). The details of the design, experiment and evaluation of the proposed dashboards are presented in Chapters 4 and 5 of the dissertation.

1.4.3 Publications

The dissertation is organized and presented as a compendium of the following research articles published or submitted for review at the time of presenting the dissertation. The list only includes those publications in which the dissertation's author is the first author.

- Publications in JCR-indexed international peer-reviewed journals:

  (J1) Amarasinghe, I., Hernández-Leo, D., Manathunga, K., & Jonsson, A. (2018). Sustaining continuous collaborative learning flows in MOOCs: Orchestration agent approach. *Journal of Universal Computer Science, 24*(8), 1034–1051. https://doi.org/10.3217/jucs-024-08-1034 **(ISI JCR)**

  (J2) Amarasinghe, I., Hernández-Leo, D., & Jonsson, A. (2019). Data-informed design parameters for adaptive collaborative scripting in across-spaces learning situations. *User Modeling and User-Adapted Interaction, 29*(4), 869–892. https://doi.org/10.1007/s11257-019-09233-8 **(ISI JCR)**

  (J3) Amarasinghe, I., Hernández-Leo, D., Michos, K., & Vujovic, M. (2020). An actionable orchestration dashboard to enhance collaboration in the classroom. *IEEE Transactions on Learning Technologies*. (in press). **(ISI JCR)**

  (J4) Amarasinghe, I., Hernández-Leo, D., & Hoppe, H. U. (2020). Teacher dashboards for the orchestration of CSCL scripts - Comparing mirroring and guiding approaches. (Submitted to journal, currently under review).

- Publications in international conference proceedings:

  (C1) Amarasinghe, I., Hernández-Leo, D., & Jonsson, A. (2017). Intelligent group formation in computer-supported collaborative learning scripts. In *Proceedings of the 2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT)* (pp. 201–203). IEEE. https://doi.org/10.1109/ICALT.2017.62

(C2) Amarasinghe, I., & Hernández-Leo, D. (2019). Adaptive orchestration of scripted collaborative learning in MOOCs. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, J. Schneider (Eds.), *Transforming Learning with Meaningful Technologies. European Conference on Technology-Enhanced Learning (EC-TEL) 2019. Lecture Notes in Computer Science, vol 11722*. (pp. 591–594). Springer. https://doi.org/10.1007/978-3-030-29736-7_46

(C3) Amarasinghe, I., Hernández-Leo, D., Manatunga, K., Beardsley, M., Bosch, J., Carrió, M., Chacón-Pérez, J., Jimenez-Morales, M., Llanos, D., Lope, S., Martinez-Moreno, J., Santos, P., & Vujovic, M. (2020). Collaborative learning designs using pyramidapp. *Proceedings of the 11th International Conference on University Teaching and Innovation (CIDUI): Beyond competencies: new challenges in a digital society*. (in press).

- Publications in international workshops:

(W1) Amarasinghe, I., Hernández-Leo, D., & Jonsson, A. (2017). Towards data-informed group formation support across learning spaces. In L. P. Prieto, R. Martinez-Maldonado, D. Spikol, D. Hernández-Leo, M. J. Rodríguez-Triana & X. Ochoa (Eds.), *Joint proceedings of the sixth multimodal learning analytics (MMLA) workshop and the second cross-lak workshop co-located with 7th international learning analytics and knowledge conference (LAK 2017), vol. 1828* (pp. 31–38). Aachen: CEUR. Available: http://ceur-ws.org/Vol-1828/paper-05.pdf

(W2) Amarasinghe, I., Vujovic, M., & Hernández-Leo, D. (2020). Towards teacher orchestration load-aware teacher-facing dashboards. In M. Giannakos, D. Spikol, I. Molenaar, D. Di Mitri, K. Sharma, X. Ochoa & R. Hammad (Eds.), *Joint proceedings* *of CrossMMLA in practice: Collecting, annotating and analyzing multimodal data across spaces co-located with 10th international learning and analytics conference (LAK 2020), vol. 2610* (pp. 7–10). Aachen: CEUR. Available: http://ceur-ws.org/Vol-2610/paper2.pdf

1.4.4 Projects

Research work carried out during this dissertation contributed to certain objectives of the following research projects:

- Name of the Project: **RESET (REformulating Scalable Educational ecosysTems)**
  Duration: 2017-2018
  Funding entity: Spanish Ministry of Science and Innovation (TIN2014-53199-C3-3-R)
  Participant entities: Universidad Carlos III de Madrid (UC3M), Universidad de Valladolid (UVA), Universitat Pompeu Fabra (UPF)
  Principal Investigators (UPF): Josep Blat and Davinia Hernández-Leo
  Website: `http://reset.gast.it.uc3m.es/`

- Name of the Project: **CoT (Communities of Teaching as a data-informed design science and contextualized practice)**
  Duration: 2017 – 2019
  Funding entity: RecerCaixa, Catalonia
  Participant entity: UPF
  Principal Investigator: Davinia Hernández-Leo
  Website: `http://ilde2.upf.edu/CoTprojectRC/`

- Name of the Project: **MDM (Maria De Maeztu DTIC Strategic Research Program) – Educational Data Science (EDS)**

Duration: 2017 – 2020
Funding entity: Spanish Ministry of Science and Innovation (MDM-2015-0502)
Participant entity: UPF. Principal Investigator of EDS sub project: Davinia Hernández-Leo

- Name of the Project: **SMARTLET (Learning analytics to enhance the design and orchestration in scalable, IoT-enriched, and ubiquitous Smart Learning Environments)**
  Duration: 2018 – 2020
  Funding entity: European Regional Development Fund as well as by the National Research Agency of the Spanish Ministry of Science, Innovations and Universities (TIN2017- 85179-C3-3-R)
  Participant entities: UC3M, UVA, UPF
  Principal Investigator (UPF): Davinia Hernández-Leo
  Website: `https://smartlet.gsic.uva.es/`

1.5 Limitations

In this dissertation, we have studied orchestration challenges associated with CSCL scenarios deployed in classroom and distance learning contexts. We proposed different LA interventions to address the identified orchestration issues and reported our practical experience with the proposed LA solutions in real-world settings. However, proposing LA solutions and conducting evaluation studies 'in the wild' was challenging and presented several limitations. The limitations described below could shed light on future research meant to build practical LA solutions for orchestration problems in authentic learning situations.

1. Methodological limitations

   A methodological limitation of this work is the lack of LA solution iterations performed over a long period of time. For instance, in the MOOC studies, lack of access to ongoing MOOCs prevented us from conducting multiple evaluation studies. If done, this would have informed and improved the design of the proposed LA interventions. Moreover, although the primary focus of this dissertation was designing LA solutions to address orchestration issues in scripted collaborative learning situations, from a pedagogical perspective, it is important to conduct a deeper analysis to understand whether the proposed LA interventions, e.g., teacher regulation of collaboration using dashboard and automatic orchestration interventions (i.e., group formation policies based on predictive analytics and the intervention of orchestration agents in MOOCs) led to students' learning gains. Limited time available for classroom experimentation, as well as ethics and privacy concerns with MOOCs, restricted us from conducting pre-post test procedures to evaluate learning gains. These aspects constitute limitations of our work and require further research.

2. Focus on Pyramid CLFP and use of PyramidApp

   In this dissertation, we focused on Pyramid CLFP-based scripted CSCL situations and used PyramidApp to facilitate collaboration in the classroom and distance learning contexts. Although we believe in the Pyramid CLFP's pedagogical value, implementation complexity and applicability to multiple contexts and subjects makes it an interesting research focus, the replicability of the results obtained to generalise the findings and claims generated in our studies to inform broader practice considering learning activities that are scripted according to other CLFPs is difficult. Moreover, PyramidApp implements a particularisation of the Pyramid CLFP. The specific features and functionalities of the PyramidApp tool affected the type of data we could collect, and, by extension, the nature of LA solutions proposed and the modelling we could conduct.

   The overall collaborative learning experience of teachers and students may have also been influenced by the specific implementation of the Pyramid CLFP offered by PyramidApp. The designs of the PyramidApp and dashboards are prototypes that requires further improvements. Despite the aforementioned limitations and the intrinsic limitations of the applied methodology, DBR acknowledges its own replicability limitations (Barab & Squire, 2004). We hope that the level of detail provided herein with respect to the research context, proposed interventions and results can offer insight into the 'local dynamics' within which the claims are made.

3. Limitations related to data collection and sample size

   An LA intervention proposed in this dissertation focused on sustaining continuous collaborative learning flows in MOOCs by employing orchestration agent interventions. However, due to limitations in data collection, we could not perform analysis on how different learner profile attributes, e.g., language proficiency, educational background, gender, commitment to social learning, previous experiences, motivation, interests and expectations affected their participation in collaborative learning activities. Recent reviews conducted in the field have identified that MOOC studies have disregarded such learner attributes, which makes it challenging to generalise the findings of other studies (Deng et al., 2019).

   Another LA intervention proposed in this dissertation focused on using predictive analytics to suggest adaptive group formation policies. A limitation of the proposed predictions is the use of training data sets that constituted a limited number of samples were also imbalanced with regard to the target class. A larger and more balanced data set could have potentially enhanced the model performance and obtained more accurate test results. Moreover, training data that depicted the dynamic behaviour of students in classrooms may have improved the performance of the machine learning classifiers. Such information could be captured in different modalities using novel tracking technologies, e.g., eye gaze, posture, positioning and speech. Moreover, the practical problems related to placing evaluation studies in classroom situations at different timeframes, which do not correspond to the timeframes in which the training data was collected, impacted the overall accuracy of the classifiers.

Regarding the dashboard studies, the limited number of teachers who participated in our studies, as well as the similarities in their backgrounds (e.g., information and communication technologies) may have also influenced the design and results of the proposed LA dashboard. A larger sample of teachers with various backgrounds could have reported different needs for the proposed LA solutions. Access to a professional teacher-training programme could have provided a diverse sample through which we may have captured varying design needs. Although the teachers involved in our studies supported us as best they could, their busy schedules limited the number of evaluation studies and participation in semi-structured interviews.

1.6 Conclusions

As explained in Section 1.2, the objectives of this dissertation focused on identifying orchestration challenges related to scripted collaborative learning activities deployed in distance and classroom learning contexts and proposing LA interventions to address those challenges. The main conclusions derived with respect to the three main objectives of this dissertation are described below.

1. [**OBJ_1**] **To study the orchestration challenges of scripted collaboration in distance and classroom learning contexts**

   In addressing our first objective, which relates to studying the orchestration challenges of scripted collaboration in the distance learning context, we conducted an exploratory case study in a MOOC. The results of this study showed that the number of participants, as well as their overall activity participation in collaboration spaces deployed in MOOCs, decreased over weeks of the course. Based on the differences in individual students' collaborative activity participation, we proposed a categorisation in which five participant categories were identified: *Lurkers, Initiators, Contributors, Runners* and *Raters*. It was found that the majority of participants fell into the *Lurkers* category and did not contribute to Pyramid activities; only a few participants were *Contributors* and contributed at every stage of the script. Moreover, qualitative analysis of students' post-activity questionnaire responses revealed that the lack of discussion participation between peers within the Pyramid learning activity made students feel isolated during collaboration. It became clear that the aforementioned activity participation differences in students lead to unproductive scripted learning activities deployed in MOOCs.

It was also found that the choice of script design parameters, e.g., activity duration, could affect collaboration and require adaptive modification according to participation levels. For instance, allocating longer collaboration durations resulted in increased waiting times for the activity participants to move to the next level of the scripts, whereas overly short durations did not provide adequate time for collaboration.

The above findings indicate that conducting Pyramid pattern-based scripted learning activities in MOOCs is challenging, and students' lack of activity participation in different stages of the script damages the pedagogical method structure it proposes. Lack of activity participation within one group impacted both internal collaboration and that of other groups, since the pattern merges groups as the flow advances. It was noted that the incorporation of additional scaffolding mechanisms and adaptive design of collaborative learning activities are vital in managing scripted collaboration flows in MOOC settings.

To understand the orchestration challenges associated with scripted collaborative learning activities and to support teachers in the classroom learning context, we studied the problems teachers face when conducting collaborative learning sessions. Responses collected from the teachers revealed that they require access to real-time information related to student activity participation to make decisions and take regulation actions. Teachers also pointed out the importance of having access to controls enabling them to modify script design parameters, e.g., duration of script phases, to better adapt scripts on the fly according to the current classroom situation. The findings of the sessions conducted with teachers, in addition to the knowledge acquired through the literature review, helped us understand the challenges associated with collaborative learning and teachers' desires for technological solutions to address those challenges, which informed the design decisions of a teacher-facing LA dashboard.

2. [**OBJ_2**] **To propose LA interventions to orchestrate scripted collaboration in the distance learning context**

   In addressing the second objective of the dissertation, we have proposed two different LA interventions to orchestrate collaboration in the distance learning context. One approach that we proposed entailed orchestration agent intervention. The other approach related to the use of predictive analytics to inform adaptive group formation policies (this approach was also evaluated within the classroom learning context). In the following, we present the conclusions derived from our practical experiences in deploying the proposed LA interventions in MOOCs.

   Regarding the orchestration agent interventions, we first evaluated the conceptual design of the orchestration agent following a WoZ evaluation strategy. The results of this study revealed that the proposed agent intervention became necessary in different phases of the Pyramid scripts (especially within group phases) to maintain uninterrupted yet meaningful flows of collaboration.

   Later, a revised implementation of the proposed orchestration agent functionalities was built into the PyramidApp. The findings of a pilot study conducted in a MOOC revealed that the proposed interventions became useful for meaningful flow orchestration in the activities generated at the end of each week of the course. For instance, there were not enough participants to create Pyramid activities, which required the addition of simulated students. Additionally, within the small group phases of the Pyramid activities, a lack of voting participation was detected and necessitated simulated teacher interventions. It was also noted that while course participants responded to timed discussion prompts inserted automatically in the group chat, the number of participants and to which timed prompts they responded to (e.g., greetings or requests for self-explanations) varied. Interestingly, students who responded to timed interventions in the small group phase of the Pyramid script were later seen to build conversations in the large group phase of the activity.

Next, we attempted to use predictive analytics to predict students' future participation in a Pyramid script activity using data collected from different learning spaces. Studies have shown that less attention has been paid to the prediction of individual learner's collaborative learning activity participation considering their participation in learning activities in different learning spaces (Martinez-Maldonado et al., 2019). Hence, we attempted to deploy an adaptive group formation policy in real time that adapts to the degree of activity of individual students considering their diverse learning behaviors in different learning spaces.

In the training phase of the machine learning classifiers, we obtained considerably high cross-validation accuracy scores. This indicated that the data collected from heterogeneous learning spaces were informative to classify students based on their activity participation differences. We then performed evaluation studies in an ongoing MOOC. In our first attempt, the classifier performed poorly, which led us to introduce new features and retrain the classifier. As we did not have access to an ongoing MOOC, we had to evaluate the overall prediction accuracy of the improved classifier offline.

The limited number of samples available for training classifiers, learning under class imbalance, the limited number of features and the varying nature of the courses used to collect data and situate the evaluation studies resulted in a difficult prediction task. The lessons learnt from using predictive analytics to inform script design parameters in across-spaces learning situations shed light on important practical aspects that must be taken into account when introducing similar LA interventions in real educational scenarios.

3. [**OBJ_3**] **To propose LA interventions to orchestrate scripted collaboration in the classroom learning context**

   In this objective, we proposed two different LA interventions to facilitate the orchestration of scripted collaboration in the classroom learning context. The first intervention focused on using predictive analytics to inform the formulation of adaptive learning groups considering learners' activity history in cross-context learning situations. The second intervention focused on designing and implementing a teacher-facing dashboard to help teachers orchestrate collaboration in the classroom learning context.

   As also described previously under in OBJ_2, in the first intervention we focused on using predictive analytics to inform the formulation of adaptive groups in a Pyramid script that adapts to the degree of activity of individual students. In contrast to the MOOC learning context, within this objective we focused on the classroom learning context. Data collected from a Moodle LMS course and Pyramid activities conducted in classroom sessions were used to train supervised machine learning classifiers for prediction purposes. Based on the cross-validation accuracy scores of the models, SVMs outperformed NNs and RFs in the classroom learning context. We then conducted evaluation studies in classroom sessions in which real-time predictions of students' degree of activity participation was used to formulate adaptive groups. The results of the evaluation studies indicated that log data (used to train machine learning models) offered limited information regarding classroom dynamics. The importance of capturing and incorporating features that represent students' classroom behaviours using different novel tracking technologies for similar prediction purposes were outlined.

In the second intervention, a teacher-facing dashboard was proposed to support teachers in orchestrating Pyramid pattern-based scripted collaborative learning situations. For a given Pyramid activity, the dashboard visualised students' activity participation and other relevant learning design-related information, i.e. extracted analytics (Wise et al., 2013), in real time. Evaluation studies were conducted in naturalistic settings and the impact of dashboard use on both teachers and students was reported. The results of the first iteration of the dashboard evaluation studies indicated that the actionability of the dashboard was determined not only based on automatic detection of low-participating groups, but also by how teachers used the information presented on the dashboard to inform their pedagogical actions (e.g., *whole-class scaffolding, targeted scaffolding*) and how teachers' decisions promoted positive changes in students' activity participation.

In the second iteration of the dashboard, we studied in detail how teachers' orchestration actions varied using different teaching supports, i.e., no dashboard, mirroring support and guiding support. We modelled teachers' actions based on support type. Some of the main results of this study indicated that without access to the dashboard, teachers had 1) less awareness of script evolution over time, 2) problems focusing on the epistemic aspects of learning activities and 3) limited agency. In both mirroring and guiding conditions, teachers mentioned that having access to the dashboard was useful. However, mirroring and guiding support has influenced teachers' orchestration actions differently, as illustrated also by ENA. In the mirroring condition, it was found that teachers missed chances to address activity orchestration aspects, such as by changing activity duration, as they were more focused on the epistemic facets of the learning situation, e.g., reading students' answers. In the guiding condition, teachers found that automatic alerts were useful because they provided guidance on how to act and manage activities. Teachers' orchestration actions were also found to benefit student collaboration in this context and is thus more beneficial in orchestrating collaboration compared to mirroring support. That said, in contrast to the mirroring condition, teachers reported high cognitive load in the guiding condition. We attempted to understand the reported cognitive load by introducing different facets of orchestration load derived through the lenses of teachers' actionable differences observed under different supporting conditions. We also identified the tension between orchestration load and other competing loads, e.g., the epistemic dimension of the learning activities, that may influence teachers' actions.

The studies we conducted in naturalistic classroom settings can shed light on similar research aimed at supporting the adoption of LA tools in classroom practice. The design guidelines derived from our research and the impact of different types of teaching support provided, e.g., mirroring and guiding support, can inform future research aimed at deploying teacher-facing dashboards (or similar tools) to support teachers in orchestrating collaborative classroom learning activities. As we have pointed out, the different facets of orchestration load may affect teachers' actionability. Finally, we believe the notion of the orchestration load requires further research, as many studies refer to this notion as a 'black box' without elaborating on why. We will continue our research on this notion not only based on subjective measures, but also using physiological measures as illustrated using EDA (see Appendix D).

1.7 Future Work

The limitations encountered and the research conducted during three DBR cycles have resulted in interesting further research directions as described below.

1. Educator configurable orchestration agent and human-machine hy-

brid aspects

Although in a MOOC context the proposed interventions were seen beneficial to maintain uninterrupted flows of collaboration, acknowledging the role of the educators in configuring the orchestration agent functionalities can open new research-directions in terms of human-machine hybrid aspects. Instructors can be provided with a dashboard or similar that allows configuration of the agent functionalities and to customize the interventions, e.g., quality criteria for evaluating students' answers, based on the type of the task given to the students. This would facilitate busy teachers as they do not require to monitor the system always, rather if they miss critical events the system should be able to take autonomous actions. Moreover, the flexibility of when to activate and deactivate the agent functionality could also be part of the proposed dashboard application. Such flexible features embedded in tools would increase the agency of the teachers. In contrast to the technologies that inform teachers' actions, teachers' can inform the technologies. This would take into account the teachers' preferences and would empower them to control and override decisions made by technologies.

2. Intelligent agent functionalities

   The proposed orchestration agent can be enhanced by incorporating natural language processing techniques. For instance, instead of up-voting answers randomly to the next phases of the script, we can evaluate the quality of the student's answers against a given quality criteria using natural language processing. This will facilitate up-voting the most relevant answers to the next levels of the Pyramid script or a given question. Moreover, without simply prompting students to explain their answers, the agent can be augmented to carry out a more realistic discussion with the students. Although this may be difficult to be conducted in an open-ended task domain (as we have used the PyramidApp tool so far) in a restricted domain, e.g., mathematics learning, the agent can provide direct assistance to students to better understand domain concepts. Moreover, apart from the domain-level support, different psychological realm of support can be designed and provided simultaneously e.g., meta-cognitive support, motivational support (e.g., (Muldner, Burleson, & VanLehn, 2010; Ogan, Aleven, Jones, & Kim, 2011; Roll, Aleven, McLaren, & Koedinger, 2007)); although combining different dimensions of support may result in a difficult task.

3. Use of Multimodal LA to enhance the prediction accuracy

   As described earlier, a LA intervention proposed in this dissertation is based on predictive analytics to formulate adaptive collaborative groups. However, when conducting the evaluation studies in the classroom context we realized not only the features extracted from log data but also features that describe learners behavior in the classroom, e.g., screen pointing, leaning forward, joint attention (looking at screen), that can be captured using physiological measures would help to better capture their collaborative learning activity participation, hence improving the model performance (Cukurova, Luckin, Millán, & Mavrikis, 2018; Spikol, Ruffaldi, Dabisias, & Cukurova, 2018; Grover et al., 2016). Moreover, cognitive-affective states such as emotions, moods, feelings, which could be captured in the physical space using sensory inputs can provide useful information to generate fine-grained predictive models as those states may affect the activity participation of students. Incorporation of such data captured using different data sources and in different modalities may enhance the predictive model performance.

4. Enhancements to the teacher-facing dashboard and orchestration-load aware measurements

   Teachers proposed the importance of customizing the criteria for generating dashboard warnings according to the unique needs of their sessions. For instance, consider two pyramid activities, one that asks students to propose questions to peers to improve presentation skills after a presentation task versus an activity that asks students to share ideas on how to improve a written article after reading an article. In those two activities a warning that triggers if 50% of the class did not submit answers within 50% of the time allocated to the task might work best for the presentations related activity, but may not work for the article related activity. For instance, teachers mentioned that in a particular activity they require the system to trigger a warning if 50% of the class did not submit answers within 70% of the time allocated to the task. This shows that the criteria that generate warnings requires to take into account the specific subject task and its needs in alignment with the pedagogical intent of the teacher. Moreover, teachers also mentioned that the type of information that they require to have access to may differ depending on the nature of a given course. For instance, teachers suggested that in creative subject domains, e.g. video production, they prefer to visualize students' activity participation differences not only based on the voting and discussion participation of students but also with respect to students' profile attributes e.g., gender. We suggest that such preferences can be documented along with the learning design parameters which can be later translated into rules to generate customized warnings and visualisations that are tailored to the needs of teachers that will give them a greater control over the information presented and warning generated in the dashboards also considering the activity type and subject domains. Although there are initial ideas on implementing customized dashboards, those aspects have not yet been adopted widely considering teacher-facing dashboards in LA research

Moreover, we have noticed that the teachers perceived cognitive load while using the dashboard with warnings, i.e., guiding condition, was higher when compared to the no dashboard and dashboard without warnings, i.e., mirroring, conditions. However, only a few studies have attempted to characterize the and measure orchestration load experienced by the teachers during colocated collaborative learning sessions (Prieto, Sharma, Kidzinski, & Dillenbourg, 2018). To this end, we think it is important to study further on how to design teacher-facing dashboards that take into account the teachers' orchestration load (e.g., teacher orchestration-load aware teacher-facing dashboards) and measures to estimate orchestration load using mixed methods. Finally, the colors used, visualisations and the size of the different GUI elements in the proposed dashboard can be improved to enhance end-user experience.

5. Conducting dashboard evaluation studies considering teachers' Technological, Pedagogical and Content Knowledge (TPACK)

   Teachers who participated in our experiments were computer literate and had similar experiences in using technology for their day-to-day teaching activities. It would be interesting to conduct further studies to explore how teachers technological, pedagogical and content Knowledge (TPACK framework) (Mishra & Koehler, 2006) impact the use of dashboards in authentic settings. Recent studies have pointed out that teachers' data literacy, trust in technology affects teachers' use of LA tools (Verbert, Ochoa, De Croon, Dourado, & De Laet, 2020; Feng, Krumm, Bowers, & Podkul, 2016). Hence, conducting further studies with teachers who have different profiles considering the three knowledge areas of the TPACK framework can broaden our understanding of how it impacts the use of proposed LA tools therefore teaching practices.

6. Evaluate the use of dashboard warnings to support teachers in collaborative learning activities planned for longer durations

   Our collaborative learning activities were planned for a shorter duration. We assume that conducting learning activities that are planned for a longer duration may also influence teachers actions. For instance, although teachers may value receiving warnings in the dashboard for activities that are planned for a shorter duration, maybe this is different in activities planned for a longer duration. Teachers may have enough time to interpret and take action even without the support of explicit warnings.

7. Enhancements to PyramidApp mechanisms

   Although the voting mechanism proposed within the PyramidApp tool facilitates students to evaluate peers' answers we realised that this mechanism also promotes more individual participation over collaboration. Moreover, in the classroom learning context we observed that students' discussion participation using the tool was limited as the classrooms naturally create an environment for face-to-face interactions. To alleviate these issues the PyramidApp features need to be improved. In order to enhance the collaborative effort in evaluating answers from peers it is important to change the PyramidApp mechanism. For instance, instead of allowing students to evaluate the peers' answers individually, we can introduce a mandatory discussion phase within which students require to discuss their rating decisions as a group. Also, the discussion criteria need to be established. This way the on-topic discussions can be reinforced among group members. Once the group members decide the voting decisions students need to be provided with the flexibility to vote the existing answers or to submit improved answers for the next levels. Such mechanisms will facilitate to improve the finally reached consensus of the activity.

1.8 Structure of the Dissertation

We have presented this dissertation as a compilation of the articles published or submitted for review at the time of depositing the dissertation. We have organized the following chapters to include different articles as presented in Table1.3. In order to integrate our research work, and to provide a sense of how each of the work presented in each chapter fits within the objectives stated, each chapter first provides a short introduction explaining how each article is related to the objectives of the dissertation. As shown in Table1.3, at the end of the chapters we have also included other articles and some related information as appendix which are complementary to the work being presented in the chapters of the dissertation.

Table 1.3: Distribution of the publications among the chapters of the dissertation.

Chapter	**Title**	**Publication(s) ***
Chapter 2	Automatic Orchestration of Scripted Collaboration in MOOCs	J1, C2
Chapter 3	Adaptive Group Formation Considering Across-Spaces Learning Situations	J2
Chapter 4	A Teacher-facing Dashboard to Enhance Collaboration in the Classrooms	J3
Chapter 5	Teachers' Adaptation of Scripted Collaboration in the Classroom	J4, W2
Appendix A	Intelligent Group Formation in Computer-Supported Collaborative Learning Scripts	C1
Appendix B	Collaborative Learning Designs Using PyramidApp	C3
Appendix C	Towards Data-Informed Group Formation Support Across Learning Spaces	W1
Appendix D	Towards Estimating Orchestration Load Using Physiological and Subjective Measures	N/A

*J: journal article; C: Conference paper; W: Workshop paper (see section 1.4.3 for details)

Chapter 2

AUTOMATIC ORCHESTRATION OF SCRIPTED COLLABORATION IN MOOCS

This chapter tackles part of the first objective and the second objective of this dissertation, in which we focused on eliciting the orchestration challenges accompanied by the scripted CSCL activities in MOOCs to propose LA interventions that may facilitate to regulate Pyramid pattern-based collaborative learning flows deployed within MOOCs (Figure 2.1). The content of this chapter is composed of a JCR-indexed international peer-reviewed journal article and a conference paper which provides details of the research conducted during the first DBR cycle (Figure 2.2).

The journal article first provides an overview of the MOOC learners' participation in Pyramid pattern-based collaborative learning flows. Then it presents the design of an *orchestration agent* that implements different intervention strategies adapting to the activity participation differences of students observed within Pyramid pattern-based collaborative learning flows deployed in MOOCs. Finally, the results of an evaluation study conducted to understand the usefulness of the proposed mechanisms in orchestrating collaboration are illustrated.

The conference paper provides details of a revised implementation of the proposed orchestration agent functionalities within the PyramidApp. Details of the automatic interventions proposed and the findings of evaluation studies conducted are presented.

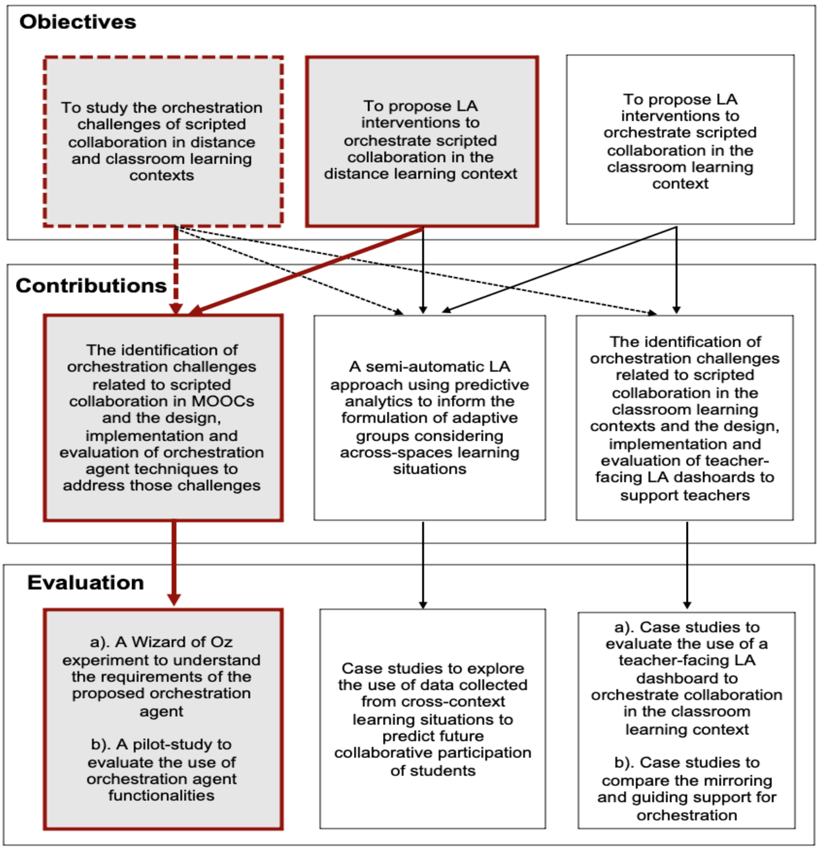

Figure 2.1: Objectives, contributions and evaluation studies covered by Chapter 2.

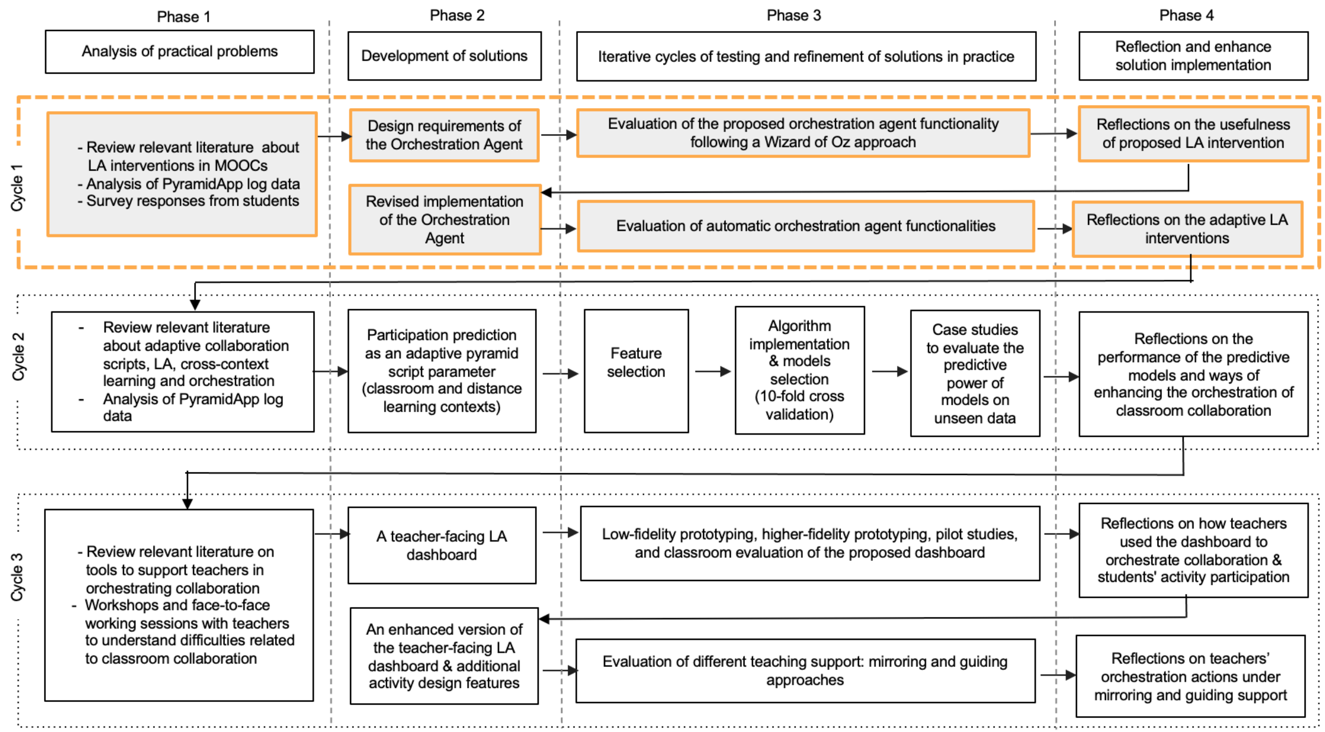

Figure 2.2: Part of the research process related to Chapter 2.

2.1 Sustaining Continuous Collaborative Learning Flows in MOOCs: Orchestration Agent Approach

The content of this section was published in the following JCR-indexed international peer-reviewed journal article:

Amarasinghe, I., Hernández-Leo, D., Manathunga, K., & Jonsson, A. (2018). Sustaining continuous collaborative learning flows in MOOCs: Orchestration agent approach. *Journal of Universal Computer Science, 24*(8), 1034–1051. https://doi.org/10.3217/jucs-024-08-1034

Journal of Universal Computer Science, vol. 24, no. 8 (2018), 1034-1051
submitted: 15/12/17, accepted: 5/7/18, appeared: 28/8/18 © *J.UCS*

Sustaining Continuous Collaborative Learning Flows in MOOCs: Orchestration Agent Approach

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Abstract: Collaborative learning spaces deployed in Massive Open Online Courses (MOOCs) provide productive social learning opportunities. However, sustaining collaboration in these spaces is challenging. This paper provides a classification of MOOCs participants based on their behavior in a structured collaborative learning space. This analysis leads to requirements for new technological interventions to orchestrate collaborative learning flows in MOOCs. The paper proposes the design of an intelligent agent to address these requirements and reports a study which shows that the intervention of the proposed orchestration agent in a MOOC facilitates to maintain continuous yet meaningful collaboration learning flows.

Keywords: Computer-Supported Collaborative Learning (CSCL), Intelligent Agents, Massive Open Online Courses (MOOCs), Collaborative Learning Flow Patterns (CLFPs)
Categories: H.5.0, I.2.0, K.3.1, L.2.0, L.3.6

1 Introduction

Massive Open Online Courses (MOOCs) have created learning opportunities towards a massive amount of students disregard their financial, educational and geographical boundaries. Within the concept of "education for all" MOOCs offer chances for millions of students to browse, pick and choose courses offered by well-recognized universities while students can follow their own agenda which was not feasible in earlier models of online education [Yang et al. 2013]. With the aim of offering opportunities for fruitful learning, at present many MOOCs provide social learning spaces and activities towards course participants [Manathunga et al. 2017]. However, sustaining learners' engagement in these collaborative spaces is challenging as levels of participation vary across learners and new cohorts of learners start course activities from week to week [Yang et al. 2013]. The problem is that for social learning opportunities to be fruitful, there need to be sufficient levels of active participation that keep meaningful flows in the collaborative activities [Rosé and Ferschke 2016].

In the field of Computer Supported Collaborative Learning (CSCL), carefully designed scripts aim to structure social interactions via different strategies i.e., defining roles, sequences of activities, etc. that can have positive effects in learning [Dillenbourg and Tchounikine 2007]. Collaborative Learning Flow Patterns (CLFPs) formulate the essence of script structures that have been proven effective in multiple educational situations [Hernández-Leo et al. 2010]. For example, the Pyramid CLFP proposes an activity flow in which learners start solving a task individually. Then learners form small groups to share their solution and agree on a common solution, to later form increasingly larger groups that further discuss and agree on common solutions. The Pyramid pattern facilitates opportunities for all learners to express and discuss their solutions and to learn and reflect on others' solutions. In a MOOC context, the Pyramid pattern also offer a scalable collaborative method, in that it keeps to a reasonable amount the number of solutions to be read and discussed by each individual learner (those solutions within each group in the Pyramid) and by the educators (if educators choose to monitor only the agreed solutions by Pyramid) [Manathunga and Hernández-Leo 2017]. CLFPs structure the flow of potentially fruitful collaborative learning activities, but the uncertainty of participation in these activities in MOOC contexts can hinder a meaningful progression in the flow of activities (e.g., inactive participants in a Pyramid group waiting for an agreement in order to join increasingly larger groups). A suitable real-time management (or orchestration [Dillenbourg and Tchounikine 2007]) of the learning scenario is vital for a successful collaboration flow that is uninterrupted and keeps the pedagogical method structure.

In this paper, we study the difficulties involved in maintaining continuous and meaningful flows of Pyramid activities and propose an experiment that incorporates intelligent agent technologies to address these difficulties. Data collected from an exploratory MOOC case, in which seven Pyramid activities are proposed, is used to identify the difficulties. A second MOOC case is designed and carried with twenty-eight Pyramid activities and Wizard of Oz (WOZ) integrated intelligent agents to overcome these difficulties. The evaluation of this second case focuses on studying whether the proposed intelligent agent can maintain an uninterrupted yet meaningful collaborative learning flow via monitoring and intervening to the flow when necessary.

This article is organized as follows. In section 2 we describe relevant literature considering social learning aspects in MOOCs, application of intelligent and adaptive techniques in educational systems and applicability of such techniques in MOOCs settings to foster collaboration. In section 3 a MOOC case study is presented in which we analyzed MOOC participants collaborative learning behavior in a Pyramid based collaborative learning scenario. Section 4 describes our empirical study which focused on design aspects of the intelligent agent to facilitate uninterrupted collaborative learning flows in MOOCs setting. The final section provides concluding remarks followed by future research directions.

2 Literature

2.1 Social Learning in MOOCs

CSCL is an effective pedagogical approach in which learners collaborate with peers to achieve learning goals while constructing shared knowledge and understanding [Fischer et al. 2007]. However, research has shown that learners do not collaborate spontaneously [Fischer et al. 2007]. On the other hand, maintaining a continuous collaborative learning flow becomes significantly important during collaborative script enactment, since these scripts consist a number of phases that occur one after the other in a consecutive manner [Hernández-Leo et al. 2010]. Failure to maintain desired collaborative learning behavior within phases negatively affects the flow of collaboration [Dillenbourg and Tchounikine 2007]. Achieving success in such collaborative settings heavily depends on the continuous and active participation of students.

In a Face to Face (F2F) classroom setting, in appropriately sized classes, student's collaborative learning behavior can be closely and continuously supervised by an educator [Pontes et al. 2010]. In such settings not only each individual student's engagement but also the behavior of a bunch of students as a group can be monitored by an educator to confirm that individuals and groups are actively involved in the collaborative learning task. However, even with the close guidance of an educator in a F2F setting maintaining a continuous collaborative learning flow is not easy. The passive behavior of some students can hamper collaboration [Vizcaíno 2005].

On the other hand, MOOCs have created opportunities to carry out course-related activities remotely from anywhere at any time and has gained social success. The history of MOOCs dated back to 2008 where George Siemens and Stephen Downes conducted the first MOOC titled 'Connectivism and Connective Knowledge' (CCK08) [Downes 2008]. Since then MOOCs evolved in different ways providing opportunities to plan, test and validate disruptive approaches to education [García-Peñalvo et al. 2017]. According to the underpinning pedagogical methodology, design, scope and management of resources and activities MOOCs have been categorized into two main types: cMOOCs and xMOOCs [García-Peñalvo et al. 2017]. Adapting from the connectivism learning theory cMOOCs (also known as the first-generation of MOOCs) are based on connectivist (that emphasizes social learning) while xMOOCs (also referred to as the second-generation of MOOCs) are based on instructionism and individualism [Fidalgo-Blanco et al. 2015]. Currently, many MOOC platforms adapt xMOOCs technologies e.g., Udacity, Coursera, edx [Fidalgo-Blanco et al. 2015] and have employed different social interaction spaces into the platform using different strategies. Although forum threads are the dominant channel [Brinton et al. 2014] through which teachers and students interact meet-ups at learning hubs introduced by Coursera and content-wide and course-wide cohorts on the edX platform [Manathunga et al. 2017] can be pointed out as some other instance for initiatives offering social and collaborative learning opportunities within MOOCs.

However, as it was pointed out earlier, deploying collaborative learning activities even in a synchronous F2F setting under the close guidance of an educator, poses difficulties i.e., maintaining a continuous flow of activities, student motivation, etc. Hence, deploying collaborative learning activities in MOOC settings can result in added complexity due to many reasons. Variability of learner's schedules, diverse individual characteristics and expectations, lack of educator influence, higher learner dropout rates and asynchronous nature of collaboration are to name a few. Coordination and management of group processes in such settings are a serious and a challenging task since learners are distributed both in time and space [Fidalgo-Blanco et al. 2015]. The continuous flow of collaboration can be easily interrupted in such settings due to aforementioned reasons, resulting unsavory learning experiences for motivated students [Tomar et al. 2016]. In light of this fact, it was observed that designing and implementing appropriate scaffolding strategies to maintain continuous collaborative learning flows become a need in MOOC settings. Exploration and deployment of new technological interventions that contribute to sustain collaborative learning activities can help to harness benefits of social learning in MOOC context [Rosé et al. 2014].

2.2 Adaptive and Intelligent Techniques in MOOCs

Recently a growing research interest towards incorporating adaptive and intelligent techniques into MOOCs have been observed. Existing literature has highlighted the need and the importance of incorporating adaptive techniques into MOOCs platforms in order to improve pedagogical effectiveness [Sonwalkar 2013] as well as to personalize and better adapt the learning process to the characteristics of students [Fidalgo-Blanco et al. 2015]. Different technological frameworks and innovative ways of supporting adaptivity in MOOCs have been proposed. For instance, [Sonwalkar 2013] have described the cloud computing architecture of an adaptive MOOC (aMOOC) platform that renders content adapting to five distinct learning strategies. [Leris et al. 2017] have identified and proposed six adaptive indicators (based on self-regulation and cooperation aspects of learning) that help to implement adaptivity within MOOCs context.

On the other hand, when considering intelligent techniques that are incorporated into MOOCs context intelligent agents play an important role. Different types of agents i.e., pedagogical agents, conversational agents have been deployed into MOOCs to keep learners motivated towards collaboration. As described in [Bendou et al. 2017] integration of animated pedagogical agents into online learning environments (LMS or MOOC) has helped to create natural human-machine interactions. Although pedagogical agents are not necessarily artificially intelligent these lifelike characters that appear on computer screens have helped to increase learner's motivation while decreasing dropouts [Bassi et al. 2014]. Ferschke et al. [2015] and Wen [2015] have described the integration of conversational agents into collaborative chat environments deployed in MOOCs. Agents facilitated to engage students in intensive discussions during collaboration.

However, it is worth mentioning that existing studies which incorporate intelligent assistance towards collaboration in MOOCs have mostly considered specific aspects of collaborations e.g., chat participation during a collaborative learning task. Most of these studies have taken for granted in one way or the other that continuous collaborations among participants occur automatically although less engagement of learner's participation in MOOCs is well-known. In a recent study carried out by [Fauvel and Yu 2016] has pointed out that intelligent agent techniques have not yet been applied to provide peer support in MOOCs context, although providing peer support in such settings is vital. Although Artificial Intelligent (AI) techniques can be integrated into almost every aspect of the MOOC ecosystem, only a few tools have been tested and deployed into the actual MOOCs context regardless of the fact that effective integration of these type of intelligent techniques could result in benefits [Bassi et al. 2014, Rosé and Ferschke 2016].

In a broader perspective, although technologies such as intelligent agents have proven to be effective in online education paradigms these technologies have not yet been fully leveraged within the MOOC context [Fauvel and Yu 2016]. Apart from being an animated character or a conversational partner, agents can be used to analyze data produced by the MOOC platform, in order to provide intelligent or mechanical assistance to improve design, delivery and assessment [Bassi et al. 2014].

3 An exploratory study of Pyramid collaborative learning activities in a MOOC

Research shows that identification of participants' profile differences in MOOCs facilitates to determine effective engagement mechanisms [Alario-Hoyos et al. 2014]. However, lack of attention towards analyzing participants' engagement differences in collaborative learning spaces deployed in MOOCs was observed. Inspired by the work already done in the field [Milligan et al. 2013, Alario-Hoyos et al. 2014] during this study we analyzed the behavior of learner's participation in a collaborative learning activity deployed in a MOOC course. The major objective of this case study was to determine how individual participation differences affect collaborative learning flows deployed in MOOC contexts. The exploratory MOOC case study was deployed in spring 2016, in the FutureLearn MOOC platform. A tool called 'PyramidApp' was used structure the collaborative enactment.

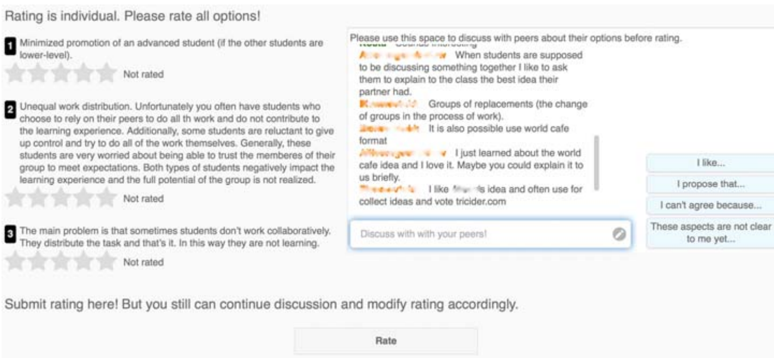


Figure 1: A screenshot of the PyramidApp showing rating space (left) and the negotiation space (right)

3.1 PyramidApp

PyramidApp [Manathunga and Hernández-Leo 2017] is a web-based application that implements flow orchestration of collaborative learning activities inspired by the Pyramid pattern [Hernández-Leo 2005]. A Pyramid flow is initiated with individual students solving a global task. Then, in a second level of the Pyramid, such individual solutions are discussed in small groups and agreed upon a common proposal. These small groups then form larger-groups iteratively and large group discussions will continue till a consensus is reached at the global level. PyramidApp implements an activity design tool for educators to author such collaborative activities with easy configurations such as the number of participants per Pyramid, number of rating submission stages, group size and timing configurations. Once a Pyramid flow activity is designed by the educator and published, it becomes accessible via a public URL. MOOC participants can then access the activity by logging to the PyramidApp tool using the given URL. Within a single Pyramid activity, each participant engages in the collaborative learning activity at two major levels including individual option submission stage and rating submission stages. Inbuilt discussion board of the tool provided a negotiation space for participants at group levels. Fig. 1 shows a sample screenshot of the PyramidApp as it is used in a MOOC setting. The social interactions facilitated by the PyramidApp in a MOOC context differentiates from other collaboration spaces with its structured accumulative collaborations that grow from individual level to small group discussions to large groups, promoting positive interdependence and negotiation skills that rather lacks in global forum discussions [Manathunga and Hernández-Leo 2017].

Week	**Pyramid flow abbrev.**	**No. of Pyramids**	**Pyramid abbrev.**
Week 1	Flow 1	1	W1F1P1
Week 1	Flow 2	1	W1F2P1
Week 1	Flow 3	2	W1F3P1 & W1F3P2
Week 2	Flow 1	2	W2F1P1 & W2F1P2
Week 3	Flow 1	1	W3F1P1

Table 1: Pyramid activities deployed in exploratory case study

3.2 Experimental Design

Within 3 consecutive weeks of the FutureLearn MOOC, we deployed 5 Pyramid flows (meaning 5 different tasks following a Pyramid flow), including 3 flows during the first week, 1 flow during the second week and 1 flow during the third week. Based on design configurations of the PyramidApp i.e., minimum number of learners allocated per Pyramid during a Pyramid flow, a number of Pyramids were instantiated allocating MOOC participants to Pyramids who logged into the system in different times. see [Tab. 1]. Initial design parameters of each Pyramid are given in Tab. 2. The first column in Tab. 2 indicates the abbreviation to identify each Pyramid. The second column indicates the minimum number of students required to create a Pyramid. The third column indicates the number of rating submission stages in each Pyramid. For instance, a number of Pyramid rating submission stages equal to 2 indicates that there are two rating submission stages, i.e., the first and the second rating submission stages. The fourth column indicates the number of students collaborated during the first rating submission stage. Since each Pyramid has only two rating stages this parameter refers to the size of each small group created during the first rating submission stage. In the second rating submission stage all participants were grouped together resulting four participants in each large group. Finally, the fifth and sixth columns indicate the time limits for initial option submission stage and subsequent rating stages (in hours). As this was a preliminary experiment using PyramidApp in a MOOC context, long timing durations were allocated for Pyramid phases to learn the participant behavior and structured collaborative learning feasibility in MOOC settings.

3.3 Subjects

Students enrolled in *3D graphics for Web Developers* MOOC course participated in the Pyramid activity deployed in the MOOC. The total number of students enrolled for the course was around 4300. Participants were informed that the activity was voluntary and that activity participation was part of a research experience and responses collected will be treated anonymously. Students were asked to use PyramidApp to share experiences and challenges faced when using novel 3D applications. Participants were assigned to Pyramid groups randomly. Based on PyramidApp log data, during the first week of the MOOC 76 participants accessed the Pyramid activity, while in the third week this number dropped to 15 and in the fifth week it dropped further until 8. In total 99 students have accessed the collaborative learning activity. The following section describes participants' collaborative activity enactment behaviour.

Pyramid abbrev.	**Min. students per Pyramid**	**No. of rating levels**	**Group size**	**Option sub. time limit**	**Rating sub. time limit**
W1F1P1	8	2	2	18 h	18 h
W1F2P1	8	2	2	18 h	18 h
W1F3P1	8	2	2	18 h	18 h
W1F3P2	8	2	2	18 h	18 h
W2F1P1	4	2	2	18 h	18 h
W2F1P2	4	2	2	18 h	18 h
W3F1P1	4	2	2	18 h	18 h

Table 2: Pyramid activity configurations

3.4 Results and analyses

PyramidApp log data was analyzed to determine collaborative learning behavior of MOOC participants. An overall activity participation analysis and an individual student level analysis was carried out.

Results of the overall activity participation analysis have shown that engagement in collaborative learning activity varied within weeks of the MOOC course, see [Fig. 2]. As it was described in section 3.3, not only the number of participants has become fewer in size, but also their overall engagement with the activity has decreased over-time. This observation also complies with the common attrition behavior of MOOC participants, in which they are highly active and engaged with the course in the first few weeks but degraded over the course progression [Sinha et al. 2014].

We then conducted an individual student level analysis in order to analyze how individual participation varied across different Pyramid stages. Results of the analysis revealed that some MOOC participants have participated in both initial and rating stages of the Pyramid activity, while some participants have escaped either initial option submission stage or subsequent rating stages. Further, some participants have only logged into the system but had not participated in the activity. Based on these behavioral differences we have categorized individual students into 5 major categories namely *Lurkers*, *Initiators*, *Contributors*, *Runners* and *Raters* which also complies with the participant categorizations proposed in previous work [Milligan et al. 2013, Alario-Hoyos et al. 2014].

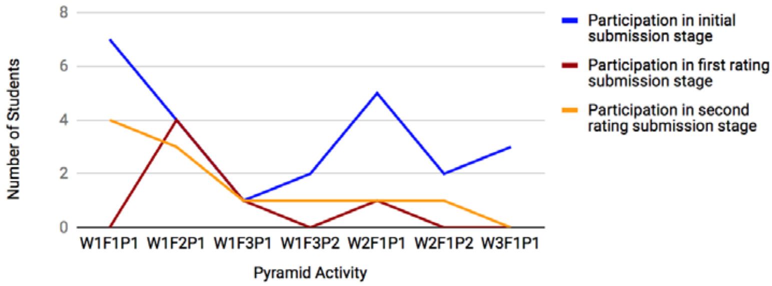


Figure 2: MOOC Pyramid activity participation

Lurkers are the MOOC participants who only logged into the PyramidApp but did not participate actively in any level of the collaborative learning activity. In other words, these participants do not add any contribution to the collaborative learning task. The opposite category of *Lurkers* was named as *Contributors* who have participated in all levels of the collaborative learning activity, contributing to reaching a group consensus. Other three categories namely *Initiators*, *Runners* and *Raters* have contributed to the collaborative learning activity in different levels. *Initiators* have participated only during the initial option submission stage. They have contributed to the collaborative learning activity providing their opinion about the question at hand. *Raters* are the participants who have not participated in the initial option submission stage but have participated only in rating levels. MOOC participants who have participated in initial level and at least one rating level i.e., first or second rating level were named as *Runners* since they contribute to maintain continuous collaborative learning flows. Fig. 3 summarizes the learner participation distribution according to aforementioned categorization across different Pyramid activities. Participants of the Pyramid W3F1P1 were excluded from this study since during that Pyramid participants only participated in the initial option submission level.

Apart from participation across different stages of Pyramids, we have also analyzed how each individual participated in the integrated chat of the PyramidApp. This chat environment facilitates small groups to collaboratively select the best option to rate via discussing their opinions. We have coded manually how many students have used the chat to discuss individual options submitted prior rating, via posting their opinion either as a question or a comment and how other students have collaborated via posting a response. Results of the analysis revealed that students have used chat to express their opinions only during the Pyramid activities occurred in the first week of the MOOC. Students have not used the chat during later weeks of the MOOC course.

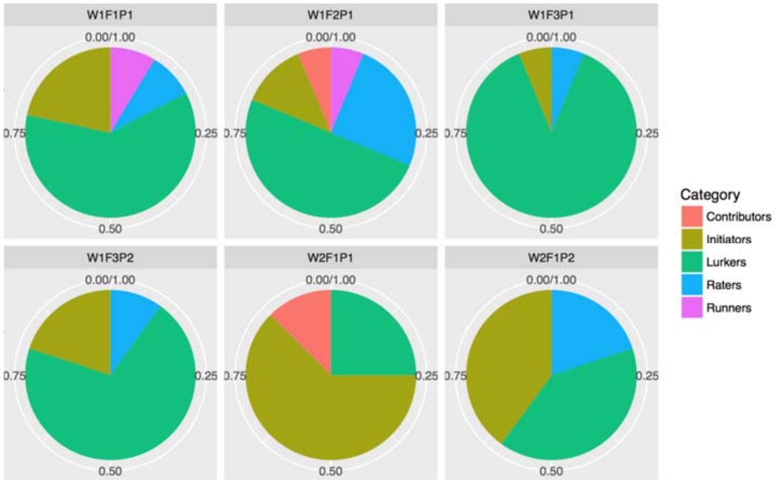


Figure 3: Individual student participation in different Pyramid activities

3.5 Difficulties identified

Based on the results of the analysis, it was seen that participants' overall engagement with the collaborative learning activity is fairly low. A majority of learners falls into the category of *Lurkers*. It was also noticed that a significant portion of the learners participated in the initial option submission level and some participated only during rating stages. When compared to *initiators* and *raters*, *runners* who have participated in both initial and rating submission stages were relatively low. Finally, the most important category the *contributors*, who participated in both initial submission level and rating levels, are very low which leads to unsuccessful Pyramid activity flows. Further, it was also observed that some students tried to collaborate with others seeking help to solve their doubts using chat. However, many questions left open without responses due to lack of activity engagement of the participants.

On the other hand, individual differences might have an influence on Pyramid activity participation. We have not conducted an analysis considering those aspects due to limitations in obtaining participants demographics details. However, based on the results of the analysis conducted it was determined that the choice of collaborative script design parameters can also have an impact towards different collaborative learning behaviours. As it was described earlier, design parameters such as the number of rating levels, time limits etc. has to be carefully selected. For instance, it was noticed that in some Pyramids, although individuals finished rating, the application wait until the predefined timer expires i.e., 18 hours, without progressing to the next levels. Lack of support towards dynamic script parameter changes in such situations resulting in increased waiting times can hinder learner's motivation towards the collaborative learning activity as activity progression is not visible even after a longer duration.

Apart from log data, we have also analyzed qualitative feedback obtained from activity participants. An online survey was used to obtain participants overall opinion about the activity. Some participants have commented that lack of participation of their group members have made them feel isolated. For instance "..no one replied to my questions at all.." and "..seeing one question per day felt inefficient..". Some participants have also commented that "..Time constraints rather tight for a FutureLearn course which can be done out of real-time..". Based on results of both quantitative and qualitative analysis it was seen that collaborative learning activities deployed in MOOCs context requires careful orchestration of script design parameters, and also continuous interaction and feedback generation towards questions that arise from collaborative learning environments, to maintain student's engagement and motivation towards a continuous collaborative learning flow.

4 Empirical study for the design of an Orchestration Agent for Pyramid activities in MOOCs

Based on our exploratory case study it was observed that sustaining continuous collaborative learning flows in MOOCs is challenging. Learner's continuous engagement with the activity is often hindered due to many reasons, damaging continuous flows of collaboration. Different participant behaviors and rigid script design parameters can have a major impact towards collaboration, see [Section 3.5]. These type of interruptions especially affect contributors who truly seek to enjoy benefits of collaborative participation. Hence it is important to look into technological interventions that would facilitate to maintain continuous flows of collaboration.

4.1 Orchestration Agent intervention in PyramidApp

With the motivation of creating collaborative learning opportunities towards motivated learners and by considering the work already done in the field, it was seen that incorporating intelligent agents into MOOCs could result in added advantages. Intelligent agents can assist to maintain continuous collaborative learning flows while monitoring interactions among learners eliciting the requirement of manual intervention of educators. However, due to the high cost associated with this type of agent implementations research suggests to adapt Wizard of Oz (WOZ) studies, to clarify design requirements [Maulsby et al. 1993]. Hence, to better identify design considerations of an intelligent agent, which will orchestrate collaborative learning activities while maintaining a continuous flow of collaboration, we conducted a WOZ experiment. The agent will be referred as *Orchestration Agent* hereafter. The experiment was carried out during a MOOC course named *Innovative collaborative learning with ICT* in February 2017 which was deployed in the Canvas Network Platform. The total number of students enrolled for the course was 1031. We determined different stages of the Pyramid activity in which agent intervention becomes important to maintain a continuous flow of collaboration as follows.

a. Pyramid Instantiating Phase: As it was mentioned earlier, in order to create a Pyramid a minimum number of students required to be logged into the system. Unlike in a classroom setting in which students log into the system as soon as they are given the URL, in a MOOC participants access the activity URL at different times. Due to this variability in login times students who accessed the system earlier requires to wait without being allocated to a Pyramid until the minimum number of students are logged into the system. Increased waiting times result in decreased motivation of learners towards the activity. Hence we decided that waiting time could be minimized if the orchestration agent logs into the system simulating student behavior after a predefined period of time e.g., 20 minutes after the first student accessed the URL.

b. Initial Option Submission Phase: Next, if the agent observes that none of the students have submitted an initial option during the initial option submission stage (before a predefined period, e.g., 2 minutes prior finishing initial option submission stage) we require the agent to post a model answer as an option. This intervention limits the progression of Pyramids which does not have options to rate in the subsequent rating stages.

c. Rating Submission Phases: During the rating submission stages, if the agent observes that a particular rating stage is frozen due to no ratings (before a predefined period, e.g., 2 minutes prior finishing each rating stage) we require the agent to provide a 3-star neutral rating to all options submitted by course participants. This action facilitated the groups to proceed to the next levels. Further, if the agent noticed that the options to rate include options submitted by the agent itself (due to the reason mentioned in *(b)*) those options should be given only a 1-star rating in order to degrade its own submissions while facilitating options submitted by students to be promoted to the next level. Fig. 4 summarizes agent actions.

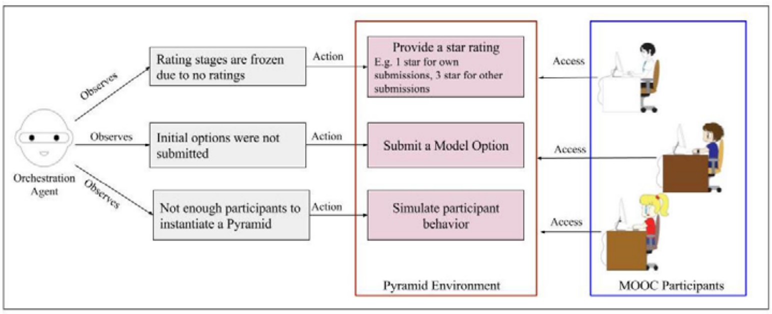


Figure 4: Orchestration Agent interventions in PyramidApp

4.2 Experimental Design

During the first and second week of the MOOC, we introduced collaborative learning activities using the PyramidApp in parallel to the course content. Initial design parameters of each Pyramid activity are given in Tab. 3. The first column in Tab. 3 indicates the activity type. We created four different types of Pyramid activities via differentiating the time allocated for each activity, namely *Very Rapid, Rapid, Long* and *Very Long*. The second column refers to the minimum number of students allocated for each Pyramid. We varied this attribute in the range of 4 to 6 during experiments in order to evaluate how different minimum sizes affect activity. However, we did not increase this attribute value more than 6 as we observed less number of participants during our previous collaborative learning activity. The third column refers to the number of Pyramid rating levels. We limited the value of this attribute to 2 in order to be consistent with the previous study. The fourth column refers to the number of students collaborated during the first rating submission stage. The fifth and sixth columns reflect the time allocated for initial option submission stage and subsequent rating stages based on the activity types described in the first column. Since we have categorized collaborative learning activities into four different categories based on time allocated for each activity the WOZ study also reflected how agent intervention requires being adapted according to different learning designs. However, it should be noted that due to limited time availability in MOOC it was not possible to carry out a balanced number of activities for each category. In summary we were able to carry out a total of 28 Pyramids, including 11 of *very rapid* type, 5 of *rapid* type, 10 of *long* type and 2 of *very long* type.

Activity type	**Min. students per Pyramid**	**Rating levels**	**Group size**	**Option sub. time limit**	**Rating sub. time limit**
Very Rapid	4 or 6	2	2	12 mints	12 mints
Rapid	4 or 6	2	2	47 mints.	47 mints.
Long	4 or 6	2	2	2 h	2 h
Very Long	4 or 6	2	2	6 h	6 h

Table 3: Configurations of Pyramid activities

4.3 Subjects

Students who were enrolled in *Innovative collaborative learning with ICT* MOOC course participated in the Pyramid collaborative learning activity deployed during the first and second week of the MOOC. Participants were informed that the activity participation was voluntary and that activity participation was part of a research experience and responses collected will be treated anonymously. Students were asked to use PyramidApp to discuss benefits and problems of CSCL until they reach a common group consensus to identify the most valuable benefit or the most popular problem. Participants were assigned to Pyramid groups randomly. During this empirical study, the role of the Orchestration Agent was enacted by the experimenter, the 'Wizard'. Based on PyramidApp log data, 28 participants accessed the *very rapid* type Pyramid activities while 22 participants accessed the *rapid* type, 37 participants accessed the *long* type and only 5 participants accessed the *very long* type Pyramid activities. The following section describes results and analysis of the WOZ experiment.

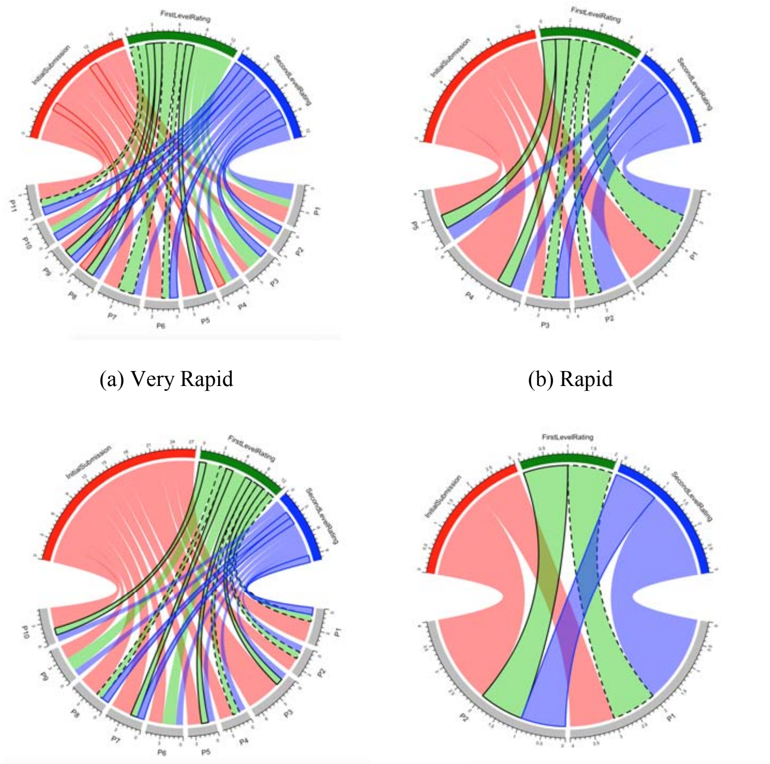
4.4 Results and analyses

PyramidApp log data was analyzed to determine collaborative learning behavior of MOOC participants and agent interventions. Chord diagrams were used to visualize learner's engagement in different levels of the Pyramid since these diagrams provide a compact way of representing information [Wei et al. 2016]. Log data was pre-processed to obtain input adjacency matrices for chord diagrams, in which the value in i^{th} row and j^{th} column represents the relation from object in the i^{th} row and the object in the j^{th} column while the absolute value measures the strength of the relation. R circlize package [1] was used to plot diagrams.

As can be seen in Fig. 5 (a), (b), (c), (d) each chord diagram consists of two sectors, namely the *Pyramid Sector* and *Submission Stage* sector. The Pyramid sector represents Pyramids that were created during each experimental activity. Pyramids were labeled starting from P1. The Submission stage sector represents different submission stages, i.e., initial option submission stage, first rating submission stage, second rating submission stage, which are colored in red, green and blue. Fig. 5(a) shows the chord diagram visualization for a total of 28 learners engagement in *very rapid* type Pyramid activities. Fig. 5(b) shows the visualization for a total of 22 learners engagement in *rapid* type Pyramid activities. Fig. 5(c) shows the visualization for a total of 37 learners engagement with *long* type Pyramid activities and finally Fig. 5(d) shows the visualization of 5 learners engagement with *very long* type Pyramid activities.

The width of each submission stage track represents the total number of submissions made for each submission stage by all participants allocated to different Pyramids. The width of each Pyramid sector denotes the total number of submissions made for all submission stages by participants in a particular Pyramid. Links between two sectors represent each submission stage engagement of participants who were allocated to different Pyramids. The thickness of each link is proportional to the number of submissions made by participants who were allocated to different Pyramids. Further, we have highlighted the links in order to emphasize the importance of orchestration agent participation in each Pyramid. For instance, a link with thick border denotes that the mandatory agent intervention was required for the Pyramid to proceed to the next levels, while a link with dashed border denotes that the agent participation was optional for the Pyramid to proceed to the next levels, but agent participation was required to create a meaningful collaborative learning scenario. This behavior of the agent became important during the first rating submission stage of each Pyramid activity, since only some small groups submitted ratings. Although lack of small group participation does not stop Pyramid from proceeding to the second rating submission stage, it is important that every small group participate in rating, as it affects the options which will be populated to the second (in this case the final) rating submission stage. We have emphasized this participation difference among small groups in first rating submission stage via thick and dashed border links. The following section describes the orchestration agent interventions in different Pyramid activities during the empirical study in detail.

[1] https://cran.r-project.org/web/packages/circlize/index.html



(a) Very Rapid (b) Rapid

(c) Long (d) Very Long

Figure 5: Patterns of engagement in different types of Pyramid activities

As it was mentioned earlier we have carried out 11 *very rapid* type Pyramid activities. It was observed that 7 out of 11 of these activities required orchestration agent to simulate student behavior to fulfil minimum student count requirement to generate a Pyramid within the allocated time frame. Also 10 out of 11 required agent intervention at least in one submission stage fully or partially due to lack of *contributors*. Not only lack of *contributors* but also lack of *initiators*, *runners* and *raters* have affected different submission stages. As it is denoted in Fig. 5(a), P4 and P8 Pyramids required mandatory agent intervention during initial option submission stage since there were no *initiators* or *runners*. Further, P5, P8 and P9 Pyramids required the mandatory intervention of the agent during first rating stage. However, in P6, P7 and P11 Pyramids agent participation were marked as optional because only one small group has participated in first rating submission stage. Hence, agent intervention was optionally required to create meaningful collaboration among small groups. Due to lack of *raters* and *runners*, P2, P3, P6, P9, P10 and P11 Pyramids also required agent mandatory intervention during second rating submission stage.

In *rapid* type activities only 1 Pyramid required orchestration agent to simulate student behavior to fulfil minimum student count requirement to generate a Pyramid. As denoted in Fig. 5(b), none of the Pyramids required mandatory agent intervention during the initial option submission stage, which indicated a strong presence of *initiators*. However, the same participation was not observed during the first rating submission stage. P1, P2 and P3 Pyramids required the optional participation of the agent while P4 and P5 Pyramids required mandatory participation of the agent to proceed to the next level. A higher student participation was also observed in the second rating submission stage. Mandatory agent intervention was only required during a single Pyramid P3.

In *long* type Pyramid activities 6 out of 10 Pyramids required orchestration agent to simulate student behavior to fulfil the minimum student count requirement to generate a Pyramid. As shown in Fig. 5(c) it can be seen that mandatory agent intervention during initial option submission stage was not required in any Pyramid. However, Pyramids P3, P5, P7 and P10 required mandatory agent intervention during the first rating submission stage to proceed to the next level while Pyramids P1, P2, P4 and P8 required optional agent intervention to create meaningful collaborations among small groups. Further, Pyramids P1, P7 and P8 required mandatory agent intervention during second rating submission stage. It should be noted that Pyramids P6 and P9 had a satisfactory participation of students in all Pyramid levels hence agent intervention was not required in any of the 3 submission stages. Finally, in very long type activities it was observed that both Pyramids required orchestration agent to simulate student behavior to fulfil the minimum student count requirement to generate a Pyramid. Further, as it is denoted in Fig. 5(d) agent mandatory intervention was required during both first and second rating submission stages of P2, while optional intervention during first rating submission stage was required in Pyramid P1.

4.5 Discussion

Results of the analysis revealed orchestration agent intervention to fulfil the minimum student count requirement to generate a Pyramid became important in 63.63% of *very rapid* activities, 20% of *rapid* activities, 60% of *long* activities and 100% of *very long* activities.

When considering different submission stages of the Pyramid it was observed that only *very rapid* activities required agent intervention in the initial submission stage (18.18%). In other 3 types of activities i.e., *rapid*, *long* and *very long* agent intervention was not required in the initial submission stage which indicated that learners have a higher engagement in the initial submission stage. However, it was observed that learner engagement with first rating submission stage and second rating submission stage varied. Mandatory agent intervention during first rating submission stage was required across all activity types including 27.27% in *very rapid* type activities, 40% in *rapid* type activities, 40% in *long* type activities and 50% in *very long* type activities. Optional agent intervention was also required across all activity types to create meaningful collaborations including 27.27% in *very rapid* type activities, 60% in *rapid* type activities, 40% in *long* activities and 50% in *very long* activities. Further, during the second rating submission stage it was observed that *very rapid* and *very long* activities required a higher intervention of the agent which was 54.55% and 50%. However, in *rapid* and *long* activities the requirement for agent intervention during the same stage was relatively low i.e. 20% and 30%.

In summary, based on the results of the analysis it became clearer that the orchestration agent participation in Pyramid activity becomes important in different stages in order to maintain an uninterrupted yet meaningful collaborative learning flows. Further, it was observed that orchestration agent intervention during Pyramid instantiating phase become also important in all activity types with the exception of rapid type activities.

5 Conclusions and Future Work

CSCL is a dynamic and an interdisciplinary field of research which mainly focuses on technological interventions towards education which could provide explicit or implicit support to facilitate the sharing and creation of knowledge through peer interactions and group learning processes. Working in groups create practical opportunities for students to resolve their doubts and to refine their knowledge on different learning aspects through discussions and rehearsals with peers. In the field of CSCL, CLFPs e.g., Pyramid essentially pre-structure the collaboration supporting practitioners to design learning tasks which will result in establishing productive interactions among learners. Deployment of such collaboration spaces scripted based on CLFPs creates productive yet meaningful collaboration opportunities towards MOOCs participants.

However, sustaining continuous yet meaningful collaborative learning flows in MOOCs are tedious due to many reasons. An exploratory MOOC case study carried out has shown that different participation behaviors and rigid script design parameters can have a major impact towards continuous collaboration. Findings of the exploratory MOOCs case study highlighted the requirement towards further investigations on technological interventions that facilitate to maintain continuous flows of collaboration, which will create collaborative learning opportunities towards motivated learners. Incorporation of intelligent agents was seen as a promising direction, as such techniques can be used to monitor interactions among learners eliciting the requirement of manual intervention of educators while facilitating the orchestration of collaboration. A WOZ study conducted in a MOOC has shown that intelligent agent intervention during collaboration enactment facilitates to sustain continuous yet meaningful collaboration learning flows, driving collaboration towards a productive state. Further, during the WOZ study, it became evident that only learning design parameter changes i.e., time allocation cannot drive collaboration towards a success, but it requires additional scaffolds. In the next steps of the research, it is of importance to investigate AI techniques which facilitates implementation of these agents, providing opportunities for its application and adaption in large-scale online learning settings.

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2.2 Adaptive Orchestration of Scripted Collaborative Learning in MOOCs

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Adaptive Orchestration of Scripted Collaborative Learning in MOOCs

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Abstract. This study presents the design, implementation and evaluation of several intervention strategies to address orchestration challenges associated with scripted collaborative learning activities in Massive Open Online Courses (MOOCs). The interventions are based on artificially simulated students and teachers. Findings of pilot studies conducted in real-world contexts revealed that the proposed interventions facilitate collaboration orchestration in MOOCs and help to trigger beneficial collaboration interactions among students.

Keywords: CSCL · Scripts · MOOCs · Orchestration · Adaptive systems

1 Introduction

In the domain of Computer Supported Collaborative Learning (CSCL), carefully designed scripts facilitate to structure group processes while triggering beneficial social interactions that may be rare in free collaboration [1]. In CSCL, Collaborative Learning Flow Patterns (CLFPs) formulate the essence of script structures and represent best practices to structure the flows of collaboration [2]. However, the achievement of success within scripted collaboration depends on the continuous activity participation of the learners as scripts constitute successive phases [2]. On the other hand, orchestration or the real-time management of scripted collaborative learning sessions deployed within Massive Open Online Courses (MOOCs) were seen challenging due to learner's activity distribution in time and level of involvement [3]. Implementation of carefully designed adaptive and intelligent techniques that facilitate to maintain pedagogical method structures proposed by scripts was seen beneficial in such spaces [3]. This study presents several adaptive intervention strategies based on the use of artificial simulated students and teachers to achieve orchestration of the scripted collaboration within MOOCs in presence of diverse individual learner behaviors.

2 Proposed Approach

In this study, a tool called PyramidApp [4] inspired by the pyramid collaborative learning flow pattern was used to design and deploy scripted CSCL activities. The collaboration flow within the tool initiates as individual students provide answers to a

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given task. In the next levels of the script, students are allocated into increasingly larger groups to discuss and rate the individual answers to reach a consensus at the group level and finally at the class level as the flow advances. The interventions to facilitate the orchestration of Pyramid activities in MOOCs are categorized into two categories namely (a) a Simulated Teacher (ST) and (b) a Simulated Student (SS) intervention, for the sake of clarity in representation. A ST is a software functionality that detects lack of rating and discussion engagement within collaborative groups and performs appropriate interventions (Table 1). A SS is also a software functionality which is pre-configured by the real-teacher during the activity design stage by assigning a pre-configured email and an answer to the given task (the answers are independent of real-students' answers). Whenever the minimum number of real-students required to create a Pyramid flow is not presented the SS's were automatically logged into the PyramidApp to initiate collaboration. The design requirements for the implementation of the proposed intervention strategies are described in detail in previous work [3].

Table 1. Adaptive intervention strategies proposed to orchestrate Pyramid based collaboration.

Pyramid level and problems identified in MOOC contexts	Proposed intervention
Pyramid instantiation phase: A Pyramid will be generated only when the minimum number of students stated in the activity design is satisfied. If the number of students logged into the system is less than the minimum count system keeps waiting until the minimum count is reached	As soon as the time limit mentioned in the activity design is reached SS are logged into the system with pre-configured email
Initial Option Submission Phase: Each student requires to submit an individual answer. A problem is students do not write answers, generating groups without answers to discuss	SS's answers are shown to the students, eliminating groups that do not have options to discuss
Small and large group collaboration Phases: Lack of rating participation	ST chooses a random answer to be populated at the next level
Small and large group collaboration Phases: Lack of discussion participation	ST sends a greeting in the chat. e.g., *Hello* ST sends a reminder in the chat. e.g., *Shall we start rating?* ST asks students for self-explanation. e.g., *Hi Jane, I'm not clear about your answer. Can you elaborate a bit on it?* ST motivates students for collaboration. e.g. *It's been a nice collaborative learning experience!*

3 Pilot Study

The proposed interventions have been implemented to the PyramidApp tool [4] and deployed within the first and second weeks of a MOOC course. The collaborative learning task within the first week was to discuss the importance of Responsible Research and Innovation (RRI). The two tasks within the second week were to discuss which RRI key issues are easier and harder to implement. According to the PyramidApp mechanism a pyramid can be instantiated when the minimum number of students required to generate a pyramid is logged into the system. In the pilot studies the minimum size of a Pyramid was set to 15. Each pyramid was configured to have two rating levels (small group and large group levels) and the small group size within a Pyramid was set to 5. Students were automatically allocated to Pyramids and subsequently to small groups randomly. Small groups were later combined into larger groups within each Pyramid. In pilot studies, the number of participants logged into the PyramidApp varied across weeks. e.g., 62, 51 and 43 participants. 3 Pyramids were generated for activity in the first week, 3 Pyramids were generated for activity 1 and 3 pyramids were generated for activity 2 in the second week. Log data collected from the tool was analyzed to report results. Based on the log data analysis it was seen that the SS and ST interventions became important at different stages of Pyramids for meaningful flow orchestration. For instance, there were not enough participants to generate pyramids hence the addition of SS was required (marked as x number of SS required in Table 2). Further, lack of rating participation was detected (marked as "Yes" in Table 2) which required the ST interventions. However, in the large group phase, no ST interventions were required as students displayed satisfactory rating participation.

Table 2. Simulated Student and Simulated Teacher intervention in pyramids.

Problem	Week 1 – Pyramid 3			Week 2- Activity1 Pyramid 3			Week 2- Activity 2 Pyramid 3		
	Small Groups			Small Groups			Small Groups		
	A	B	C	D	E	F	G	H	I
Lack of students	X1	X1		X1	X1	X1	X3	X3	X2
Lack of rating participation		Y	Y		Y	Y	Y	Y	Y
Lack of discussion participation	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. of prompts sent by ST before receiving replies	1	N/A	N/A	1	N/A	N/A	7	N/A	N/A
No. of students responded	1	0	0	2	0	0	2	0	0
No. of responses	2	0	0	4	0	0	7	0	0
	Large Groups			Large Groups			Large Groups		
Lack of rating or discussion									

* Gray colored cells show where no interventions are performed

MOOC participants also responded to the timed ST prompts in the chat, although the number of participants who responded and after which timed ST prompt they submitted a response varied. In group A and Group D (see Table 2) students responded 2 min after receiving a greeting message from the ST. In group G one student responded 2 min after receiving a greeting and the other student after 4 min receiving the self-explanation request from the ST. Further, students who responded to the timed interventions performed by the ST in the small group collaboration phases were seen to build collaborative conversations in the large group phase of the Pyramid activity.

4 Conclusions and Future Work

The results of the log data analysis showed that the proposed interventions became important in the CSCL activities that were generated at the end of each week of the MOOC. This shows that the proposed interventions could facilitate to orchestrate collaboration in such time-frames automatically where lack of engagement is detected. Hence this study contributes by proposing adaptive intervention strategies to orchestrate CSCL activities deployed in MOOC spaces. However, a limitation of the study is that we did not vary learning design configurations (e.g., the number of rating levels per Pyramids, small group size) during pilot studies. In future studies we are planning to experiment further the adaptiveness of the proposed strategies when enacting different learning designs. Further, we still believe that the role of the teacher managing the behavior of these adaptive aids in the orchestration is very important. We are currently working on an actionable orchestration dashboard that enables teachers to monitor PyramidApp activities and intervene with a set of actions when needed. The activation and deactivation of simulated students and a simulated teacher are part of these actions.

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Chapter 3

ADAPTIVE GROUP FORMATION CONSIDERING ACROSS-SPACES LEARNING SITUATIONS

This chapter tackles parts of the first, second and third objectives of this dissertation, in which we aimed at proposing appropriate LA interventions to facilitate the regulation of Pyramid pattern-based collaborative learning flows in authentic educational contexts at different scales (Figure 3.1). The content of this chapter consists of a JCR-indexed international peer-reviewed journal article which represents the research conducted during the second DBR cycle (Figure 3.2).

The article provides details of a data-driven LA approach that informs the formulation of adaptive collaborative learning groups considering across-spaces learning situations. The proposed group formation strategy employs predictive analytics to model students' future collaborative learning activity participation based on their past individual and collaborative learning behaviours recorded in different learning spaces. Details of the evaluation studies conducted in authentic learning situations and the practical challenges associated with deploying such LA interventions are elucidated.

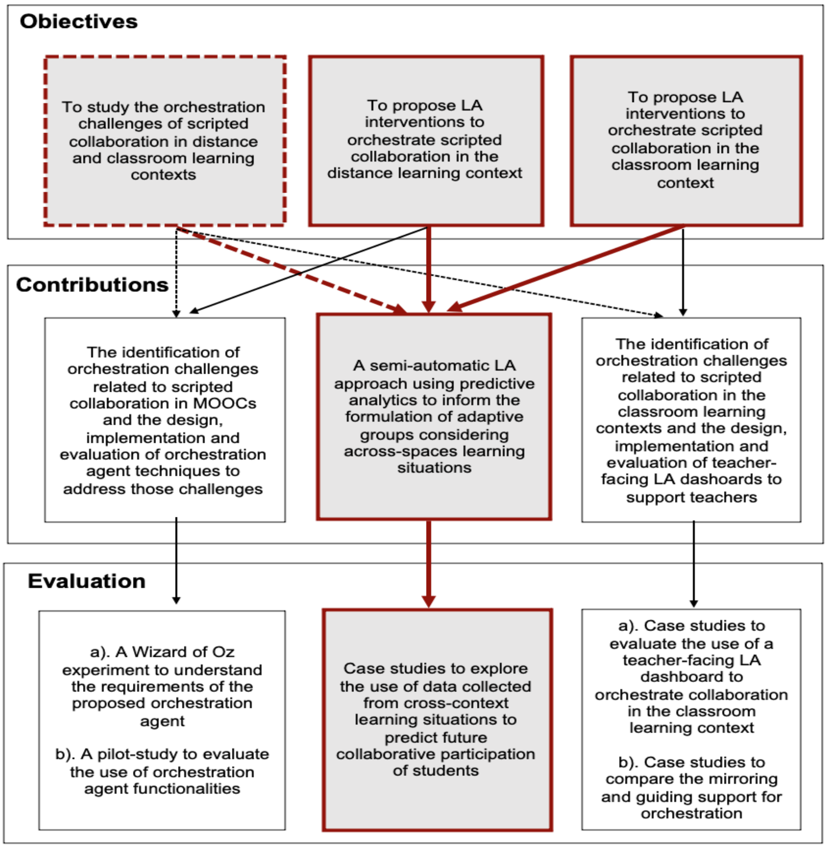

Figure 3.1: Objectives, contributions and evaluation studies covered by Chapter 3.

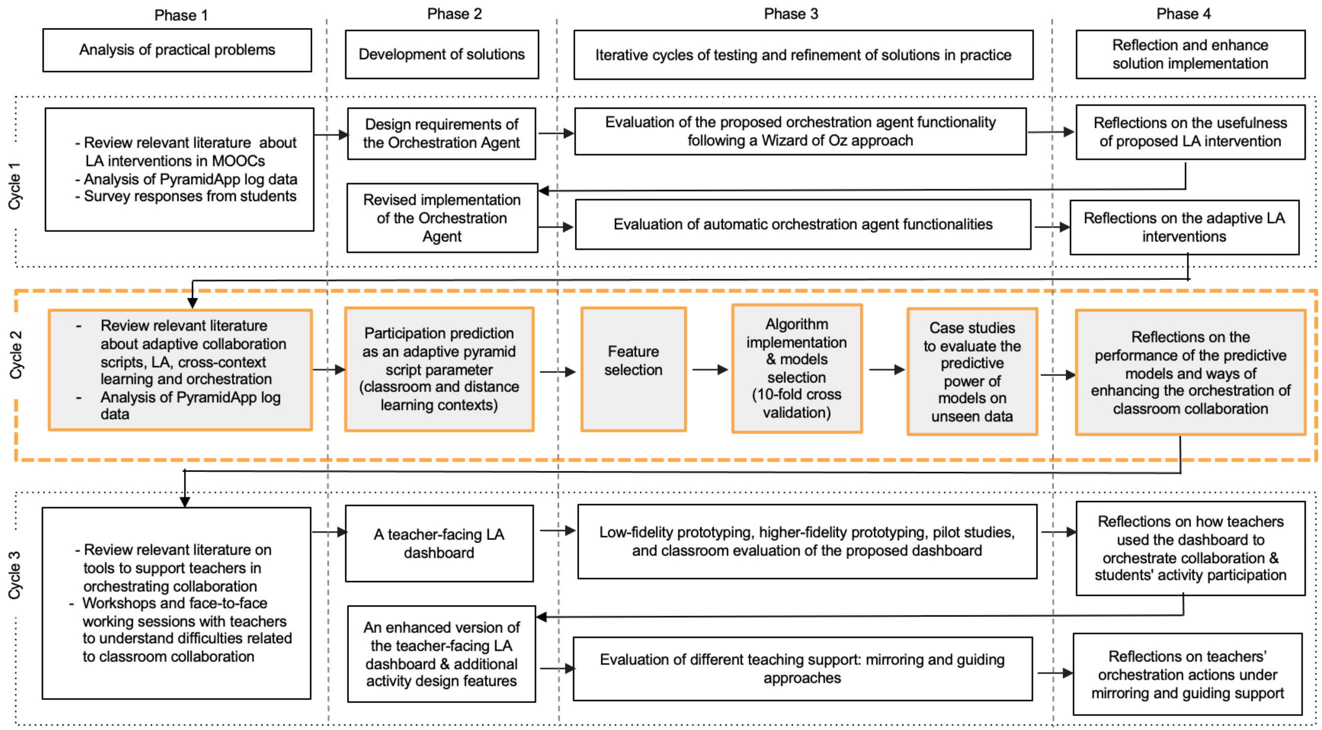

Figure 3.2: Part of the research process related to Chapter 3.

3.1 Data-Informed Design Parameters for Adaptive Collaborative Scripting in Across-Spaces Learning Situations

The content of this section was published in the following JCR-indexed international peer-reviewed journal article:

Amarasinghe, I., Hernández-Leo, D., & Jonsson, A. (2019). Data-informed design parameters for adaptive collaborative scripting in across-spaces learning situations. *User Modeling and User-Adapted Interaction, 29*(4), 869–892. https://doi.org/10.1007/s11257-019-09233-8

Data-informed design parameters for adaptive collaborative scripting in across-spaces learning situations

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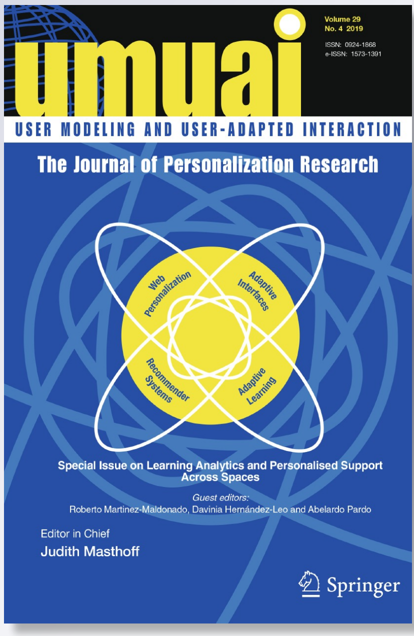

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Data-informed design parameters for adaptive collaborative scripting in across-spaces learning situations

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Abstract
This study presents how predictive analytics can be used to inform the formulation of adaptive collaborative learning groups in the context of Computer Supported Collaborative Learning considering across-spaces learning situations. During the study we have collected data from different learning spaces which depicted both individual and collaborative learning activity engagement of students in two different learning contexts (namely the classroom learning and distance learning context) and attempted to predict individual student's future collaborative learning activity participation in a pyramid-based collaborative learning activity using supervised machine learning techniques. We conducted experimental case studies in the classroom and in distance learning settings, in which real-time predictions of student's future collaborative learning activity participation were used to formulate adaptive collaborative learner groups. Findings of the case studies showed that the data collected from across-spaces learning scenarios is informative when predicting future collaborative learning activity participation of students hence facilitating the formulation of adaptive collaborative group configurations that adapt to the activity participation differences of students in real-time. Limitations of the proposed approach and future research direction are illustrated.

Keywords Computer Supported Collaborative Learning (CSCL) · Adaptive collaborative scripting · Collaborative learning flow patterns (CLFP) · Supervised machine learning · Prediction algorithms

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1 Introduction

Technological advancements have caused a multiplicity of learning spaces, creating learning opportunities towards students beyond the physical classroom spaces defined by the formal educational context (Ellis and Goodyear 2018; Kloos et al. 2012). With the increased availability of diverse digital learning spaces students learn, interact, share knowledge and engage in productive discussions with peers leaving behind a vast amount of digital data traces. Retrieving meaningful information combining trace data emerged from multiple sources is challenging and requires specialized knowledge, despite the fact that the analysis and interpretation of this data can provide meaningful insights to design and implement pedagogically meaningful learning activities in different learning spaces (Amarasinghe et al. 2017; Prieto et al. 2017; Martinez-Maldonado et al. 2017; Hernández-Leo et al. 2012; Tsovaltzi et al. 2015).

In the past few decades, Computer Supported Collaborative Learning (CSCL) emerged as a branch of the learning sciences, focusing on how people learn together with the help of computers (Stahl et al. 2006). In contrast to individual learning, CSCL is characterized by social learning phenomena, in which learning occurs socially through group interactions among students (Roschelle and Teasley 1995). It has been shown that working in groups increase students' learning and pro-social attitudes while solving problems with others, agreeing or disagreeing to different points of views at the same time giving or by receiving help from peers (Fall et al. 2000). In CSCL social interactions among students are being effectively mediated using computers, facilitating synchronous or asynchronous learning in the classroom and distance learning environments. Nonetheless, interactions observed in such learning settings are much more complex than that of the individual learning (Cen et al. 2016) which makes it challenging to conduct fruitful collaborative learning activities in both synchronous and asynchronous modes of collaboration.

In the domain of collaborative learning, *scripts* aim to promote productive interactions among groups of learners by shaping the way they interact with each other (Dillenbourg and Tchounikine 2007; Kobbe et al. 2007). Using different techniques (e.g., defining the activity sequence, role allocation etc.) scripts attempt to increase the probability of productive student-student and student–teacher learning interactions that would occur rarely or not at all in spontaneous collaboration (Dillenbourg and Tchounikine 2007; Demetriadis and Karakostas 2008; Kobbe et al. 2007). In CSCL, collaborative learning scripts have been operationalized using computers formulating CSCL scripts as it facilitates the mediation of collaboration (partly or totally) among distance and co-present learners (Dillenbourg and Tchounikine 2007; Demetriadis and Karakostas 2008; Kobbe et al. 2007; Villasclaras-Fernández et al. 2009).

Nonetheless, research has shown that the static support provided by scripts is not responsive to what is occurring in the actual collaborative learning environment (Kumar et al. 2007). It has been argued that adaptive collaborative scripting, in which collaborative interactions are modeled as they occur (Walker et al. 2009) in an adaptive mode can considerably improve the collaborative learning experience (Demetriadis and Karakostas 2008). When considering the across-spaces learning scenarios, adapted scripted collaboration becomes challenging since the actions of students in previous activities carried out in diverse spaces or with different technologies is relevant for the planning of following up activities in a new space (Hernández-Leo et al. 2012).

From a learning analytics perspective, fine-grained learning analytics techniques can be employed to interpret data captured across different learning spaces in different modalities (Martinez-Maldonado et al. 2017). Meaningful insights gained from learning analytics can be used to identify relevant adaptive script features hence facilitating the formulation of adaptive collaboration scripts in across-spaces learning situations in real-time (Amarasinghe et al. 2017). Towards this end, the focus of our work is on investigating how predictive analytics can support the formulation of adaptive collaborative scripts in cross-context learning situations. Predictive analytics is described as a subset of data science that facilitates to uncover relationships and patterns within large volumes of data that can be used to make predictions about future events (Waller and Fawcett 2013; Nyce and Cpcu 2007). Within this study, predictive analytics have been used to predict future collaborative learning activity participation of students, to facilitate the formulation of collaborative learner groups that adapt to the activity participation differences of students. We have collected data from different learning spaces and used supervised machine learning techniques for prediction purposes. The main research question addressed in this study is the following: Can participation prediction be used to inform decisions for adaptive collaborative scripts in across-spaces learning situations? The main research question composed of the following sub research questions: (i) How to use supervised machine learning techniques to predict future collaborative learning activity participation of students based on data collected from across-spaces learning situations? (ii) How an estimate of future collaborative learning activity participation of students can be incorporated into CSCL scripts in real-time to facilitate the formulation of adaptive collaborative learning scripts?

The rest of this paper is structured as follows. Section 2 presents relevant literature considering adaptive collaborative scripting, its association with across-spaces learning scenarios and different learning analytic techniques that have been deployed in previous studies to support collaborative learning. Section 3 illustrates the proposed approach, along with data collection methods in different learning contexts, feature generation and model selection in detail. Section 4 presents case studies that demonstrate the applicability of the suggested intervention in formulating adaptive collaborative scripts in real-world collaborative learning sessions along with the lessons learned and the limitations of the proposed approach. The final section provides concluding remarks followed by future research directions.

2 Background

2.1 Adaptive collaboration scripts

CSCL scripts aim to facilitate productive interactions among distant or co-present learners as free collaboration fails often to trigger productive group interactions (Dillenbourg and Tchounikine 2007). Scripts are based on the scripted cooperation approach and provide a method for structured collaboration which intends to achieve higher levels of cognitive processing and better learning outcomes (Demetriadis and

Karakostas 2008). Scripts provide instructions “for small groups of learners on what activities need to be executed, when and by whom they need to be executed in order to foster individual knowledge acquisition” (Weinberger et al. 2007). Many studies have reported the effectiveness of using collaborative scripts towards achieving benefits of collaboration (Rummel and Spada 2007; Kollar et al. 2006).

Yet, at the same time, CSCL scripts have also been criticized for being overly constrained limiting its modifiability during the script runtime (Dillenbourg and Tchounikine 2007). Lack of flexibility associated with CSCL scripts and potential risks of over-scripting collaboration has highlighted the requirement towards adaptive collaboration scripts that adjust script parameters during script execution (Demetriadis and Karakostas 2008). As described in Demetriadis and Karakostas (2008) adaptive collaboration scripting “is the idea that collaboration scripts can be adapted during runtime in several of their aspects, to provide learning experiences tailored to individual and group characteristics”. However, it is not possible to model any script feature as an adaptation. Intrinsic constraints that preserve the underlying pedagogy of a script are not considered as candidates for adaptation (Dillenbourg and Tchounikine 2007). For instance, in a Jigsaw script, a constraint that specifies each Jigsaw group requires to consist at least one member from each expert group is an intrinsic constraint that is mandatory to be satisfied and cannot be modeled as an adaptive script parameter. On the other hand, extrinsic constraints are related to the contextual aspects that lead to a particular implementation of the pedagogy. As further illustrated in Demetriadis and Karakostas (2008) extrinsic constraints can be further divided into two categories namely “Non-pedagogical” and “Pedagogical” constraints and can be considered as candidates for adaptation. *Non-pedagogical* constraints (constraints that do not possess any pedagogical relevance) e.g., duration of a script phase, can be altered by teachers or students to better accommodate the script to the given learning situation while *Pedagogical* constraints (e.g., increasing the level of support given to avoid learners’ misconceptions) should be adapted to facilitate a better learning experience. CSCL scripting systems that embed adaptive scripting techniques have been referred to as “Adaptive Collaboration Scripting systems” or ACS (Demetriadis and Karakostas 2008). ACS have been reported to be more effective than non-adaptive collaborative learning systems as ACSs tailor the learning experience to the needs and characteristics of both individuals and learner groups maximizing the benefits from the scripted collaboration (Rummel et al. 2008).

Research has provided evidence that adaptive collaboration support provided in the form of prompts has a beneficial impact on student learning. In Kumar et al. (2007) adaptive collaborative learning support has been deployed using tutorial dialogue agents. It has been found that the students who gained dynamic support in terms of adaptive prompts have benefited significantly from collaboration when compared to the no support condition. Walker et al. (2014) have built an ACS to support peer tutoring in high school algebra. The adaptive support has been built into the system (in terms of reflective prompts that appear in the chat), to support peer tutors to provide correct and effective help. Authors have investigated the impact of adaptive support on peer tutor learning and have shown that students in the adaptive support condition learned more than the students in the non-adaptive condition. Further, as the adaptive support increases, the difference between learning gain in the adaptive condition and the non-adaptive conditions became more apparent. In Baghaei et al. (2007) adaptive support was built into an intelligent tutoring system in which students construct UML class diagrams that satisfy a given set of requirements. Adaptive feedback was provided to groups while collaborating on the design of UML class diagrams in order to guide them towards the correct solution. It has been found out that students who received adaptive feedback while working with the system performed significantly better on the collaborative task. In Karakostas and Demetriadis (2011), authors have examined the use of adaptive prompts to enhance domain learning. The ACS implemented in their study monitored students' discussions in order to detect whether students have missed to discuss important subject relevant concepts during their discussions. When a missing concept was detected the system provided a prompt to students showing the missing information. Authors have shown that this mechanism has resulted in improved learning outcomes. In Demetriadis et al. (2018) authors have proposed the potential use of conversational agents in Massive Open Online Courses (MOOCs) to enhance the MOOC experience of course participants. The study has described how conversational agents can be applied to peer interaction sessions in order to enhance the course engagement of MOOC participants that will help to reduce the overall MOOC dropout rates while facilitating educators to better orchestrate MOOC activities.

However, as emphasized in Karakostas and Demetriadis (2011) ACSs are still at an early stage of research and most of the efforts that have implemented adaptive support are strongly related to a particular domain of instruction. Towards this end, the objective of our study is to emphasize the need for implementing adaptive collaborative learning support considering not only learning that occurs within a specific domain in a particular space, but considering diverse behaviours that occur in cross-context learning situations.

2.2 Cross-context learning and collaboration orchestration

With the increased access to emerging communication technologies, Learning Management Systems (LMS), MOOCs, Virtual Learning Environments (VLEs), Social Networking Sites (SNS), and 3D Virtual Worlds (3DVWs) to name a few, students learn across different digital learning spaces that spread beyond the boundaries of physical spaces defined by traditional classroom environments (Kloos et al. 2012; Martinez-Maldonado et al. 2016; Tsovaltzi et al. 2015). Students engage in different learning activities in different learning spaces and associate different learning communities disregard the place and time in which learning occurs. Such learning scenarios are referred to as across-spaces learning situations, in which learning activities are not restricted or constrained to a single physical or digital environment (Kloos et al. 2012). Across-spaces learning scenarios provide valuable opportunities towards learning, since physical and social interactions that occur in 'real-world', outside the traditional classroom, promote the acquisition of certain skills (Kloos et al. 2012).

Although distinct learning spaces provide a wide variety of learning opportunities towards learners, understanding how learning occurs across-spaces in its totality combining multiple spaces is a complex task (Prieto et al. 2017). This leads to challenges in being able to create interconnected flows between different learning spaces (e.g., formal, informal, virtual spaces) in order to support learners while maintaining smooth transitions across different learning spaces (Kloos et al. 2012). How existing pedagogical strategies e.g., collaborative learning, game-based learning can be effectively utilized considering more complex and dynamic across-spaces learning situations that spreads beyond the traditional classroom walls have been identified as an interesting field worth exploring (Kloos et al. 2012).

In the domain of CSCL, managing learning scenarios while adapting to a number of different parameters both in real-time and across longer scales of time, is referred to as “orchestration” of the collaborative learning activity (Dillenbourg et al. 2011; Tissenbaum and Slotta 2015). When considering the cross-context learning situations the real-time management or the orchestration of collaboration become more challenging for educators than managing traditional scripts in a single space e.g., classroom, as both macro and micro script parameters now require being adjusted according to learning activities that occurs across-contexts that associates complex technologies (Tissenbaum and Slotta 2015). Design and execution of complex collaborative scripts in such scenarios demand increased levels of information processing needs of educators and learners (Tissenbaum and Slotta 2015). In such a context, learning analytics can be effectively utilized to make simplified views on complex across-spaces learning scenarios facilitating educators to make data-informed script design decisions. These script design decisions can then be used to formulate adaptive collaboration scripts that tailor learning experiences to individual students and group characteristics (Tissenbaum and Slotta 2015). Further during the execution of the scripts, learning analytics can be used to update the educator on the status of collaboration occurs at different levels (e.g., individual level, group level) by showing which script parameters requires being adjusted (e.g., time) and also by proposing dynamic group re-configurations (e.g., learner dropouts in the middle of the activity) or by highlighting groups that require intervention (Tissenbaum and Slotta 2015). Apart from formulating adaptive collaboration scripts, the association of intelligent agents and real-time data mining techniques into learning environments have been shown beneficial towards the orchestration of scripted cross-context learning situations (Tissenbaum and Slotta 2015).

2.3 Collaborative learning and learning analytics

Learning analytics is defined as the “measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environment in which it occurs” (Ferguson 2012). Recently learning analytics gained a lot of attention as it provides different mechanisms and techniques to better understand learners (Dawson 2006) while providing insights to improve teaching practices (Dyckhoff et al. 2013; Ferguson 2012). During recent times, different learning analytics techniques accompanied with data mining and machine learning have been widely adopted in different learning contexts for different purposes as it provides new ways to analyze data on students’ interactions, engagement, and performances (Coffrin et al. 2014).

Different learning analytics techniques have been used in the domain of CSCL to better understand collaborative interactions, participation behaviours, knowledge building behaviours etc. of students in order to make productive interventions during collaboration interactions. A number of mechanisms such as process mining, sequential mining, data mining, social networking analysis and different machine learning techniques such as predictive analytics, Bayesian networks, and fuzzy logic have been effectively utilized in different studies to address a number of research questions that have covered different aspects of collaboration. For instance, some researchers have used data mining and process mining techniques to analyze data collected in classroom collaborative sessions to distinguish high from low achieving groups (Martinez-Maldonado et al. 2013) while some researchers have used machine learning techniques, i.e., Hidden Markov Models and multidimensional scaling techniques to analyze conversational data collected during collaborative learning activities to detect effective and non-effective knowledge sharing episodes (Soller 2004). Learning analytics have also been used to make productive interventions during the collaborative construction of written documents (McNely et al. 2012).

With the incorporation of predictive machine learning techniques, some research has attempted to predict group learning performance in collaborative learning sessions as it helps to determine better group-based assessment measurements. For instance, Xing et al. (2015) used activity theory to holistically quantify student's participation in CSCL activities, which was then used to build a student performance prediction model, using Genetic Programming. Goode and Caicedo (2014) have analyzed log data collected from a social media website to measure group participation during a collaborative learning task. A model was then proposed to predict team performance in future collaborative learning activities using system-tracked log data. Cen et al. (2016) have used supervised machine learning techniques, i.e., classification and regression to predict group performance using data which depicted member interactions. Research has also focused on predicting post-test scores by taking into account pair interactions (Rafferty et al. 2013). Olsen et al. (2015) have argued that much of the research on learning predictions have focused on modeling individual learning and much of the work does not attempt to predict student performance as students collaboratively solve problems. In their work Olsen et al. (2015) have used a standard logistic regression model, i.e., Additive Factors Models which is widely used for predicting individual student performance in the context of Intelligent Tutoring Systems (ITS) to predict collaborative problem-solving performances of students in an ITS environment.

Based on some research already done in the field it was seen that different learning analytics techniques have been broadly utilized to better understand collaborative group learning processes as well as to predict group learning performances. However, less attention is given to predict individual learners' collaborative learning participation behaviour considering across-spaces learning situations, although such predictions can inform the formulation of adaptive collaborative learning scripts that adapts to diverse individual learning behaviours observed in different learning spaces.

3 Participation prediction as an adaptive collaborative script parameter for pyramid based collaborative learning scripts

Implementation of tools and techniques to enhance students' engagement in collaborative learning activities has been a research question of interest in the Technology Enhanced Learning (TEL) research community for many years. Formulation of homogeneous or heterogeneous learner groups based on learner's profile details (e.g., preferences, knowledge levels etc.) which were captured using questionnaires or surveys prior to the group formation process is one of the frequently adopted method for criteria-based group formation until recent times. This method has reported being effective at achieving specific objectives in different collaborative learning situations (Spoelstra et al. 2015; Moreno et al. 2012). However, with the increased use of online learning platforms for teaching and learning, recent research has highlighted the feasibility of using data-driven learning analytics techniques to analyze trace data collected from online learning platforms to formulate meaningful collaborative learning groups. The use of different data-driven techniques to identify team-formation criteria was seen as beneficial to conduct fruitful collaborative sessions in both co-located and distance learning environments (Sanz-Martínez et al. 2017).

In the work presented in this study we propose an adaptive group formation strategy in which an estimation of students' future collaborative learning activity participation was modeled as an adaptive script parameter considering their cross-context learning behaviours. Predicted future activity participation differences of students were used in real-time to formulate heterogeneous groups automatically in a pyramid-based collaborative learning script. A tool called "PyramidApp" was used to operationalize pyramid-based collaborative learning scripts (Manathunga and Hernández-Leo 2018).

A pyramid flow is initiated with individual students proposing individual answers to a global task. Then, in a second level of the pyramid, individual students are allocated to a number of small collaborative learning groups in which solutions are discussed and rated to agree upon a common proposal. Inbuilt discussion board of the tool provides a negotiation space for participants at group levels to discuss and agree upon the individual options submitted. Once a pyramid activity is designed and published by the educator it becomes accessible to students via a public URL. Activity participants can access the activity by logging to the PyramidApp tool using the given URL. A screenshot of the PyramidApp is shown in Fig. 1.

The proposed adaptive group formation strategy is seen vital in a pyramid-based collaborative learning script for many reasons. Firstly, predictions inform the formulation of meaningful group configurations. For instance formulation of heterogeneous groups based on predicted activity participation differences avoid the creation of homogeneous groups that consist only one type of participants e.g., groups consist only inactive participants, yet facilitating the meaningful progression of the collaborative learning activity.

Secondly, as the Pyramid script evolves over time creating increasingly larger groups, an active group i.e., a homogeneous group consist of active participants, collaborating with an inactive group i.e., a homogeneous group consist of inactive participants in the next levels of a pyramid will not result in creating beneficial collaborative learning opportunities for the members of the active group as they cannot build

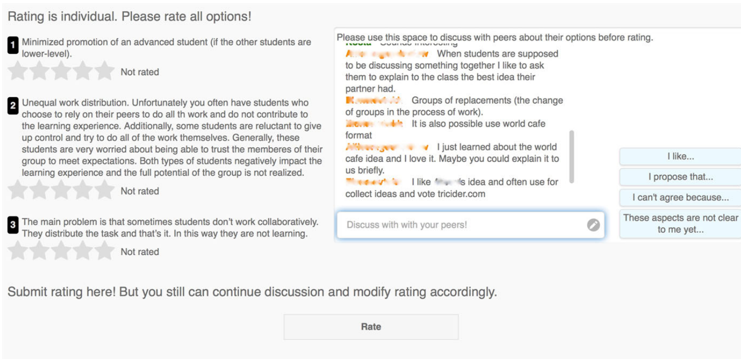

Fig. 1 A screenshot of the PyramidApp showing rating space (left) and the negotiation space (right)

rich pedagogical interactions with members of the inactive group who exhibited little or no interest towards collaboration. Combining these type of homogeneous groups as one big group in the next levels of the pyramid can demotivate members of the active group causing unpleasant learning experiences.

Finally, the formulation of heterogeneous groups based on activity engagement differences of students ensures that every group consists of at least a portion of active participants who will actively contribute to the collaborative learning task at hand. Assigning at least a few active participants in a group can positively influence the inactive participants, as inactive participants get a chance to observe meaningful collaborative interactions and productive communicative acts occur among active participants. Being informed on the positive interactions that occur among active participants can motivate and encourage inactive participants to take part in the pyramid script in the next levels.

3.1 Proposed approach

3.1.1 Formalization of the learning problem and feature representation

The prediction problem addressed in this study was treated as a binary classification problem, in which we attempted to use supervised machine learning techniques to learn a classifier to predict the future collaborative learning activity participation of individual students. The prediction problem addressed in this study can be formulated using mathematical notations as follows.

Given a dataset of observations $S = (x_1, y_1), \ldots, (x_m, y_m)$ where x_i is a vector specifying various individual student features (extracted from student-platform interaction data) and $y_i \in 0, 1$ representing whether or not a given student will participate in collaborative learning activity, the problem is to learn a classifier to infer value of y_i given x_i. The following sections describes how we collected training data, feature generation and model selection processes adhered in detail.

3.1.2 Data collection

The training data used in this study were collected from two different learning contexts: (i) Classroom learning context and (ii) Distance learning context. In each learning context, two different learning spaces were used to collect training data that described students' individual and collaborative learning behaviours.

In the classroom context, we extracted data from a Moodle—an open source Learning Management System (LMS)—course (164 cases). In the distance learning context, we collected data from a MOOC course querying the Canvas LMS REST API, which described student's learning behaviour in a different digital learning space (230 cases). In both spaces, the data consisted of records that provided insights on individual student-platform interactions details (e.g., course content page views, forum discussion views, assignment submissions, quiz attempts, quiz submissions and forum post submissions).

We conducted collaborative learning activities in the classroom and distance learning contexts to collect training data that depicted students' collaborative learning behaviours. The collaborative learning activities were implemented using PyramidApp. The Pyramid script adopted in both contexts consisted of five phases: (i) an individual phase where students study a learning material and formulate their own answers to a given question related to the material studied (ii) an individual phase where students log in to the PyramidApp and submit individual answers (iii) a small group collaborative phase where students discuss and rate individual answers submitted (iv) a larger group collaborative phase in which students further discuss and rate answers previously selected or best rated in small group levels (v) a debriefing session, where the teacher explained the best rated/ winning answers of each pyramid.

Since the training data collected was originated from different data sources i.e., PyramidApp, Moodle LMS course, MOOC course, data preprocessing became mandatory in order to interpret meaningful information out of raw data. During data preprocessing, for each individual student s, we considered event history up to time t in Moodle LMS course log data and MOOC course log data, given that the student has participated in small group collaboration phase in pyramid script at time t. During pre-processing we had to deal with unstructured data as there had no predefined data model in-place for data gathering from multiple sources in cross-context learning situations. In particular, date-time formats were not consistent and needed to convert them to a common date-time format without losing any important information.

After data preprocessing stage, we built two data sets: (i) a data set merging PyramidApp log data with Moodle LMS course data that described collaborative and individual learning behaviours of a particular set of students (ii) a data set merging PyramidApp log data with MOOC course data that described collaborative and individual learning behaviours of a particular set of students (see Fig. 2). The two data sets were later used to train and test machine learning classifiers.

3.1.3 Feature selection

The accuracy of a given classification task depends on the choice of informative and discriminating features that are provided as inputs to the supervised learning algorithm

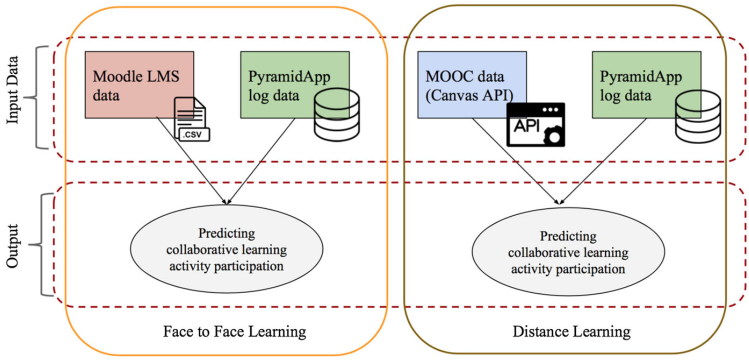

Fig. 2 Heterogeneous data sources

(Cen et al. 2016). In the following, we describe the features used in this study for prediction purposes.

We used a correlation-based approach for feature selection since the removal of irrelevant and redundant features often improves the performance of machine learning algorithms (Yu and Liu 2003). Based on correlation coefficient values it was observed that in both learning contexts some features positively or negatively correlated with the class, while some features do not have a relationship with class variable (correlation coefficient was zero). Based on the results of the correlation analysis in the classroom context the input vector x_i included seven input features (generated using Moodle LMS log data and PyramidApp Log Data) as mentioned below:

- Total number of course page views before collaborative activity participation
- Total number of forum discussion entry views before collaborative activity participation
- Total number of quiz attempts before collaborative activity participation
- Total number of quiz submissions before collaborative activity participation
- Total number of assignment submitted before collaborative activity participation
- Student's participation in the initial stage of the pyramid activity
- Student's collaborative activity participation (class variable).

In the distance learning context the input vector x_i included ten input features (generated using MOOC course log data and PyramidApp log data) as mentioned below:

- Total number of course page views before collaborative activity participation
- Total number of assignment submitted before collaborative activity participation
- Total number of discussion entries posted before collaborative activity participation
- Total number of quiz submissions before collaborative activity participation
- Total number of quiz attempts before collaborative activity participation
- Total number of quizzes answered correctly
- Total number of quizzes answered incorrectly
- Total quiz score

– Student's participation in the initial stage of the pyramid activity
– Student's collaborative activity participation (class variable).

In both contexts, the class variable y_i was used to specify each individual student's collaborative activity participation. In other words, y_i can take one out of the two values in the classification task in which, 1 depicting 'yes' and 0 depicting 'no' with regard to the small group collaborative phase participation of each individual during pyramid script enactment.

3.1.4 Algorithm implementation and model selection

To predict individual student's collaborative activity participation in Pyramid activities, we explored the applicability of three widely adapted supervised machine learning techniques: Support Vector Machines (SVMs), Feed Forward Neural Networks (FFNNs) and Random Forests (RFs). In the following, we provide a brief explanation of each model.

The SVMs are pioneered by Vapnik (2013) and have been used to solve both classification and regression problems in different contexts, although it is widely used to solve classification problems. The SVMs construct a hyperplane(s) usually in the high dimensional space, in order to separate two data classes, i.e., positive and negative instances in a given dataset. Intuitively, the maximum-margin hyperplane, which represents the largest margin between two data classes achieves the best possible separation and has been proven to lower the classifier's expected generalization error (Kotsiantis et al. 2007). The FFNN is an artificial neural network which simulates the functionality and behaviour of biological neurons (Hagan et al. 1996). FFNNs typically consist three types of layers: (i) input layer—consists of input nodes, (ii) one or more hidden layers–consist of hidden nodes, and (iii) output layer–consists output nodes. In FFNNs information flow only in one direction through the network from the input layer to the output layer, without forming cycles in the network. During the training phase of the network, network parameters (e.g., weights and biases) requires being adjusted using back-propagation algorithm. Afterward, the trained network can be presented with unseen test data for classification tasks. Finally, RFs is an ensemble learning technique used for classification tasks. In general ensemble learning techniques generate many classifiers and aggregate their results to provide a final classification output. During the training phase of RFs, a number of decision trees are being generated and the mode of the classes output by individual trees is provided as the prediction output (Breiman 2001).

The aforementioned classification algorithms were implemented using scikit-learn machine learning library.[1] Each algorithm was trained separately in both learning contexts, i.e., classroom and distance learning, to determine the best performing classifier. To obtain the best hyper-parameters for each algorithm a grid search was carried out. Each model, i.e., an algorithm with best hyper-parameters, was then evaluated using K-fold cross-validation method given its benefits over train/test split procedure. In particular, we implemented 10-fold cross-validation, which has been shown as a reliable estimate in the literature towards model evaluation (Cen et al. 2016). Table 1 provides the cross-validation accuracy of each model. Based on cross-validation accuracy scores

[1] http://scikit-learn.org.

Table 1 Prediction performance accuracy comparisons of different models using 10-fold cross validation

Learning context	Model	Accuracy score
Classroom	SVMs*	0.82
	NNs	0.81
	RFs	0.79
Distance	SVMs	0.80
	NNs*	0.81
	RFs	0.78

*Best performed model in each learning context

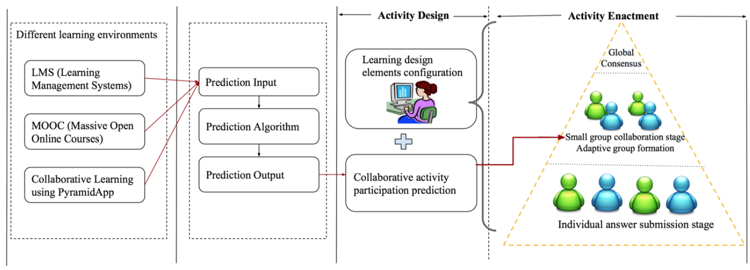

Fig. 3 Pipeline-integrating prediction results as collaborative script parameters

it was seen that SVMs outperformed other models when predicting collaborative activity participation in classroom context while NNs performed slightly better than SVMs in distance learning context.

4 Evaluation: formulation of adaptive collaborative learning groups in pyramid scripts in real-time

In the following sections, we present case studies in which we used the prediction outcomes of the best performed models i.e., SVMs in classroom learning context and NNs for distance learning context (see Table 1) to formulate adaptive collaborative learning groups in pyramid scripts in real-time.

Figure 3 shows the architecture adapted for this purpose. As can be seen in Fig. 3 the prediction output (which differentiated active vs. inactive participants) was associated with the other learning design parameters (e.g., group size, time allocation, number of pyramid levels) of the Pyramid script during the activity design stage. Heterogeneous groups were then formulated in real-time during small group collaboration stage of the Pyramid script automatically.

4.1 Case studies

4.1.1 Collaborative learning activities in classroom context

We carried out collaborative learning activities in four undergraduate classes in January 2018. First year undergraduate engineering students who were enrolled in *Computer*

Table 2 PyramidApp design parameters for classroom activities

Design parameter	Value
No. of pyramid levels	3 (e.g., initial answer submission stage, small group collaboration stage and large group collaboration stage)
Minimum students per pyramid	6
Small group size	3
Initial answer submission time	5 min
Rating submission time	4 min

Organization course participated, with informed consent, in the collaborative learning activities. Prior to the activity enactment, we did a demonstration explaining the flow of the activity.

Design elements associated with pyramid activities conducted in classroom sessions are shown in Table 2. Based on design configurations of the PyramidApp, i.e., the minimum number of learners per Pyramid, a number of pyramids were instantiated allocating participants to Pyramids who logged into the system at different times. Further details about the implementation of this tool can be found in Manathunga and Hernández-Leo (2018). The task given to students was related to a programming problem, in which the students were asked to collaboratively decide the best answer to the given programming problem. Predicted future collaborative learning activity participation of each student (obtained from trained SVM model) was incorporated to formulate heterogeneous groups automatically in the small group collaboration level of the Pyramid script.

4.1.2 Results

We adopted a similar decision scheme proposed in Lykourentzou et al. (2009) to evaluate the prediction accuracy of the machine learning models during case studies conducted in the real-world context. We modified their decision scheme to match with the specific prediction problem we are interested in, although the original work was related to dropout prediction in an e-learning system. Following paragraphs describe the decision scheme adapted and the interpretation of the results.

The overall accuracy criterion (see Eq. 1) measures on average the proportion of accurately predicted active and inactive participants given the total number of activity participants. Figure 4 depicts the overall accuracy results of the machine learning model. The vertical axis in Fig. 4 presents the overall accuracy and the horizontal axis represents each pyramid starting from P1 which refers to the first pyramid and so on in each classroom session.

$$\text{Overall accuracy} = \frac{\begin{array}{l}\text{Correctlypredictedactive}\\ \text{participants}\end{array} + \begin{array}{l}\text{Correctlypredictedinactive}\\ \text{participants}\end{array}}{\text{Total activity participants}} \quad (1)$$

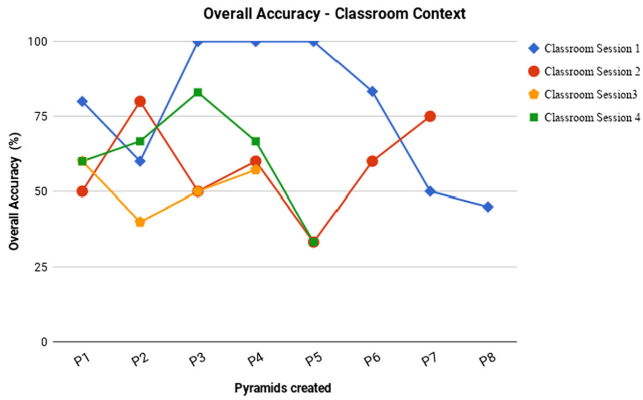

Fig. 4 Overall accuracy of prediction in classroom context

Based on the overall prediction accuracy results, it was observed that in many pyramids the classifier has achieved an overall prediction accuracy which was above 50%. However in P8 generated in classroom session 1, P5 generated in classroom session 2, P2 generated in classroom session 3 and in P5 generated in classroom session 4, the overall accuracy has dropped below 50%, which is much less than the performance accuracy score reported during 10-fold cross-validation for SVM classifier which was 0.82 (see Table 1).

4.1.3 Collaborative learning activities in MOOC context

We conducted two Pyramid collaborative learning activities in a MOOC course named *Concepts and Practice of Responsible Research and Innovation* in February 2018. The first pyramid activity asked course participants to discuss which responsible research and innovation practices are easier to implement while in the second activity students were asked to discuss which responsible research and innovation practices are difficult to implement. Design parameters associated with the Pyramid activities are given in Table 3. Participants were informed that the activity was voluntary and that activity participation was part of a research experience and responses collected will be treated anonymously.

4.1.4 Results

In contrast to the classroom pyramid activities presented earlier (see Sect. 4.1.1) in which we formulated adaptive collaborative groups based on prediction results, within the MOOC context we were unable to do the same due to the poor performance of the trained NNs classifier. The predicted outcome of the classifier was 0 for all the students which indicated that none of the students will participate in the collaborative learning activity. Training data sets that constituted a limited number of samples that are also

Table 3 PyramidApp design parameters for MOOC activities

Design Parameter	Value
No. of pyramid levels	3 (e.g., initial answer submission level, small group level and large group level)
Minimum students per pyramid	15
Small group size	5
initial answer submission time	1 day
Rating submission time	1 day

imbalanced with regard to the target class may have caused the aforementioned issue. Hence, we attempted to improve the classifier's performance by using normalized features and by introducing new features which were calculated based on percentile ranks (see below) that have been reported to enhance the performance of the classifier accuracy in previous studies conducted in the field (Taylor et al. 2014). We have used the same training data set described in Sect. 3.1.2 to recalculate the features to train and test the NNs classifiers using 10-fold cross validation.

- Total number of course page views before collaborative activity participation (normalized)
- Total number of assignment submitted before collaborative activity participation (normalized)
- Total number of discussion entries posted before collaborative activity participation (normalized)
- Total number of quiz submissions before collaborative activity participation (normalized)
- Total number of quiz attempts (normalized)
- Total number of quizzes answered correctly (normalized)
- Total number of quizzes answered incorrectly (normalized)
- Total quiz score (normalized)
- Total number of course page views before collaborative activity participation as a percentile
- Total number of assignment submitted before collaborative activity participation as a percentile
- Student's participation in the initial stage of the pyramid activity
- Student's collaborative activity participation (class variable)

4.1.5 Improved classifier performance

At the time of presenting the results of the study, we did not have access to an ongoing MOOC to evaluate the performance of the improved NNS classifier in real-time. In Fig. 5, we present the overall accuracy of the improved classifier as calculated considering the predicted outcome against the actual collaborative learning activity participation of students within the MOOC collaborative learning activities described in Sect. 4.1.3

When considering the overall prediction accuracy, it was observed that in both activity 1 and activity 2 classifier has achieved relatively higher levels of overall accuracy rates which are above 50%. In particular, during activity 1, in P4 the overall classification accuracy has increased over 90% which shows a good prediction performance. However, in P1 in activity 2, the overall accuracy has dropped below 60%, which is much less than the overall accuracy observed in other pyramid activities.

4.2 Discussion

Figures 4 and 5 summarize the prediction performance of the machine learning classifiers in predicting future collaborative learning activity participation of students. The overall accuracy criteria was used to measure the proportion of active (students who will participate in the collaborative learning activity) and inactive participants (students who will not participate in the collaborative learning activity) correctly predicted by the SVM and NNs classifiers in classroom and distance learning contexts respectively. A Cohen's kappa measure has been calculated to better elaborate the prediction performance of the classifiers in the two different learning contexts. In the classroom setting it was seen there was no agreement between the instances classified by the machine learning classifier and the data labeled as ground truth ($k = 0.211$, $p > 0.001$). In order to better understand the reason behind the poor performing classifier we have further analyzed the characteristics of the learner's profiles in both training and test datasets in the classroom context. It became evident that in the classroom setting the time frame in which we placed the evaluation studies has affected the classifier performance. The test data did not contain records of quiz taking behaviours of students, due to the fact that by the time we placed evaluation studies in the classroom context, no quiz related activities were posted in the LMS (as it was the beginning of the semester). Being unable to have access to the quiz related data which was seen as the most correlated variable and the fact of being inactive, describes the poor performance of the classifier in the classroom setting. In general, the noisy data in the classroom setting has resulted

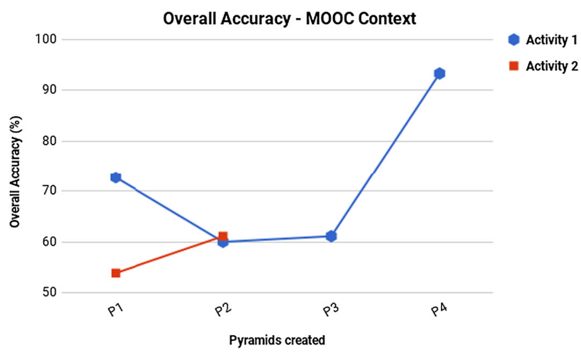

Fig. 5 Overall accuracy of prediction in MOOC context

in a poor performing classifier. A Cohen's kappa measure has also been calculated to evaluate the prediction performance of the improved classifier in the distance learning context. A moderate agreement between the instances classified by the machine learning classifier and the data labeled as ground truth ($k = 0.625$, $p < 0.001$) was observed within this context.

4.3 Limitations of the study

In this study, we have attempted to emphasize the use of predictive analytics to inform the adaptive collaborative scripting in across-spaces learning situations. We have presented how machine learning techniques can be used to obtain an estimate on future collaborative learning activity participation of students based on data collected from different learning spaces that described their individual and collaborative learning behaviours in previous activities. The findings of the present study should be interpreted in light of the following limitations.

One of the major limitations of our study is the use of training data sets that constituted a limited number of samples that are also imbalanced with regard to the target class. A larger and balanced dataset can potentially enhance the model performance creating opportunities to obtain more accurate test results. Although the current accuracy level of predictions is informative to achieve the objective of the study (which is to formulate adaptive collaborative learner groups based on future collaborative activity participation differences of students) more accurate predictions can provide more reliable estimates with increased overall accuracy levels.

On the other hand, the time frame in which we collected training data and the time in which we have positioned the evaluation studies (due to the designs of each real-world learning scenarios) have affected the classifier performance. In the classroom context and distance learning context the training data collected from Moodle LMS and MOOC API respectively depicted student-platform interactions for a period of one week. In the classroom context the educator conducted pyramid activities at the beginning of the course and in the distance learning context, the MOOC course was designed to have collaborative learning activities in the first and second week. As it was mentioned earlier, for each individual student s we considered event history up to time t in Moodle LMS course log data and MOOC course log data, given that the student has participated in small group collaboration phase of pyramid script at time t. Hence, the log data obtained to train classifiers from both Moodle LMS and MOOC platform consisted of records that described individual learners learning behaviour for a short period of time. On the other hand, in the classroom context, the evaluation studies were conducted in another course after three weeks from the course start date. The structure of the course was different from the course which we used to collect training data and consisted of records that described student-platform interactions over a relatively longer duration. In other words, the differences associated with the time frames in which we positioned the evaluation studies in the classroom context and the differences associated with the structure of the course make it difficult to model individual students which resulted in a more difficult prediction task.

Finally, the present study does not evaluate whether the impact of adaptive collaborative scripting is more beneficial to students than non-adapted collaborative scripts. As it was mentioned earlier, the main focus of the study was to evaluate whether predictive analytics can be used to inform the formulation of adaptive collaborative learning groups in the context of CSCL considering across-spaces learning situations and how such predictions can be used to formulate adaptive collaborative learner groups automatically in real-time. However, from a pedagogical perspective, it is important to measure whether the proposed adaptive group formation strategy has created an impact on students. Whether adaptive group configurations has resulted in increased learning gains, other than facilitating to maintain the flow of collaboration across pyramid levels is an important aspect which requires to be further researched.

5 Conclusions and future work

In this study, we have presented how predictive analytics inform the formulation of adaptive collaborative group configurations in the context of CSCL. The main contribution of the present study is the use of data collected in cross-context learning situations that exhibited students' prior activities, to predict future collaborative learning activity participation of students in a pyramid-based script. The prediction problem of interest was modeled as a supervised machine learning problem and solved using well-known supervised machine learning techniques, i.e., SVMs and NNs. Each classifier was tested using 10-fold cross-validation to evaluate model performance. During several case studies conducted in two different learning contexts i.e., classroom and distance learning context, we then incorporated the prediction results obtained from machine learning models to formulate adaptive group configurations in pyramid-based collaborative learning sessions.

Findings of the case studies showed that the data collected from across-spaces learning scenarios is informative to automatically classify students that can then allow teachers to make more informed adaptive group configurations adapting to the estimated activity engagement differences of students. Most importantly, the work presented in this article conveys that the learning occurs in one space is informative to learning that occurs in another space, which highlights the interesting connections exist across different learning spaces although understanding the complex interplay between different learning spaces and interpreting the connections that lie across-spaces is a challenging task that requires effort. Nevertheless, it should be pointed out that the present study sheds light on the applicability of learning analytics techniques i.e. predictive analytics to make those connections explicit in a useful manner suggesting that application of sophisticated learning analytic techniques can advance this field of research. We consider the work presented in the study is an important step for the field to begin to use previous behavioural data to understand how to create interventions in later activities. Although the present study lacks a discussion on how the interventions developed using the predictions impact students, we argue that understanding the predictions themselves is important and showing that these can be calculated in real-time even with scare data available that exhibited previous activities of students in cross-context learning situations is an important contribution of our work. As it was described in previous studies (Liaw and Huang 2000; Northrup 2001) interactions among participants does not occur automatically, rather intentionally designed collaborative learning activities facilitate interactions. Towards this end, we hope that the proposed adaptive group formation approach that attempts to formulate groups based on activity participation differences of students is a meaningful strategy that will facilitate students to gain benefits of collaboration.

Moreover, some of the lessons learned and observations captured while conducting evaluation studies in real-world context are interesting to be summarized in the conclusions. For instance, when conducting evaluation studies in the classroom context we realized not only the features extracted from log data but also features that describe learner's cognitive-affective states such emotions, moods, feelings, which could be captured in the physical space using sensory inputs can provide useful information to generate fine-grained predictive models as those states can vastly dominate learning activity participation of students. Incorporation of such relevant data that further describe learner's behaviours in different perspectives in different modalities may enhance the model performance. On the other hand, the technological tools that used to enable and structure collaborative learning session alone may not necessarily result in productive learning activity gains. Interactions that occur among students physically in the classroom require to be continuously reinforced by the educator in order to maintain students attention towards the learning activity which adds to the "orchestration load" of the educator (Prieto et al. 2018). We have observed in several instances that students missed the participation in different levels of the pyramid script as they speak with the colleagues sitting next to them or due to lack of attention towards collaborative learning task e.g., checking notifications on their mobile phones. Although some of these students might have been classified as active participants who would contribute to the collaborative learning task (based on the behaviour they have exhibited in the Moodle space), it was observed that the classroom behaviour of students cannot be fully described alone using log data, which highlighted the need for incorporating physiological, behavioural and subjective data that better describe learners behavior in real classroom settings (Prieto et al. 2018). For instance, the NISPI framework suggested in Cukurova et al. (2018) provides a good understanding of how physiological measures can be used to identify Collaborative Problem Solving (CPS) competence levels of students. As described in Cukurova et al. (2018) hand position and heads direction data provide useful information to predict CPS competency levels of students. The applicability of such physiological measures to predict the quality of collaboration among groups of students are presented in Spikol et al. (2018). Grover et al. (2016) have provided evidence that physiological measures such as screen pointing, leaning forward, joint attention (looking at screen), taking the mouse (with or without consent) and synchrony in body position are useful features in predicting the level of collaboration in pair programming context.

On the other hand, in the distance learning context, it was observed that the two different MOOCs that we used to collect data and to position evaluation studies are different in nature which can cause a significant effect on the accuracy of the prediction results. Training data was collected from a MOOC designed for secondary and higher education teachers while evaluation studies were placed in a MOOC which was designed for a research-oriented audience. We have observed that the engagement of

MOOC students in collaborative learning activities varied drastically in the two MOOC contexts. Lack of contextual information presented when training machine learning models can also affect the accuracy of the real-time prediction. In the future, we plan to consider these lessons learned, to extend the data sources considered, the experimentation in diverse contexts, the evaluation of its impact in terms of learning gains, and the provision of orchestration dashboards for teachers to monitor and regulate the adaptive scripts.

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Chapter 4

A TEACHER-FACING DASHBOARD TO ENHANCE COLLABORATION IN THE CLASSROOMS

This chapter tackles parts of the first objective and the third objective of this dissertation in which we focused on the orchestration of scripted collaboration in the classroom learning context (Figure 4.1). The content of this chapter consists of a JCR-indexed international peer-reviewed journal article which represents the research conducted as part of the third DBR cycle (Figure 4.2).

The article illustrates the problems related to classroom (scripted) collaboration and teachers' requirements of supportive technologies. These requirements led to the design of a teacher-facing LA dashboard to facilitate the orchestration of Pyramid pattern-based scripted collaborative learning situations in the classroom learning context. The details of the dashboard design process and the evaluation studies conducted in naturalistic classroom sessions are provided. How teachers acted upon the dashboard's information and how teachers' orchestration actions affected students' activity participation are presented.

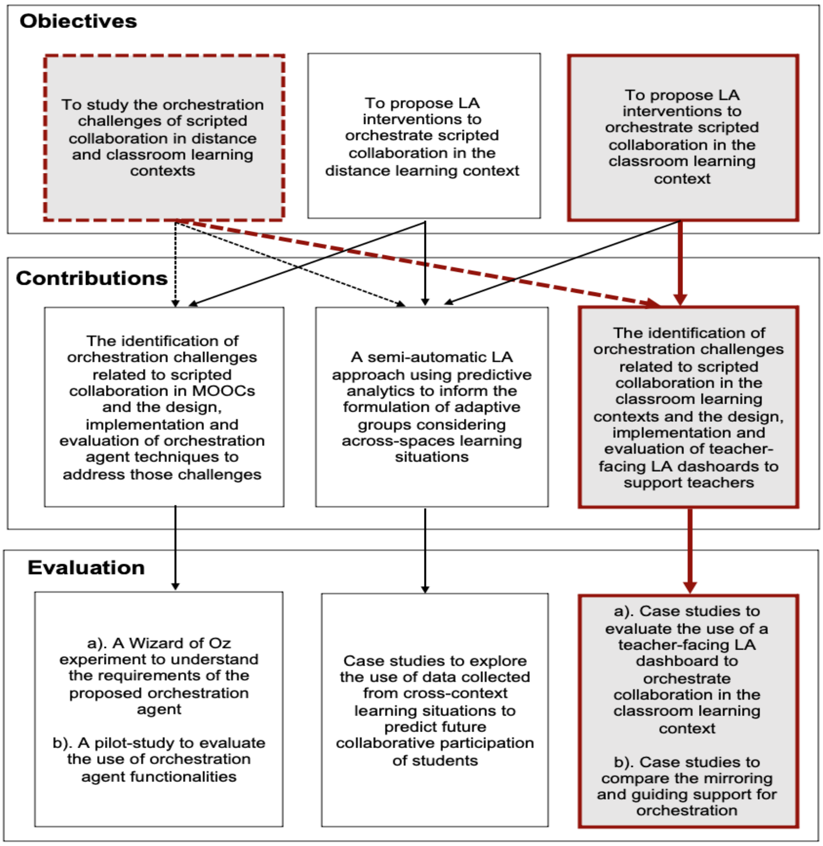

Figure 4.1: Objectives, contributions and evaluation studies covered by Chapter 4.

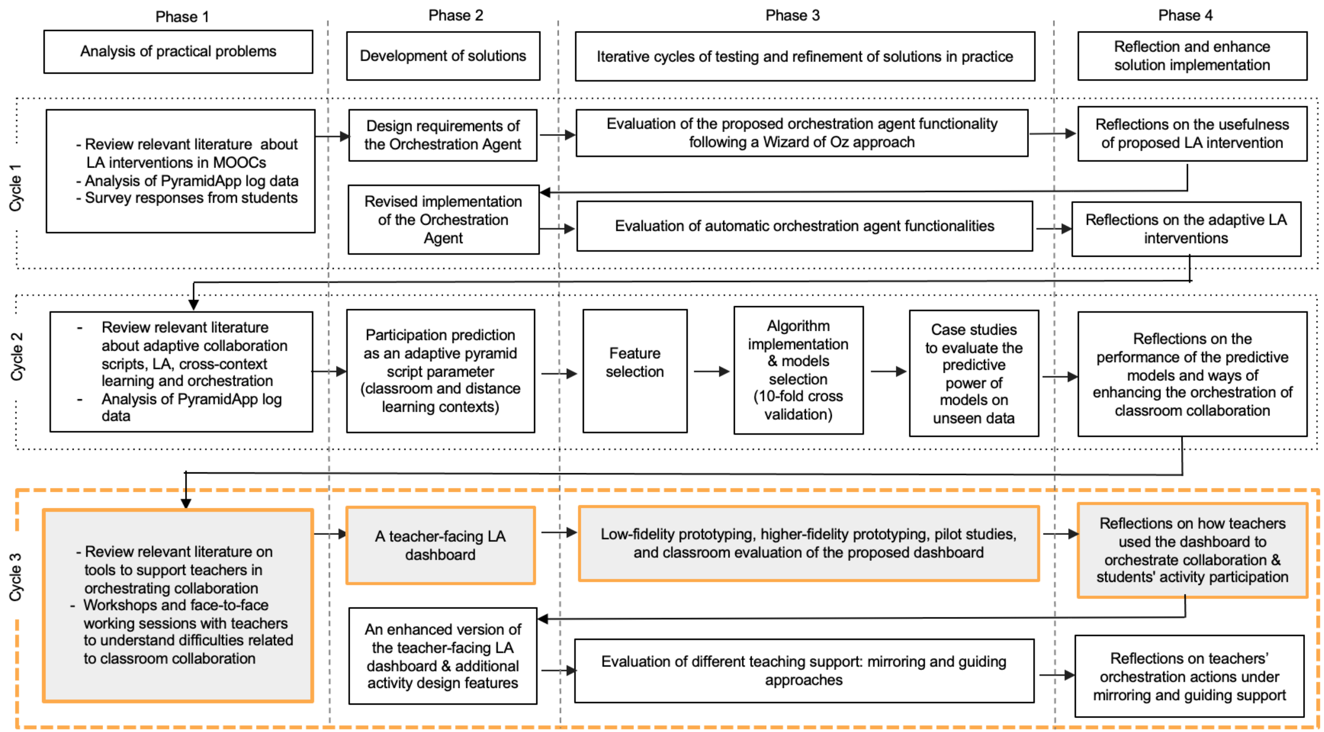

Figure 4.2: Part of the research process related to Chapter 4.

4.1 An Actionable Orchestration Dashboard to Enhance Collaboration in the Classroom

The content of this section was accepted to be published in the following JCR-indexed international peer-reviewed journal:

Amarasinghe, I., Hernández-Leo, D., Michos, K., & Vujovic, M. (in press). An actionable orchestration dashboard to enhance collaboration in the classroom. *IEEE Transactions on Learning Technologies*.

An Actionable Orchestration Dashboard to Enhance Collaboration in the Classroom

Ishari Amarasinghe, Davinia Hernández-Leo, Konstantinos Michos, and Milica Vujovic

***Abstract*—The orchestration of collaborative learning activities in technology-enhanced classrooms has become a non-trivial endeavour for educators. Depending on the behaviours and needs of students that emerge in real educational situations, educators may need to orchestrate activity adaptations on the fly. These adaptations may range from the provision of additional scaffolding by the educator (e.g. the educator's participation in a group discussion) to a change in the planned pedagogical scenario (e.g. the duration). This study aims to contribute to the orchestration of technology-mediated collaborative learning sessions in a classroom context. We present the design, implementation, and evaluation of a teacher-facing dashboard that supports teachers in orchestrating scripted collaboration. Evaluation studies were conducted in 16 classroom sessions. The findings indicate that teachers found the information on the dashboard to be actionable and help facilitate just in time support to student groups.**

***Index Terms*—Collaborative learning, scripts, learning analytics, orchestration, dashboards, learning technologies.**

I. Introduction

THE benefits of implementing computer-supported collaborative learning (CSCL) activities in technology-enhanced learning spaces are well-known [1]. Along with the integration of technological tools that aim to enhance learning in collaborative learning settings in the classroom, recently, researchers have become more interested in how to support educators who guide collaboration in these spaces, as the benefits of collaboration largely depend on how interactions occur among students [2]. On the other hand, in the context of collaborative learning, carefully designed collaboration scripts facilitate structuring of the flow of collaboration while triggering beneficial social and cognitive interactions that create positive effects on learning [1]. Different techniques (e.g. defining the activity sequence or role allocation) are used for scripts in order to increase the probability of productive student–student and student–teacher learning interactions, which would otherwise occur rarely or not at all in spontaneous collaborations [1], [3].

In the context of CSCL, collaborative learning flow patterns (CLFPs) formulate the essence of the script structures that have been proven to be effective in multiple educational situations [4]. Some well-known CLFPs include Jigsaw and Pyramid. The Pyramid CLFP provides an activity flow in which learners start to solve a task individually. Learners then formulate small groups to share their solutions and discuss, to agree on a common solution, forming increasingly larger groups as the flow advances. This CLFP provides opportunities for all learners to express and discuss their solutions and to learn and reflect on others' ideas. However, achieving success in the Pyramid script depends on the continuous and active participation of students throughout the consecutive phases of the script. A lack of continuous activity participation of students negatively affects the meaningful progression of the activity flow (e.g. inactive groups delaying the progress of the active groups in reaching a consensus) resulting in unfruitful learning experiences [5].

In the domain of CSCL, how an active and an energetic teacher manages integrated learning scenarios in real-time in a highly constrained environment is referred to as orchestration of the collaborative learning activity [6]. Even though scripts maintain the pedagogical structure of collaborative learning activities, teachers are required to play an active role in monitoring and adapting the scripts when necessary. For instance, when a collaborative learning script, such as the Pyramid CLFP, is deployed, it adds a level of complexity in the orchestration related to changes in group formation along a sequence of activities, with constraints related to expected group sizes and synchronicity among groups to enable a flow progression compliant with the pattern so as not to destroy its potential pedagogical benefits. Orchestrating such activities can prove challenging or, often, infeasible without proper technological tools, support, and infrastructure. To this end, we have studied the challenges teachers may face when orchestrating scripted collaborative learning sessions in the

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Digital Object Identifier

classroom and how a technological tool, such as a teacher-facing dashboard, could support teachers in orchestrating collaboration in real time. The proposed dashboard is novel as it provides actionable analytics on how collaboration evolves in real time.

Actionable analytics can be understood as analytics concerned with the potential for practical action rather than theoretical description or mere reporting [7]. The information presented by learning analytics (LA) tools can provide insights and create possibilities for guided actions to promote better end results. However, simply presenting information does not always help teachers to obtain a deeper understanding of the learning situation and subsequently make pedagogical decisions [8]. Rather, careful consideration must be paid to which type of information to present [9], when specifically aiming to influence future teacher decisions.

In our study, first, we conducted an analysis to better understand which information should be presented on the dashboard, and then we focused on which types of controls are required to be embedded in the dashboard to help teachers take necessary pedagogical actions. The context of our analysis is scripted collaboration in the classroom. In this context, information deemed 'actionable', alerts teachers to critical occurrences, such as low participation in a group, that requires intervention, such as diagnosis of the reason for lack of participation and provision of instructions to overcome the problem. An LA dashboard can visualise such critical moments and provide means for intervention, such as posting messages to groups. Another common problem is that students run out of time for collaboration. Information about how many groups have completed collaboration and how many groups have yet to finish the activity can create awareness and a call for action, such as increasing the time for the activity. In this way, the teacher can reconfigure the script parameters on the fly. By raising awareness of the problems and eventualities associated with collaboration, teachers can translate their knowledge into action. LA tools can be positioned as mediators that provide information about the problems and guidance for actions.

We followed the iterative workflow suggested in the Learning Awareness Tools – User eXperience (LATUX) workflow to design, deploy, and validate our proposed LA dashboard [10]. The LATUX workflow was applied since it was specifically proposed for projects that aim to design and deploy tools for improving instructors' awareness of students' learning activities in the classroom [10]. The LATUX workflow constitutes five steps: *problem definition, low-fidelity prototyping, higher-fidelity prototyping, pilot studies*, and *classroom use* or *validation in the wild*. We now describe how these workflow phases were applied within the present study.

The following two research questions are addressed:

RQ1: How did teachers use the dashboard to orchestrate collaboration?

RQ2: Do teachers' orchestration actions affect students' participation in activities?

The research aim of this paper is threefold. First, we investigate the challenges teachers face when orchestrating classroom collaboration with a focus on pyramid pattern-based scripted scenarios. Second, we explore the design details of an LA dashboard that implements different controls to support teachers in managing the collaborative learning sessions flexibly during the run-time of the activity in different ways. Third, we present an evaluation of the proposed LA dashboard, showing how teachers responded to the analytics that made information on the dashboard actionable and how teachers' pedagogical actions affected students' participation in the activity along with the lessons learned and guidelines for future research.

The rest of the paper is organised as follows. Section II presents related work describing how LA has been used to support teachers when orchestrating collaboration in previous studies. Section III presents the difficulties associated with orchestrating collaboration in classroom sessions. Section IV explains the design and implementation of the proposed LA dashboard in detail. Section V describes the methods. Section VI presents the study results. Section VII discusses the results, and Section VIII presents the study's limitations. Section IX concludes the paper and provides future research directions.

II. Related Work

LA is defined as the "measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environment in which it occurs" [11]. Recently, LA has gained a lot of attention as it offers the opportunity to better understand learning processes and gain insights into how to improve teaching practices [12], [13]. Several studies have proposed different LA interventions to support teachers as described below.

Alavi *et al.* [14] presented a tool called Lantern to support tutor–team interactions in collaborative problem-solving sessions in the classroom. The tool aimed to provide information on the work status of each group (by changing the colour, intensity, blinking, and frequency of blinking of the lantern) to the tutor, who could decide in real time which group to focus on when multiple groups requested help at the same time.

Mercier *et al.* [15] emphasised the importance of providing control tools for teachers to adapt learning activities and proposed a tool to monitor performance and manage groups engaged in solving mathematical problems in a multi-touch classroom setting. The case studies show that the tools enabled teachers to alter the difficulty of the learning task based on the student's needs.

Slotta *et al.* [16] developed an *instructor's tablet* that informed students' activity participation in a smart classroom setting. The tool enabled teachers to change activities according to groups' performance.

Schwarz *et al.* [17] focused on providing information about *critical moments* to teachers while groups worked in parallel. The authors stressed the importance of providing information about critical moments to educators in real time in order to improve orchestration and facilitate interventions, such as asking an idle group whether they are having problems that may lead to the emergence of learning in classroom settings.

Several researchers have also explored how LA dashboards can support teachers and learners [18]. LA dashboards have been defined as "single displays that aggregate different indicators about learner(s), learning process(es), and/or learning context(s) into one or multiple visualisations" [19]. Research on LA dashboards aims to identify which data are meaningful to different stakeholders and how data can be presented to support the sense-making processes of the target stakeholder group [19].

Martinez-Maldonado et al. [20] developed the MTDashboard, which provides indicators of small group collaboration and controls components intended to support teachers when orchestrating activities. Martinez-Maldonado et al. [21] also presented another LA dashboard tool that provides different visualisations (e.g. radars of touch and verbal participation) to provide an overview of the collaborative activity of learners in a tabletop environment.

Rojas *et al.* [22] proposed a dashboard that kept track of students' help requests during a laboratory session. The dashboard provided visualisations to indicate students' progress, help requests, and time-related aspects of tutoring.

Do-Lenh *et al.* [23] proposed *TinkerLamp 2.0*, an orchestration system that provided teachers with the authority to control the progression of the activity. A dashboard (i.e. *TinkerBoard*) was added to the system to visualise groups' progress, which allowed teachers to remain aware of group activities, mediate help requests, and determine when to intervene.

Some of the common controlling functions built into the aforementioned tools include: 1) controls to start and finish the activity; 2) ways to send messages to groups, such as reminders of the time left for the activity; 3) blocking and unblocking controls for the teacher to get students' attention when needed; 4) controls to move to the next stage of the task; 5) controls to change the difficulty of the task; and 6) controls to project students' screens on wall displays/interactive whiteboards. In addition, the information presented by the tools aims to raise teachers' awareness of group processes and help requests, and alerts are generated to indicate idleness and off-topic discourse within groups. By providing a quick overview of how collaboration evolves using aggregated information, LA can support teachers in overcoming the limitations of working memory and building awareness, hence facilitating productive intervention for groups that require immediate attention [24].

Despite the aforementioned benefits, recent systematic literature reviews published on LA dashboards have highlighted that existing research is rarely grounded in learning theories [18], [25] and that rigorous needs assessments are vital to understand end users' needs and determine which problems must be addressed by the proposed LA solution [26]. As emphasised in [25], existing research on LA dashboards has had significant limitations in terms of how evaluations are conducted. Very few dashboard evaluations have been conducted in authentic settings, as many of the proposals have been exploratory and built as proofs of concept [19]. Moreover, how teachers make sense of the data presented using LA dashboards and subsequently make decisions about relevant pedagogical actions in authentic contexts is not yet fully understood [27]. Schwendimann *et al.* [19] reported that although research on LA dashboards is growing in popularity, there is a lack of comparative studies on different dashboards, and the extent to which study results can be generalised to different learning contexts must be investigated. Finally, the impact of these technologies on target stakeholders has rarely been reported. For example, few studies have mentioned whether the dashboard improved the awareness of teachers and students, although the adoption and impact of LA dashboards are probably the most important aspects of research on this topic [19]. In this study, we propose a dashboard that aims to support teachers orchestrating scripted collaborative learning sessions. Using co-design techniques such as guiding questions, low fidelity prototyping, and pilot studies we attempted to involve teachers in the design process. Following the guidelines of the LATUX workflow, we report in detail the needs assessment, design process, and results of the evaluations conducted in authentic settings, highlighting the impact of the proposed technology on both teachers and students.

III. Difficulties Associated with Orchestrating Collaboration

During the first phase of the LATUX workflow (i.e. the problem identification phase), we studied the problems that teachers face when conducting collaborative learning sessions. We conducted four workshops at two secondary and vocational education schools in Spain (two workshops at each school) that aimed to identify common problems faced by teachers and to introduce different tools that could be used to facilitate collaborative learning sessions. In total, 15 teachers (with 3–26 years of teaching experience) who frequently conduct collaborative learning activities in their classrooms participated in the workshops. In the first workshop, a brainstorming activity was conducted to capture the difficulties teachers face when conducting collaborative learning activities in classrooms. Teachers' verbal responses were recorded and subsequently analysed using affinity diagrams. An iterative approach was applied to group the main themes. The results of the analysis revealed that the difficulties could be categorised into two themes. The first theme describes the difficulties associated with planning collaborative learning tasks, such as those related to the formulation of collaborative learning tasks or to the design of parameter configurations, and formation of groups. The second theme reflected the importance of maintaining students' participation during the activity.

During the second workshop, teachers were asked how technology could help to solve the challenges identified in the first workshop. The responses revealed that teachers prefer tools that allow them to flexibly control activities as they are occurring, as it is difficult to configure learning design parameters, such as duration, at the initial stage of activity design. Also, they preferred information that was visualised in an actionable format. For example, upon detecting groups with low participation, teachers wanted to perform timely interventions, such as sending text messages to encourage participation in the activity.

Four university teachers (two male and two female) from Spain with 1–5 years of teaching experience were interviewed in a face-to-face working session in order to further understand the difficulties associated with conducting scripted collaborative learning activities in classrooms. We considered a setting in which collaboration was scripted according to the Pyramid CLFP and deployed using PyramidApp (details about which are provided below) [28]. All four teachers had prior experience with using PyramidApp [28]. We discussed with the four teachers the possible problems that may occur during Pyramid activities and asked them to write down how they would attempt to solve those problems and improve orchestration (see Table I).

PyramidApp is a web-based tool that enables teachers to design and deploy Pyramid pattern-based collaborative learning activities [28]. In a classroom session, the tool helps allocate students into multiple pyramids (groups) and reach consensus for a given task following a pyramid structure. When authoring Pyramid activities, teachers must configure the following design parameters: 1) the number of participants per pyramid; 2) the number of voting levels per pyramid (the tool provides a voting mechanism to achieve agreement on common solutions within collaborative groups); 3) group size at the first voting level of the pyramid (based on this input, the tool calculates the size of the groups for the next pyramid level); and 4) duration of the initial stage of answer submission and subsequent voting stages. Once the activity is designed, the teacher can generate a public link that can be shared with students to allow them to log into the tool. Once logged in, students are required to individually write answers for the given task. Then, students are automatically randomly allocated into small groups. Within each small group, students see the individual answers submitted by their group members, and students are expected to discuss (using the discussion board built into the tool), and vote on the answers (see Fig. 1). At the end of this phase, small groups are merged to form larger groups. Within the larger groups, students can see which answers were upvoted during the previous phase and then further discuss and vote on the answers. At the end of the activity, the winning answers from different pyramids are presented.

TABLE I
RESPONSES COLLECTED FROM TEACHERS ON HOW TO HANDLE PROBLEMS DURING PYRAMID-BASED COLLABORATIVE LEARNING SESSIONS

Problem	Response [a]
Students cannot log in	**A**: Find the best way to log in **B**: Ask to join the student next to them **C**: Use the projector to show how to log in **D**: Pause the system and ask to join the student next to them
Some students skip the initial answer submission stage	**A**: Advise students to be more rigorous in the following rounds **B**: Enter the chat and initiate discussion **C**: Use the chat to encourage them to use the system correctly and provide more time if necessary **D**: Pause the system and ask about the reason
Students' answers are not up to the teachers' expectations	**A**: Tell students their work is taking the wrong direction **B**: Talk to students and restart the activity **C**: Send a message in the chat, suggesting some keywords **D**: Pause the system and ask the reason
Students do not submit answers on time	**A**: Ask students to respect time **B**: Extend the time of the activity **C**: Increase the original amount of time given **D**: Pause the system and ask the reason
Students drop out due to connectivity problems	**A**: Try to finish the activity orally **B**: Go back to regular answers and questions **C**: Pause the system and ask the reason **D**: Pause the system and ask the reason
Low on-task participation (voting and discussion)	**A**: Encourage students to participate **B**: Pause the activity and ask what is happening, pose some questions in students' discussions **C**: Pause the system and send a message clarifying how the system works **D**: Pause the system and ask the reason
Groups take more time to finish than expected	**A**: Rescale activities for the next session **B**: Consider small groups for the next time **C**: Increase the time **D**: Increase the time
Some groups finish earlier than expected and are waiting for other groups to finish	**A**: Hurry other groups to finish **B**: Limit time for other groups **C**: Send a message to encourage participation **D**: Encourage students to finish the activity

[a]A, B, C, D denote each teacher's response

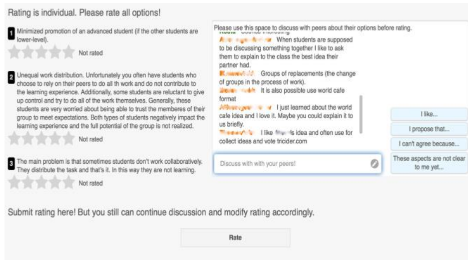

Fig. 1. User interface of the PyramidApp tool showing the answers to be voted upon (left) and discussion space (right).

Teachers' activity design configurations and students' activity enactment data are logged in the PyramidApp database. Log data captured in the PyramidApp database was used to visualize relevant information on the proposed dashboard.

Selected feedback from the four teachers regarding how they would use PyramidApp and, more specifically, how they would handle issues is documented in Table I. As revealed by the teachers' responses, teachers attempt to solve problems either verbally (by providing explanations) or via technological means to target specific problematic groups. For example, teachers may pause the activity to get the class's attention when providing instructions on how to overcome common problems. In some instances, teachers may also wish to modify initial design parameters, such as duration, to adapt the script to the requirements of the current classroom situation.

IV. An Actionable Orchestration Dashboard: Controls and Implementation in the Case of PyramidApp

Following the LATUX workflow, the next step involved building low-fidelity (paper) prototypes to obtain a representation of the intended design and enable a high-fidelity prototype to be developed subsequently. We designed four paper prototypes that depicted students' participation in a Pyramid activity. The design of these prototypes was informed through literature review [20], [21], [23] and the teachers' responses (Table I). We also followed the guidelines presented in the *Chao* software framework when presenting information on the dashboard [29]. As indicated in the Chao framework, we split data across two dimensions: progress and product. Progress-related data visualised the student's pace at a class level, and product-related data provided details about the student's submissions, such as answers, notes, and discussions [29].

The paper prototypes were tested following the LATUX workflow guidelines presented in [10]. We first evaluated the usability of the provided visualisations and then evaluated whether the visualisations provided insights regarding differences in the participation of the groups. Teachers provided feedback and suggested improvements to the paper prototypes. The feedback collected from the teachers led to the definition of three different types of controls—timing, flow, and participation —to handle problems that may occur during the activity. Timing and flow controls enable adaptation of the design parameters of the activity on the fly. For instance, timing controls enable teachers to adjust the time allocated to different phases of the script in real time. Flow controls (i.e. *pause*, *resume*, and *end*) enable teachers to get the class's attention when needed by pausing the activity or to permanently exit the collaborative learning activity when, for example, the activity takes longer than expected. Participation controls detect low participation of groups and notify teachers with warnings to facilitate timely interventions.

We held two focus group sessions with the four teachers and undertook a small pilot study in a lab session with one teacher to obtain further feedback regarding the features and functionalities of the proposed dashboard prototypes. Teachers' feedback was taken into account to enhance the visualisations and determine the functionalities of the controls introduced in the dashboard. The following paragraphs describe the final design of the dashboard that was used in real-world classroom-based trials.

Fig. 2 shows an excerpt of the upper part of the *Submission Related Information* tab with the following information: 1) the total number of students currently logged into PyramidApp; 2) the total number of individual answers submitted at a given time; 3) the number of pyramids created; and 4) the number of

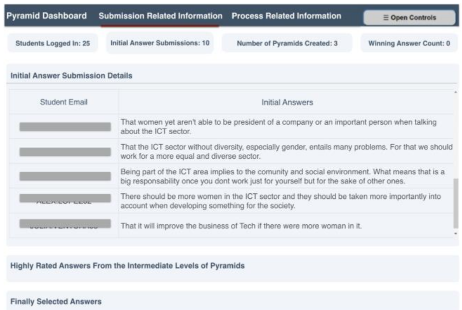

Fig. 2. Information presented in the Submission Related Information tab of the dashboard.

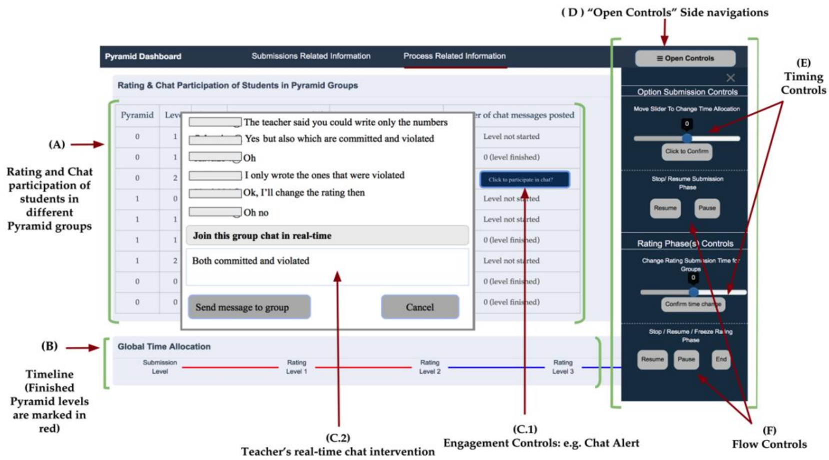

Fig. 3. Information presented in the Process Related Information tab and dashboard controls.

winning answers (indicating that certain pyramids have finished the collaborative learning activity). The lower part of the user interface was divided into three sections to distinguish between the artefacts produced or agreed upon at different phases of the Pyramid script: individual answers, highly rated answers (in intermediate phases), and winning answers (at the end of the activity).

As shown in Fig. 3, the information presented under the *Process Related Information* tab was divided into two sections. The upper part of the user interface visualised the voting (the number of students who participated in voting within each group, shown as a percentage) and discussion participation (the number of chat messages posted in each group) of students at different phases of the Pyramid script using a tabular design (see Fig. 3 (A)). A timeline was included in the lower part of the user interface to reveal the script progression in real time (see Fig. 3 (B)). The labels of the timeline were generated automatically. For instance, three phases of the Pyramid design were visualised in the timeline as submission level, rating level 1, and rating level 2. The length of the timeline was adjusted during the run-time of the activity and reflected the time allocated for each phase.

Participation controls were built into the Process Related Information tab. As described earlier, these controls kept track of students' voting and participation in discussions. The focus group teachers stated that a warning is wanted when there is a lack of participation in voting or discussions. It was decided that a voting warning would be generated when the majority (more than 50%) of a given group did not participate in voting and a discussion warning would be generated when fewer than two messages were posted by a group. When a warning should be displayed on the dashboard was discussed with the teachers, and it was agreed that warnings should appear only after 50% of the time allocated to a certain phase expired. These design decisions aimed to minimise the number of warnings simultaneously appearing on the dashboard and to provide adequate time for the students to collaborate. Fig. 4 shows an example of a voting warning. Touching a voting warning on the dashboard opened a confirmation dialog that included the following options: 1) select one answer; 2) promote a random answer; and 3) promote all answers for further discussion in the next Pyramid level. The teacher could choose their voting decision and confirm the action or dismiss the warning.

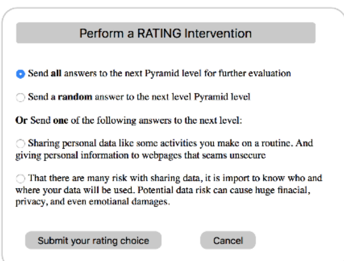

Fig. 4. An example of a voting warning.

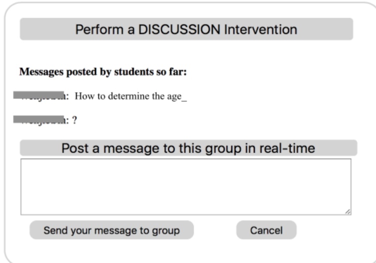

Fig. 5. An example of a discussion warning.

Fig. 5 shows an example of a discussion warning. Touching a discussion warning opens a dialog box that shows the messages posted on the group discussion board in real time and allows teachers to post messages to groups. Teachers were also able to send messages to groups at any time, even without receiving a discussion warning (see Fig. 3 (C.2)).

A panel on the right, which we refer to as the *Open Controls* panel (see Fig. 3 (D)), was also included in the dashboard. It included timing and flow controls, and it is divided into two sections—*Option Submission Controls* and *Rating Phase(s) Controls*—to represent the applicability of the controls to different levels of the Pyramid script. Within this panel, an interactive slider was included as a timing control (see Fig. 3 (E)). The slider enables the teacher to re-configure the time allocated to different Pyramid levels as required. Its default position was 0, and based on the feedback received from the teachers, the moving range of the slider was set between -1 and +1 minute. Moving the slider right increased the time by 1 minute, and moving the slider left decreased the time by 1 minute. The change of time was limited to a 1-minute difference because the teachers mentioned that they do not wish to drastically change the time allocated to the activity. Increasing the activity time was required in situations where students or groups needed more time to finish certain phases, while decreasing time was required when all groups finished the activity earlier than anticipated. The panel also included other flow controls, such as pause, resume, and end (see Fig. 3 (F)), which are described earlier.

V. Method

A. Participants

Following the LATUX workflow, we conducted validation studies in a real setting. Four teachers (two males and two females who did not take part in any of the previous stages of the workflow) from a Spanish university participated in 16 authentic class sessions. Teachers were recruited for the study given they were instructing a subject with a sufficient number of students and had available sessions for experimentation. The teachers were used to incorporating collaborative learning activities within their courses, and they were interested in using technological tools in the classroom. All four teachers had prior experience with PyramidApp. However, none of them had experience with using dashboard applications to orchestrate collaboration. First-year undergraduate students from the classes took part in the study with informed consent. Ethics approval for the study was obtained from the Institutional Committee for Ethical Review of Projects (CIREP) from the Universitat Pompeu Fabra (CIREP approval number: 129).

B. Procedure and Data Collection

First, the experiments without the dashboard were conducted, and then those with the dashboard were conducted. In the experimental condition, teachers monitored and orchestrated group activities using the dashboard, and in the control condition, the dashboard was not available. Training was provided to the teachers to ensure they were familiar with the features of the dashboard before the experiments. An overview of the sessions and the data collection instruments used to address the research questions are presented in Table II. The design configurations of the Pyramid activities in each session varied based on the teachers' requirements for collaborative learning activities in the classroom sessions. In all sessions, teachers proposed open-ended knowledge sharing tasks for students.

Students' collaboration in both conditions and teachers' dashboard actions in the experimental condition were automatically logged. In the experimental condition, teachers' dashboard actions were also recorded using screen-captured data (audio and video) from the dashboard tablet. Moreover, a researcher performed classroom observations during each session. Every time the teacher consulted the dashboard; made announcements to the class; or engaged in discussions with students, the researcher wrote down the time and detail of the

TABLE II
PYRAMID ACTIVITIES CONDUCTED IN EXPERIMENTAL AND CONTROL CONDITIONS ALONG WITH THE ACTIVITY CONFIGURATIONS, DATA SOURCES USED TO ANSWER RESEARCH QUESTIONS AND THE TYPE OF ANALYSIS PERFORMED

Condition [a]	Teacher	Session ID	Task Type [b]	Pyramid Levels	Activity Duration (mins)	Total Students	Data Collected and Type of Analysis Performed	Research Question
Control	T1	C11	A	3	13	37		
		C12	A	3	13	27		
		C13	A	3	13	28	Observation notes (Qualitative)	
		C14	B	4	15	16	Post-activity questionnaire responses from teachers (Qualitative)	RQ1: How did teachers use the dashboard to orchestrate collaboration?
	T2	C21	A	3	13	22		
		C22	B	3	13	13		
		C23	B	4	15	19		
		C24	A	3	19	36	Log data from PyramidApp (Quantitative)	
		C25	A	3	13	68		
	T3	C31	B	3	13	24	Post-activity questionnaire responses from students (Quantitative)	RQ2: Do teachers' orchestration actions affect students' participation in activities?
		C32	B	4	15	27		
	T4	C41	A	3	26	24		
Experimental	T1	E11	A	3	13	14		
		E12	A	3	13	38	Screen-captured data from the dashboard (Qualitative)	
		E13	A	3	13	26	Log data from PyramidApp (Quantitative)	RQ1: How did teachers use the dashboard to orchestrate collaboration?
		E14	A	3	13	16		
		E15	B	4	15	13	Observation notes (Qualitative)	
		E16	A	3	30	34	Post-activity questionnaire responses from teachers (Qualitative)	
	T2	E21	B	3	13	14		
		E22	A	3	18	88		
		E23	A	3	13	25		
		E24	A	3	13	20	Log data from PyramidApp (Quantitative)	
		E25	A	4	13	23		RQ2: Do teachers' orchestration actions affect students' participation in activities?
		E26	A	3	13	23	Post-activity questionnaire responses from students (Quantitative)	
	T3	E31	B	3	13	18		
		E32	B	4	13	15		
	T4	E41	B	3	20	34		
		E42	B	3	20	71		

[a]The control condition was run first by all four teachers then the experimental condition.
[b]Task A refers to case study analysis and Task B refers to problem solving activities, which both request for collaborative negotiation.

action. Two datasets were created to denote teachers' actions during the experimental and control conditions: 1) screen-captured data from the tablet, log data and observation notes (along with timestamps) to reflect teachers' actions in the experimental condition; and 2) observation notes to reflect teachers' actions in the control condition.

At the end, a post-activity questionnaire was used to collect teachers' perceptions of the activities and dashboard. A post-activity questionnaire with two questions were given to students. Students responded to the questions on a five-point Likert scale (1 = totally agree, 5 = totally disagree): 1) "I have learned a lot about the subjects discussed during the collaborative learning activity" (which reflected perceived learning); and 2) "rate your overall satisfaction with the collaborative learning experiences" (which reflected perceived satisfaction). A mixed-methods approach was used to contextualise and triangulate quantitative and qualitative data to produce results for the two conditions.

C. Coding Teachers' Actions

Wise and Jung [27] presented a model of instructors' analytics use (which is a two part structure of, sense-making and pedagogical response) to describe common activities in which instructors engage with when using analytics. We adopted the model to code actions observed in our study (see Table III).

As shown in Table III we utilised seven codes from the model to code teachers' actions in the experimental condition. For the control condition, three codes were used to code teachers' actions. Two authors of this paper coded the datasets. There was high agreement between the two coders (Cohen's Kappa = 0.95, $p < 0.005$), and any disagreements were resolved by discussion.

VI. RESULTS

A. How Did Teachers Use the Dashboard to Orchestrate Collaboration?

In the experimental condition, the four teachers read data (or checked information on the dashboard) an average of 13.5 times per session, with a standard deviation of 3.76 times. The frequency with which teachers read data from the dashboard ranged from 6 to 18 times per session, indicating variation. Teachers explained the patterns observed in the data to students an average of 2.94 times per session, with a standard deviation of 2.05 times. In terms of pedagogical responses, the most frequent action teachers took after consulting the dashboard was whole-class scaffolding (an average of 7.69 times per session, SD = 4.9). In comparison, teachers performed less targeted scaffolding after consulting the dashboard (an average of 3.56 times per session, SD = 3.4). In the 16 sessions, actions to: revise course design; wait and see; and check impact were observed less often. Revision of course design was observed an average of 0.88 times (SD = 0.62), waiting and seeing was observed an average of 1.88 times (SD = 2.03), and checking impact was observed an average of 0.25 times (SD = 0.77).

Table IV provides details on teachers' reactions to dashboard warnings and the use of dashboard controls in the experimental condition. As shown in Table IV, teachers reacted to voting warnings in 6 of the 6 experimental sessions (that generated warnings), with teacher T1 reacting in four sessions and teachers T2 and T3 each reacting within a single session. Three teachers reacted to discussion warnings in 5 of the 8 experimental sessions (that generated warnings), with teacher T1 reacting in three sessions, and teachers T3 and T4 each reacting within a single session. The sixth column in Table IV indicates whether students replied to the messages posted by the teachers (yes/no). In total, students posted 56 messages in teacher T1's sessions and 3 messages in teacher T3's session, showing that teachers' intervention in chats in real time triggered discussions among students. However, no replies were received for the discussion interventions performed by teacher T4. To achieve further understanding, we analysed the types of messages posted by the three teachers. The analysis revealed that discussions were triggered only when T1 and T3 asked students to discuss their voting decisions. T4 posted only greeting messages (e.g. Hello) to groups, which did not trigger discussions among students.

Regarding the flow controls, log data indicated that 12 of the 16 sessions (i.e. E12, E13, E14, E15, E16, E22, E24, E25, E26, E32, E41, and E42) were terminated by four teachers using the end control before the time limit was reached. According to the

TABLE III
CODING SCHEME USED TO DESCRIBE TEACHERS' ACTIONS

Category	Code [a]	Explanation
Sense-making	Read data	Teacher is reading the data presented on the dashboard.
	Explain pattern	Teacher explains the observed collaboration patterns. In the experimental condition, dashboard data was used to explain patterns. In the control condition, the teacher used perceptions and observations of individual students' devices to explain patterns (e.g. "Some groups have already finished the voting, but some of you still haven't yet.")
Pedagogical Responses	Whole-class scaffolding	Teacher provides support at the class level, describing the PyramidApp mechanism, task, script progression, participation, and quality of artefacts (e.g. "Click submit when you finish.")
	Targeted scaffolding	Teacher supports individual students and groups in resolving their doubts and encourages participation (e.g. "Use your university email to log in.")
	Revise course (learning) design	Teacher uses timing and flow controls of the dashboard, to revise the script.
	Wait and see	Teachers delay their reaction to dashboard warnings and take actions using timing and flow controls (e.g. opening and closing the *open controls* panel without using controls).
	Check impact	Teachers revisit group messages to check whether students replied to the messages posted by the teachers.

[a]All seven codes were used to code teachers' actions in the experimental condition. For the control condition, three codes were used: explain pattern; whole-class scaffolding; and targeted scaffolding.

TABLE IV
TEACHERS' USE OF DASHBOARD CONTROLS

Teacher	Session ID	No. of voting warnings received & No. of voting warnings reacted	No. of discussion warnings received & No. of discussion warnings reacted	Total no. of chat messages posted by teacher in continuing discussion with groups	Replies received from students (Yes/No) [a]	Flow controls used [a,b]	Timing controls used [a]
T1	E11	1 (1)	2 (2)	2	Y	N	N
	E12	6 (2)	0 (0)	n/a	n/a	Y (end)	N
	E13	9 (4)	1 (0)	n/a	n/a	Y (end)	N
	E14	7 (4)	2 (1)	1	Y	Y (end)	N
	E15	0 (0)	0 (0)	n/a	n/a	Y (end)	N
	E16	0 (0)	1 (1)	14	Y	Y (end)	N
T2	E21	0 (0)	0 (0)	n/a	n/a	N	N
	E22	0 (0)	1 (0)	n/a	n/a	Y (end)	N
	E23	0 (0)	2 (0)	n/a	n/a	N	N
	E24	0 (0)	0 (0)	n/a	n/a	Y (end)	N
	E25	0 (0)	0 (0)	n/a	n/a	Y (end)	Y
	E26	1 (1)	0 (0)	n/a	n/a	Y (end)	N
T3	E31	2 (2)	2 (1)	1	Y	N	N
	E32	0 (0)	0 (0)	n/a	n/a	Y (end)	N
T4	E41	0 (0)	0 (0)	n/a	n/a	Y (end)	Y
	E42	0 (0)	2 (1)	1	N	Y (end)	N

[a]Y refers to Yes and N refers to No.
[b]Only end flow control was used by the teachers. Pause and resume controls were not used.

observation notes, during those sessions, teachers presented the selected answers to the class when the majority of the groups had not reached the final voting level (e.g. "We have one winning answer. I'll wait 1 minute more, and I'll discuss some other chosen ones.") However, none of the teachers used the pause and resume controls. Timing controls were used only by two teachers in 2 of the 16 experimental sessions (E25 and E41) to reduce the time allocated to the voting and answer submission phases, respectively, allowing students to move to the next level of the script without waiting till the original design time expires.

In the control condition (without a dashboard), teachers explained patterns an average of 0.83 times per session (SD = 0.93). Further, whole-class scaffolding and targeted scaffolding were conducted an average of 2.33 times (SD = 1.82) and 2.58 times per session (SD = 1.38), respectively.

B. Do Teachers' Orchestration Actions Affect Students' Participation in Activities?

To address the second research question of the study, we examined how teachers' orchestration actions affect students' activity participation. Log data collected from the PyramidApp was used to calculate the percentage of students who participated in the voting and discussion out of the total number of students who started the activity. Then, the overall percentage of participation was calculated by summing up the percentages of voting participation and discussion participation and dividing by two (see Fig. 6).

In the experimental condition, students had a higher overall activity participation (M = 72.05, SD = 14.75) compared to the control condition (M= 64.66, SD = 12.62) but the difference was not significant; t(25) = 1.400, p = 0.174. Students' discussion participation was higher in the experimental condition (M = 53.21, SD = 29.78) compared to the control condition (M = 41.81, SD = 21.82) but the difference was not significant; t(25) = 1.146, p = 0.263. The voting participation was high (more than 87%) in both the experimental condition (M = 90.52, SD = 7.74) and control condition (M = 87.52, SD = 8.07) with no significant difference between the two conditions, t(25) = 0.976, p = 0.339.

The log data indicated that the percentage of individual answer submissions was higher in the experimental condition (87%) than in the control condition (83%). Students' post-activity questionnaire responses (see Section V.B for the questions) indicated that there were no significant differences with respect to their perceived learning (Q1) and satisfaction

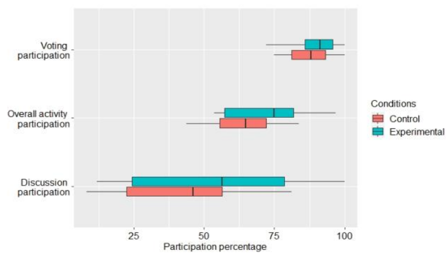

Fig. 6. Differences in students' discussion, overall and voting participation in control and experimental conditions.

(Q2) in both the control (Q1: M = 2.2, SD = 0.945; Q2: M = 2.25, SD = 0.885) and experimental conditions (Q1: M = 2.3, SD = 1.002; Q2: M = 2.22, SD = 0.9444).

To understand the relation between teachers' actions (see Table III) and students' participation we conducted Spearman's correlation tests in both conditions (data was not normally distributed). In the experimental condition, significant correlations were found between the teachers' targeted scaffolding and students' discussion participation ($r_s = 0.673$, $p = 0.004$) and teachers' targeted scaffolding and overall activity participation ($r_s = 0.646$, $p = 0.007$). In the control condition, there were no significant correlations between teachers' targeted scaffolding and students' discussion participation ($r_s = 0.055$, $p = 0.865$) or students' overall participation ($r_s = 0.009$, $p = 0.977$). These results suggest that in the experimental condition when teachers' interventions were increasing at individual and group level, students' discussion and overall activity participation also increased or vice versa. Moreover, significant negative correlations were found between teachers' read data action and students' voting participation ($r_s = - 0.523$, $p = 0.038$) and between teachers' actions to whole class scaffolding and voting participation ($r_s = - 0.517$, $p = 0.040$). These results suggest that when students' voting participation was decreasing, teachers were reading more often the dashboard data and provided more support at the class level, or the reverse relation between teachers and students' actions occurred.

VII. Discussion

A. How Did Teachers Use the Dashboard to Orchestrate Collaboration?

Based on the results, in the experimental condition, the sense-making action of reading data was observed more frequently than explaining patterns. In the post-activity questionnaire, teachers reported that the information presented in the dashboard helped them to: 1) gain awareness of activity participation (e.g. "All the information presented in the dashboard were useful to understand students' responses and participation"); 2) to be aware of the script progression (e.g. "I liked the time indicator and the red and blue visualisation because I knew when the students will proceed to the next level"); and 3) to combine dashboard information with their classroom observations (e.g. "I could combine what I was directly observing in the classroom with the information in the dashboard.") We interpret the findings as indicating that the information presented in the dashboard became useful and that the teachers sometimes used this information (reading data) to confirm their own understanding of (rather than explicitly mentioning) students' participation in the activity and progression through the script. This aligns with similar research that was conducted previously [30].

However, when compared to the experimental condition, in the control condition, explaining patterns were very low, indicating that access to the LA dashboard allowed teachers to gain awareness of collaboration.

In terms of pedagogical responses, in the experimental condition, both whole-class scaffolding and targeted scaffolding were observed less often in the control condition. This seemed to indicate that introducing an LA dashboard did not take teachers' attention away from the classroom, but helped teachers to provide more scaffolds at the class, group and individual levels, which influenced their teaching practices.

The presence of the wait-and-see posture in the experimental condition (e.g. teachers did not react immediately to the warnings associated with low-group participation, opening the control panel, and closing it without taking actions) can be explained by taking into account the teacher's responses to the post-activity questionnaire. Two teachers pointed out that participation warnings indicated the requirements for intervention—"Seeing the percentage of voting participation or the warnings was very useful," "Knowing that students did not chat, I will try to find ways for more interactions in a subsequent activity," "Entering in the chat was useful and enabled me to see the information in the chat (previous discussion, etc.)"—but the limited time allocated to the activity made it difficult to understand the influence of the intervention: "due to [the] fast grouping levels that occur in the classroom, it is hard to see how my prompts influence the students." Based on this, we believe that simultaneously receiving a number of warnings within the short activity duration in the dashboard may have created a situation in which some teachers could not decide which group(s) to attend to and faced difficulty in accessing the effects of feedback, which resulted in a wait-and-see posture. As pointed out in [31], there is a trade-off regarding the immediateness of teachers' actions, as actions taken too quickly based on warnings that take into account only partial representations of the students participation may not provide enough time for students to handle problems. Finding the right balance between when to generate warnings and when to provide immediate or delayed feedback may depend on a number of factors, including context and task type. This notion requires further research.

Regarding the teachers' use of dashboard controls, as indicated in Table IV, teachers did not often use flow and timing controls to revise the learning designs. In the post-activity questionnaire, teachers elaborated upon several reasons for this behaviour. First, it was not necessary to revise the designs of some activities, as the activities were planned quite conservatively: "I did not intensively use the controls, but I saw them as very useful. Changing times was not needed as my designs worked well in most sessions, but I needed to end Pyramid before [the time that was] planned in some sessions as [we] were running out of time and [I] thought that for slow Pyramids it was sufficient with two levels (although three levels were initially planned)." Second, teachers mentioned that they were reluctant to revise certain learning design parameters at run time, in particular time, and that they required further training or guidance regarding when to use such controls: "I didn't use a lot of timing controls because they will influence the whole activity and I was not sure if I can experiment [with] this in the class." Finally, teachers noted improvements that could be made regarding the placement of controls: "The controls were hidden and its presentation gave a feeling of complexity."

Although the teachers did not use the pause and resume controls in any of the experimental sessions, two teachers mentioned that those controls could be useful for orchestration: "In any case, I find it useful to be able to pause the class." The end flow control was extensively used by all four teachers (12|16 sessions) to stop activities before the time as planned in the original design. This indicates that having access to such controls is often useful when facing time constraints in the classroom.

Moreover, screen-captured data and observation notes indicated that the teachers that had not reacted to the voting or discussion warnings were due to one of the following reasons: 1) they were observing information in the Submission Related Information tab and missed the warnings that appeared in the process Related Information tab; 2) they were communicating with students and were not focusing on the dashboard; and 3) teachers already decided to end the activity before the planned duration and were summarizing the winning answers to the class and disregarded the warnings that appeared.

The teachers also pointed out that the user interface of the dashboard required improvements, especially if it were to be used on a more regular basis. For instance, the visualisations of groups' activity participation needs to be refined: "With the tables it was hard to compare groups; thus, a visualisation will clearly show which group participate more or less." Teachers also pointed out that having access to checkpoint analytics [32] would help them to detect and directly support late starters: "I'd have appreciated info about how many students were entering the activities in the beginning of the Pyramid so that I [could] go and check the problems of slow students." Further, two teachers emphasised that the terminology in the user interface should be changed: "The wording is clear and has all the information but perhaps [it] can be closer to the vocabulary of teachers." Regarding the timing controls, the teachers pointed out that "in the slider, the number could clarify if it refers to seconds [or] minutes." The teachers also suggested requirements for a new control that would allow them to skip intermediate levels of the Pyramid script when necessary. During the activities, we observed that the teachers faced typing difficulties when they tried to post messages to groups. In the next iteration, to alleviate this issue, we will provide pre-written messages that can be directly posted to groups.

The unique constraints of the learning sessions, imperfections regarding the usability of the LA dashboard, and the novelty of using analytics [27] may explain why few controls were used by the teachers in some sessions. The teachers' use of the dashboard controls may have also been influenced by factors such as teacher's satisfaction, years of teaching experience, agency, beliefs, skills, trust, cognitive load as well as technological, pedagogical, and content knowledge [27, 33] which requires further examination.

B. Do Teachers' Orchestration Actions Affect Students' Participation in Activities?

In order to better understand whether the improved overall collaboration was achieved as a result of improved conditions for collaboration (through teachers' pedagogical actions), we explored qualitative aspects of the collaboration. As indicated in [34], successful classroom collaboration is attained through the achievement of certain conditions: common goal, positive interdependence, coordination and communication, individual accountability, awareness, and joint rewards. In Table V, we present our interpretations of how each of the conditions was better facilitated in the experimental condition, in which the teacher had more control over the activity and hence could influence and increase students' participation in the activity.

VIII. Limitations of the Study

A limitation of the study is that the proposed dashboard was designed and evaluated in collaborative learning sessions that were scripted according to the Pyramid CLFP. Even if we believe that the pedagogical value, implementation complexity, and applicability to multiple contexts and subjects of the Pyramid CLFP makes it an interesting research focus, generalising the findings of the study to other structures for learning activities is difficult and requires further research. Creating a common framework that would enable comparison of empirical findings across studies with related research would help the field to form a broad body of research knowledge. In addition, more studies should evaluate whether the proposed technology could be part of teachers' common practice for orchestrating collaboration, as the teachers in this study expressed that they are interested in using the dashboard in future activities.

Another limitation is that teachers' behaviours during the sessions could have been captured using classroom recording, and the elements to which they paid attention could have been

TABLE V
Conditions of Fruitful Collaboration

Condition	Control condition (no dashboard for teachers, only PyramidApp)	Experimental condition (dashboard for teachers)
Common goal	Need to collectively reach a consensus on a common task.	Students were more responsible and focused as teachers monitored activity.
Positive Interdependence	Participants are aware that they need each other to succeed.	Students were more responsible and focused as teachers monitored activity.
Coordination	Flow aligned with the pedagogical method or intent.	Teachers used the dashboard controls to further regulate the activity.
Communication	Intensity of discussions.	The number of messages posted in the discussion was high, but not significantly high.
Individual accountability	Each student should contribute.	Students posted more answers and contributed more to voting and discussions.
Awareness of peers' work	Students see answers submitted by others.	As a result of increased answer submissions and voting on peers' answers, students took into account the answers submitted by peers.
Joint rewards	Groups that reach agreement faster will produce a winning answer.	Teachers revealed the winning answers to the class at the end of the sessions.

detected using eye-tracking technologies for fine-grained analysis. The present study did not measure whether the generated warnings and information visualisations of the dashboard added to teacher' orchestration load.

Finally, regarding the students aspects, given the limited time available in the classrooms we were unable to collect detailed qualitative responses or to conduct interviews to capture further information regarding perceived learning and satisfaction.

IX. Conclusions and Future Work.

This study reported our practical experience related to designing a teacher-facing dashboard that aimed at supporting teachers in orchestrating scripted classroom collaboration. The findings of the study revealed how teachers made information on the dashboard actionable (not only based on automatic detection of low-participating groups but also because of how teachers used the information presented on the dashboard to inform their pedagogical actions, e.g. whole-class scaffolding, targeted scaffolding) and how teachers actions induced positive change in students' activity participation. In the following, we outline design principles for actionable dashboards to support CLFPs derived from the research:1) Warn teachers of critical events concerned with the epistemic facet related to the learning task but also to the social facet affecting the collaborative learning flow mechanisms: Enabling the flexible modification of learning scenarios in run-time is a necessary feature of orchestration technology. However, it is not sufficient if the technology is not helping teachers to take informed actions. In our study, teachers mentioned that they missed chances of reacting to critical events during collaboration as they are concerned about the epistemic and social facets of the learning activity in real-time. By generating automatic warnings to inform critical events, teachers can act instantly providing just in time support for students taking advantage of the orchestrable technology; 2) Offer capabilities to customize warnings: Criteria to generate warnings may depend on the type of task and teacher's expectations. Teachers wanted to have access to authoring features that allow them to modify criteria for generating warnings; 3) Generate action-impact indicators: Teachers mentioned that they want to know how their interventions or pedagogical actions impacted students. For instance, teachers wanted to know whether posting a message to a group resulted in increased students' discussion participation; 4) Align students' artefacts with teacher's expectations: Teachers want to rapidly evaluate if the answers produced by the students are aligned with their expectations. This was challenging as pyramid CLFP tasks can be of different natures and the tasks used in our study were open-ended. Providing space for teachers to input keywords they would like to see in students' answers and matching of teacher's expected answers versus students' answers can facilitate a first approach for real-time content evaluation; 5) Avoid hidden menus: Teachers indicated that the dashboard controls placed in a hidden menu resulted in added complexity and usability issues. They wanted all information and controls of the dashboard to be visible and easily accessible; 6) Use teacher's vocabulary instead of technical terms: Teachers asked to use language close to teacher's vocabulary as technical terms used in the dashboard are difficult to interpret in real-time.; 7) Provide automatic action recommendations: Teachers mentioned that having access to dashboard controls (e.g. pause, resume, etc.) is useful. However, as shown in the study results the use of such controls in the run time of the activity is less, which indicates that there is a gap between teachers' subjective perception of such controls and their real-time use. This may occur due to the teacher's lack of familiarity with the technology, lack of confidence in revising the learning design in real-time, or due to lack of focus towards the use of controls as they are busy in evaluating epistemic and social aspects of the learning scenario. Generating automatic action recommendations of when to use dashboard controls and giving them the flexibility to accept or reject the recommendations would facilitate to bridge the gap between perception and technological affordances.

Future studies around teacher orchestration may benefit from considering the use of novel tracking technologies. For example, studies related to electrodermal activity (EDA) and its application for detecting changes in the level of arousal [35], especially within the learning context [36], suggest that this method can be used to monitor the state of teachers at the time they carry out actions when using the dashboard. Studies of cognitive load when teaching over the video, show that physiological measurements, such as arousal measured by galvanic skin response, correspond to the self-reported states of cognitive load [37]. In our future research, we will equip teachers with an Shimmer3 GSR+ device, which is suitable for measuring EDA with minimal disturbance to the teachers' usual patterns of behavior. Even though these kinds of measurements require devices to be attached to the teacher, they can provide useful data, especially for tracking the causality of teachers' actions. Another way to understand teachers' behaviour during orchestration is to track sound levels in the classroom [38]. An off-the-shelf sound meter could be carried by teachers to detect the level of sound that reaches them. This information could explain certain teachers' actions, like sudden interruptions of the activity or pauses for intervention. By combining EDA and sound measurements as well as tracking the actions carried out while using the dashboard, we could employ a multimodal system that provides various types of complementary data and focuses on teachers' behaviour. For instance, data collected from such devices together with self-reported measurements could provide information regarding perceived cognitive load of the teachers when using dashboards for orchestration purposes. Eye tracking can help indicate a correlation between more frequent looking at students when the cognitive load is increased [33]. More research on eye tracking technology implies that, combined with video recordings, this physiological measurement can be a good addition to qualitative measures in assessing cognitive load [33]. Note, however, that while this type of multimodal learning analytics is interesting for research purposes, there are ethical implications in its applicability to real scenarios [39].

Regarding student aspects, tracking technologies can be used to determine the positions of group participants, which can inform how the positioning affects overall group performance

[40]. By comparing this information to groups' performance and actions during an activity, suggestions regarding orchestration can be provided for the teacher. Similarly, EDA approaches with students can be investigated. EDA measurements in students are present in studies where the possibility of reducing stress is analyzed with the aim to obtain better learning outcomes [41]. A Multimodal system consisting of EDA, heart rate measurement device, finger-based GSR sensor and surveys, demonstrates that prediction algorithms can provide 88.8% of accuracy in predicting stress with college students [42]. By measuring voice activity (speaking time and location of the student) and relating it to the actions students take (discussion, time for voting, etc.), we can thoroughly analyse the frequency of face-to-face contact and its relevance to this approach [43]. Inertial measurement unit (IMU) sensors, such as the Shimmer3 IMU Unit, which are used for this kind of tracking, are non-invasive, and can be placed on each participant without disturbing them during the activity [44].

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Chapter 5

TEACHERS' ADAPTATION OF SCRIPTED COLLABORATION IN THE CLASSROOM

As a continuation of the work presented in Chapter 4, this chapter also tackles part of the first objective and the third objective of this dissertation which focused on the identification of the orchestration challenges of scripted collaboration in the classroom learning context and to support teachers using LA (Figure 5.1). The content of this chapter consists of a journal article (currently under review in a peer-reviewed journal) and a workshop paper presented in an international conference which represent research conducted as part of the third DBR cycle (Figure 5.2).

The journal article describes how different types of dashboard support, e.g., mirroring support and guiding support, informed teachers in taking actions to orchestrate scripted classroom collaboration. An ENA analysis was used to determine the teachers' actionable differences in different support situations. The workshop paper presents the use of tracking technologies to measure the orchestration load.

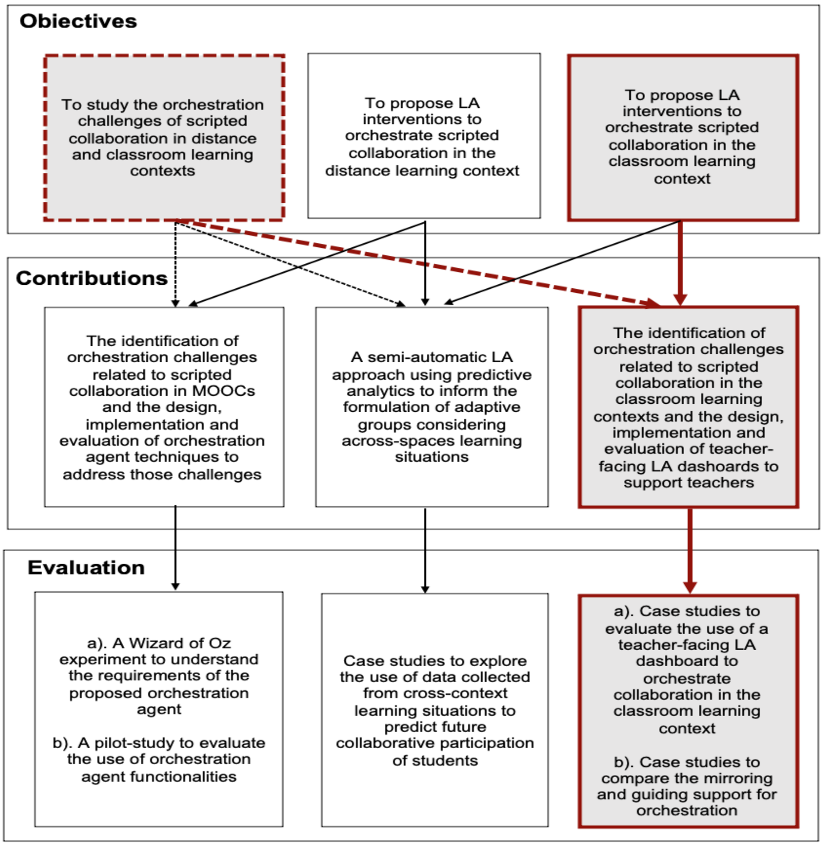

Figure 5.1: Objectives, contributions and evaluation studies covered by Chapter 5.

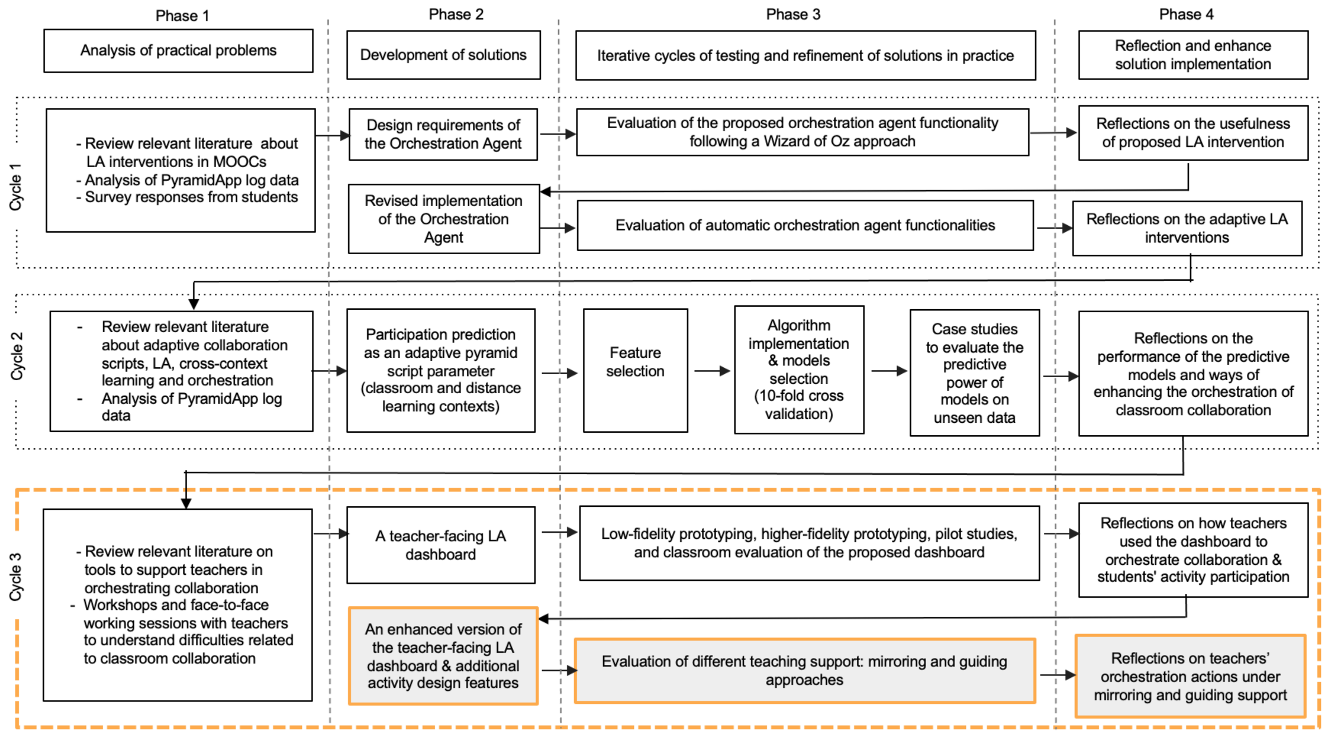

Figure 5.2: Part of the research process related to Chapter 5.

5.1 Teacher Dashboards for the Orchestration of CSCL Scripts - Comparing Mirroring and Guiding Approaches

The content of this section was submitted to a peer reviewed journal and is under review:

Amarasinghe, I., Hernández-Leo, D., & Hoppe, H. U. (2020). Teacher dashboards for the orchestration of CSCL scripts - comparing mirroring and guiding approaches. (Submitted to journal, currently under review).

Teacher dashboards for the orchestration of CSCL scripts - comparing mirroring and guiding approaches

Ishari Amarasinghe * Davinia Hernández-Leo * H. Ulrich Hoppe

Abstract Under the notion of "CSCL scripts", different pedagogical models for structuring and supporting collaboration in the classroom have been proposed. We report on practical experience with scripts based on the Pyramid pattern supported by a specific classroom app and a teacher-facing dashboard. The input data of our analysis stem from recordings of classroom interactions guided by several teachers using the PyramidApp with different levels of teaching support. For the analysis, we introduce a specific coding scheme enabling a quantitative comparison and deeper analysis using Epistemic Network Analysis (ENA). This analytics approach revealed how teachers' orchestration actions vary under different types of support provided for orchestrating collaborative learning in the classrooms. The study findings are discussed also taking into account the multifaceted nature of the orchestration load.

Keywords CSCL Scripts * Orchestration * Dashboards * Learning Analytics * Collaboration * Epistemic Network Analysis

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Teacher dashboards for the orchestration of CSCL scripts - comparing mirroring and guiding approaches

Abstract Under the notion of "CSCL scripts", different pedagogical models for structuring and supporting collaboration in the classroom have been proposed. We report on practical experience with scripts based on the Pyramid pattern supported by a specific classroom app and a teacher-facing dashboard. The input data of our analysis stem from recordings of classroom interactions guided by several teachers using the PyramidApp with different levels of teaching support. For the analysis, we introduce a specific coding scheme enabling a quantitative comparison and deeper analysis using Epistemic Network Analysis (ENA). This analytics approach revealed how teachers' orchestration actions vary under different types of support provided for orchestrating collaborative learning in the classrooms. The study findings are discussed also taking into account the multifaceted nature of the orchestration load.

Keywords CSCL Scripts * Orchestration * Dashboards * Learning Analytics * Collaboration * Epistemic Network Analysis

Introduction

In Computer-Supported Collaborative Learning (CSCL), scripts are described as a type of scaffold (Dillenbourg et al. 2009) that aims to structure collaborative learning activities by specifying how and when learners may interact with each other (Kollar et al. 2006). Scripts emerged as a means to facilitate learners to achieve fruitful learning outcomes by providing guidance and structure (Fischer et al. 2003; Kobbe et al. 2007). Such guidance becomes important as learners may have a limited understanding of how to interact in collaborative learning situations, to share useful information, to build and engage in fruitful argumentation (Liu et al. 2015). Without proper guidance, learners will fail to take advantage of collaboration (Radkowitsch et al. 2020).

Although scripts provide a structure for collaboration that favors learning, eventualities that may occur during its enactment can cause deviations from the original plan (Dillenbourg and Tchounikine, 2007). For instance, consider the deployment of a pyramid script in the classroom learning context. This script provides a structure for collaboration that encourages students to reach a consensus within a number of phases which occur one after the other following a pyramid structure (Hernández-Leo et al., 2019). The pattern integrates activities that are occurring at multiple social planes, i.e. individual, group, and class-wide levels as described below. First, learners start to solve a given problem individually. Learners then formulate small groups (usually pairs) to share their solutions and to agree on common solutions. Later small groups are merged, formulating increasingly larger groups as the activity flow advances. The increasingly larger groups formulate the Pyramid structure. The pattern mediates learning and reflection within different stages of the script. It also provides opportunities for all learners to express their solutions and to discuss their ideas with peers. Each student has to contribute and sustain participation from the beginning till the end of the consensus-building process. At the end of a successful collaborative learning activity learners' may achieve a collaborative consensus on a given problem.

Lack of individual motivation and participation at different phases of the Pyramid script can reduce the ability to reach a consensus. This will result in a less productive collaborative learning experience for motivated students. Under a lack of expert monitoring, the script may also lead students to reach a potentially misleading consensus that is not aligned with the pedagogical intentions of the teachers. Moreover, as groups work in parallel, some groups may finish the task quicker whereas other groups may require more time. This may create waiting times for faster groups that can lead to off-task behaviours in the classroom, whereas slower groups may require more time to produce collaboration outcomes. On the one hand, such eventualities can impede achieving beneficial learning outcomes and require teacher's immediate interventions for further guidance, script adaptation and regulation (Rodríguez-Triana et al. 2015). On the other hand, it is difficult for teachers to constantly distribute their attention across multiple groups to track progress as well as to decide the necessary script adaptations required at different social levels (van Leeuwen, 2015).

In the context of collaborative learning, the notion of *orchestration* has been put forward to describe how teachers productively coordinate and manage classroom activities in real-time taking into account the learning activities that occur at different social levels, e.g., individual, small group and class-wide activities (Dillenbourg et al. 2009). Teacher-centrism is a key feature within the concept of orchestration in which the role of teachers' is not conceived as the one of a *guide on the side* but rather as a *conductor*, who manages and drives the whole activity in a productive direction (Dillenbourg and Jermann 2010).

Teachers may perform many orchestration actions in regulating collaboration. For instance, such orchestration actions may include monitoring activities (in which teachers monitor the activity participation of students), diagnostic activities (in which teachers assess and attempt to detect participation deviations and misunderstandings at the content level), advising activities (in which teacher require to provide advice to less-performing groups), praising and criticising activities for positive and negative behaviors of students, script modification activities (in which teachers alter the script to align it with the emerging needs of the learning situation), debriefing activities as well as the effective use of tools and technologies available for orchestration are to name a few. As described in Soller et al. (2005) managing collaboration in real-time can also be described as a cyclic activity, in which the current state of the interactions is continuously compared against a desired state to detect discrepancies. Detection of deviations will call for remedial actions by the teachers to achieve the final goals and objectives of the learning situations. Despite the importance of these teacher-centric activities, assessing learning situations in real-time to take relevant actions is known to be a difficult task for the teachers (Soller et al. 2005).

Tools and technologies can be designed to support teachers in regulating collaboration in real-time. One such technology is the teacher-facing dashboards. These dashboards can provide *mirroring* support to the teachers in which the aggregated data about learning situations, e.g., students' interactions, unfolding of the script over time, is presented to the teachers for their reflection. Teacher's reflections of the activity may call for teacher-initiated remedial actions (Soller et al. 2005). Dashboards can also be designed to provide *guiding* support for the teachers. In *guiding* support, the system monitors the state of interactions to detect deviations. Detected deviations are conveyed to the teachers using high-level indicators, e.g., automatic alerts (Soller et al. 2005). In this way, the dashboards can propose remedial actions to the teachers providing additional support to make decisions and to act in real-time. For instance, upon detecting that students require more time to submit answers in a Pyramid activity, an automatic alert can be generated advising teachers to increase the duration of the script. Such alerts can guide teachers to take remedial actions by making critical moments of collaboration upfront.

But what kind of support teachers find useful in orchestrating collaboration? How these different types of support affect the orchestration load of the teachers? Because orchestration of collaboration is not a trivial task it is important to study the types of support teachers need in orchestrating collaboration also taking into account the orchestration load experienced in real-time. From a design perspective, technologies that disregard orchestration load as an important construct in evaluating technologies for classroom use may not support teachers rather increase their cognitive load.

Recent studies have shown that teacher's ability to take actions given different types of support in orchestrating authentic CSCL situations has not been fully explored yet (van Leeuwen et al. 2019a, Martinez-Maldonado 2019, Wise and Jung 2019). Exploring the type of support teachers require in order to be in control of the learning activity in-situ can help to design impactful orchestration technologies. To this end, in this study, we focused on how teachers' orchestration actions varied under different types of support provided in authentic CSCL situations. The central research question addressed in this study is *how do mirroring and guiding support influence the orchestration actions of the teachers?*

Following a within-subjects design, we conducted a case study in which six teachers participated. We designed and deployed a dashboard to support teachers in orchestrating classroom CSCL situations. In the *mirroring* support, teachers had access to a teacher-facing LA dashboard. But the interpretation of the data presented, and the use of dashboard controls are left to the teacher without explicit guidance. In the *guiding* support, teachers had access to the same teacher-facing LA dashboard, but alerts were automatically generated to guide teachers in taking remedial actions. As a control condition, we also included a no dashboard condition. As the name implies in this condition teachers did not have access to a teacher-facing dashboard. The interpretation of collaboration was based on classroom cue's e.g., teacher's observations and questions raised by students. Teachers' orchestration actions across the three conditions were recorded and coded using a coding scheme proposed in this study. Coded data was then analysed using the Epistemic Network Analysis (ENA) (Shaffer et al. 2016). ENA enabled us to visualise and quantitatively compare the differences between teachers' orchestration actions across the three conditions. Using a mixed-method approach we then triangulated the results of the ENA with teachers' subjective perceptions of the different supporting options. Perceived cognitive load was recorded using a questionnaire.

We expected that in the *mirroring* support, teachers may perform a less amount of orchestration actions, as making sense of the information presented to evaluate the learning situation, formulating goals, understanding the support and deciding which actions to take is left to the teacher which is demanding in real-time. We assumed that teachers may experience some control over the activity and have some focus over the epistemic facet of the learning situation, yet this demanding situation will result in a high cognitive load for the teachers.

In contrast, in the *guiding* support, we expected that teachers may perform a high amount of orchestration actions as automatic alerts were used to signal certain events that require teachers' interventions. We expected that the alerts may support them in evaluating the learning situation, formulating goals and to take actions. Due to the additional support provided and ability to take more actions we assumed that teachers may experience a high control over the activity. As alerts were used to guide teachers' actions, we expected that they may devote less cognitive resources to understand the support but may employ more cognitive resources over the epistemic facet of the learning situation (high focus). Due to all the aforementioned reasons we assumed that teachers will experience relatively a low cognitive load when compared to the cognitive load experienced under *mirroring* support.

Finally, in the no-dashboard condition, we expected that teachers may perform the lowest amount of orchestration actions as they did not have access to any supportive technological means to evaluate the learning situation, to decide and to take action regarding the learning situation. We assumed that the teachers will experience low control over the activity and difficulties in focusing on the epistemic facet of the learning situation. We expected that due to less cognitive activities teachers may engage, they will experience the lowest cognitive load in the no-dashboard condition when compared to the other two conditions, i.e., *mirroring* and *guiding*.

The following sections of the paper is organized as follows. First, we present relevant literature including classroom orchestration and LA dashboards. Next, we present details about our authentic CSCL study followed by the study results. Then we present a discussion on the results and the limitations of the study. Finally, the conclusions and directions for future research are provided.

Background

Orchestrating Classroom Collaboration

Teachers play an important role in the context of classroom collaborative learning. In formal co-located collaborative educational settings, teachers are required to prepare and design the collaborative learning activities, execute them within the classroom while coordinating, monitoring and supporting students when required.

The execution of collaborative learning activities may not always unfold according to the original plan as extraneous activities that were not predicted during the activity design time may create deviations, e.g., team members dropping out from a collaborative group, network failures, latecomers, and mistakes in learning material (Roschelle et al. 2013). Such unpredicted yet unavoidable situations that occur during activity enactment will demand teachers to take actions in order to adapt the design of the learning activities in real-time, e.g., recalculate groups, modify the activity, to attain fruitful learning outcomes and to meet students' expectations (Roschelle et al. 2013).

Regulating CSCL activities considering the emerging needs of the learning situations becomes demanding as teachers not only have to address the problems arise from collaboration but also have to handle several other constraints arise from the classroom environments, e.g., time, space, energy (Prieto et al. 2019). The activities may also occur at different social planes which requires teacher's attention distribution across multiple social planes, e.g., individual, group, class level (van Leeuwan 2015a). The *orchestration* metaphor captures the complex set of coordination activities teachers require to handle in real-time in highly constrained learning situations (Roschelle et al. 2013). Orchestrating collaboration is known to be a difficult and demanding task that needs effort (Prieto et al. 2017).

Tools and technologies can be designed to support and empower teachers in orchestrating collaboration although it has been identified as a challenging task in learning technology research (Prieto et al. 2017). Commonly referred to as *orchestration technology* an extra layer of technology can be introduced within technology-enhanced classroom spaces to support teachers. By providing information on how collaboration evolves and providing controls to adapt the learning activities flexibly according to the needs of the learning situation to achieve goals, orchestration technologies may support teachers in orchestrating integrated classroom activities in real-time (Dillenbourg et al. 2013).

Designing orchestration technologies require to take into account the *usability at the classroom level* (Dillenbourg et al. 2011). This new form of usability research considers the classroom as the user itself and acknowledges the multitude of constraints teachers require to manage in regulating learning activities in authentic classroom situations (Dillenbourg et al. 2011). Although orchestration technologies aim to facilitate teachers in orchestrating learning activities poorly designed technologies may increase the *orchestration load* of the teachers, instead of supporting them in activity regulation (Sharples, 2013).

The notion of *orchestration load* has been described as the total effort teachers need to put in when using a certain technology for orchestrating classroom activities (Prieto et al. 2015). In authentic classroom learning scenarios, not only the technology, but a number of other factors such as teacher expertise, teachers' familiarity with the classroom situation, external help available, and teaching activity may also influence teachers' orchestration load (Prieto et al. 2017). Despite considering orchestration load as an important construct that needs to be taken into account when designing orchestration technologies, the complex nature of studying orchestration load in real classroom settings has led most of the existing studies to refer to this notion as a high-level concept (Prieto et al. 2017). Research regarding orchestration load and how it informs the design of orchestration technologies is still in its infancy as existing studies mostly refer to this concept in an abstract form without drilling into details (Prieto et al. 2017).

Researchers have proposed design guidelines based on their experiences in introducing orchestration technologies for classrooms, which become useful when designing future technologies for similar purposes. It had been argued that technologies which implement minimal (technologies that avoid the addition of functionalities that are not strictly required) yet flexible (technologies that facilitate on the fly modification of the learning activities) characteristics can reduce the orchestration load experienced by the teachers as such tools share relevant information and provide a degree of freedom to modify the activity design in real-time according to the needs of the learning situation (Dillenbourg et al. 2011). By studying how teachers appropriate different types of technologies and support provided in real-time can help to further our knowledge on the types of aids that can support them in orchestrating collaboration also taking into account the perceived cognitive load. Although this new form of usability research may facilitate the implementation of useful learning technologies, recent studies have shown that this research is still in its infancy and much work remained to be done (Martinez-Maldonado, 2019; Prieto et al. 2017).

Learning Analytics Dashboards

LA dashboards can be described as *“single displays that aggregate different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualisations”* (Verbert et al. 2014; Schwendimann et al. 2016). Recently a growing research interest towards provisioning teacher-facing dashboards to support teachers has been observed (Martinez-Maldonado, 2019; van Leeuwan and Rummel, 2020; Wise and Jung, 2019). These dashboards visualises learner-educational platform interaction data and aims to support teachers in evaluating the learning situation to take remedial actions.

As described by Soller et al. (2005) in managing collaboration the current state of the activity is continuously compared against a desired set of interactions to detect deviations. Detected deviations may call for remedial actions at the user level, e.g., teachers or students, or at the system level. Similarly, LA dashboards can be used to support the regulation loop of orchestration. By aligning LA with the pedagogical intentions documented in the learning design, dashboards can be used to inform any deviation detected. Using *checkpoint* and *process analytics* teachers can look for specific patterns in the data at predefined time points, e.g., successful and unsuccessful engagement patterns, in order to provide relevant feedback for students to enhance their interactions (Lockyer et al. 2013).

Systems that support the management of collaboration can be broadly categorised into three different categories namely *mirroring tools, metacognitive tools* and *guiding systems* based on the location where decisions about interactions are made and remedial actions are decided (Soller et al. 2005). Mirroring tools collect data about interactions and then visualise the collected data to the system users, e.g., learners or teachers. Users are expected to diagnose collaboration based on the given information and to decide remedial actions needed. Metacognitive tools display both the current state of collaboration and how desired interactions may look like to facilitate comparison. Similar to mirroring tools, the metacognitive tools expect users to self-diagnose interactions and remedial actions. Finally, the guiding systems which can also be described as coaching or advising systems recommend remedial actions to enhance collaboration. A recent review conducted in van Leeuwen et al. (2019a) a similar categorisation of orchestration tools, i.e., *mirroring, alerting* and *advising tools*, have been proposed. The mirroring tools were described as systems that provide information but do not facilitate the interpretation of information. The alerting tools facilitate the interpretation of information by alerting the teachers about critical events that occur during collaboration. The advising tools advise teachers to take remedial actions. The authors have later shown that the teacher-facing dashboards which provide an advising support helped teachers to detect problematic groups often in a simulated learning environment when compared to the dashboards that provided a mirroring support (van Leeuwen and Rummel, 2020).

Despite the increased amount of research attempts to deploy teacher-facing dashboards to support teachers, recent reviews conducted in the field has shown that the adoption of dashboards as well as LA tools in general within teaching practice is still low (Schwendimann et al. 2016; Prieto et al.2019). Moreover, a detailed analysis of how teachers make sense of the information presented and subsequently translate their decisions to take relevant pedagogical actions in authentic contexts when using LA dashboards has not been fully explored yet (Wise and Jung, 2019; Martinez-Maldonado, 2019). This has raised questions regarding the deficiencies associated with the design process of such technologies, e.g., lack of inter-stakeholder communication (practitioners, students), and their involvement during LA tool design processes (Prieto et al. 2019). Buckingham et al. (2019) pointed out that the design of LA tools should go beyond the technological and pedagogical principles and require incorporating human factors questioning why and how such tools will be used in everyday practices. Understanding the types of support required by a targeted stakeholder group, e.g., teachers or learners, can facilitate the creation of tools that adapt to their needs and requirements, e.g., different levels of data literacy, skills, experiences (Prestigiacomo et al. 2020; Verbert et al. 2020) which are likely to facilitate classroom adoption of LA.

Exploring the gap between *interesting* to *actionable* analytics that inform teaching practices is relatively underexplored, although bridging this gap can support the integration of LA use into everyday teaching practices (Wise and Jung, 2019). Understanding how teachers make sense of the LA data presented and how they translate the acquired knowledge (by making sense of LA data) to take actions at the content or the process level of authentic collaborative learning situations under classroom constraints (Cuendet et al. 2015), can provide rich insights towards the affordances of teacher-facing dashboards in classroom orchestration (Martinez-Maldonado, 2019).

Methods

Technical Orchestration/Conditions (PyramidApp and Teacher-facing Dashboard)

In this study, we have considered collaborative learning activities that were scripted according to the Pyramid script (Hernández-Leo et al. 2010). A web-based tool called PyramidApp that implements a particularisation of the pyramid script was used to deploy collaborative learning activities in the classrooms (Manathunga and Hernández-Leo 2018). The tool provides an activity authoring space and an orchestration dashboard for teachers as well as an activity enactment space for students.

When authoring a Pyramid activity, teachers can enter the question to be answered by the students and configure the following parameters according to the unique requirements of their classrooms: (i) size of the class; (ii) size of small groups; (iii) the number of levels in the pyramid; (iv) the number of students per pyramid; (v) time for answer submission; (vi) time for collaboration at the group levels; (vii) keywords teachers expect to see in students answers (up to 10 maximum). Figure 1 shows the PyramidApp authoring user-interface. Apart from the aforementioned parameters teachers can also configure automatic alerts to be appeared in the dashboard informing remedial actions (see Table 1).

Within the activity enactment space collaboration among students is facilitated across Pyramid levels as follows. First, students need to login to the tool. Once logged they are required to submit an answer individually to the given question. After submitting their answers students need to wait until the predefined time for answer submission expires. At the end of the individual answer submission phase, students are grouped into small groups (usually 3-4 students) automatically. Within small groups, students can see the answers submitted by fellow group members along with a voting mechanism to vote each answer. An integrated chat facilitates discussion among students at the group levels. Small groups are later merged into larger groups in which highly voted answers at the small group levels are shown to students for further evaluation. All student actions within the tool are automatically logged. Figure 2 shows a screenshot of the PyramidApp as students use it during a group phase.

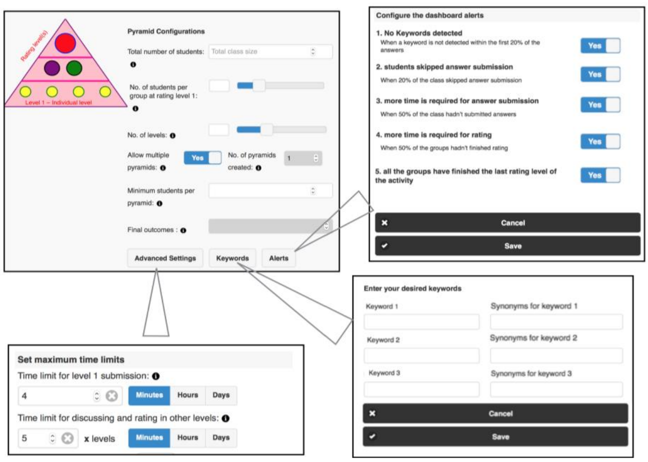

Fig. 1. PyramidApp authoring user interface, basic parameter configuration (top-left), time configuration (bottom-left), alerts configuration (top-right), keywords (bottom-right).

A teacher-facing dashboard was used to support teachers in orchestrating collaboration. The dashboard designed to consists of two tabs namely *Responses Related* and *Participation Related*. As shown in Figure 3 the *Responses Related* tab displays the individual answers submitted by students and highly voted answers at the small group level and the finally selected answers at the large group level. Keywords detected in students' answers (using a custom keyword searching algorithm) were highlighted.

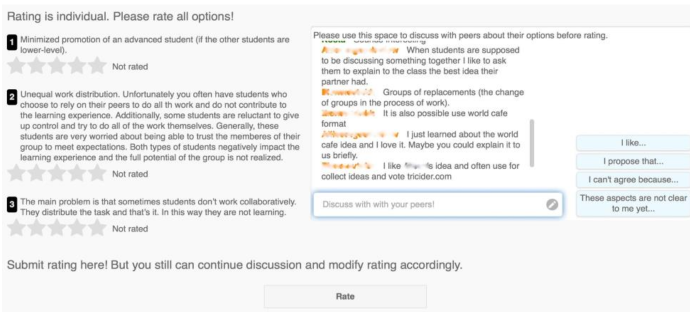

Fig. 2. Screenshot of PyramidApp, voting space (left), discussion space (right).

Table 1. Dashboard alerts

Name of the alert	Criteria or the Rule	Intended Use
No Keywords	When a keyword is not detected within the first 20% of students' answers	This will facilitate the teacher to know whether the answers submitted by the students align with teacher's expectations
Answer Submission Skipped	When 20% of the class skipped answer submission	This will provide a hint to the teacher if students start skipping answer submission
More time for submissions	When 50% of the class has not submitted answers	This will provide a hint to the teacher if the majority of the students require more time to submit answers
More time for voting submissions	When 50% of the groups have not finished voting	This will provide a hint to the teacher if the majority of the students require more time to vote answers

The *Participation Related* tab shown in Figure 4 displays activity participation differences of the groups. Each group's participation is visualised using two boxes. A larger box showed the voting participation as a percentage and a smaller box showing the number of messages posted within the group. The voting percentage and number of messages posted were updated in real-time. This group classification aimed to provide a glimpse into students' participation levels at a given moment. Upon touching group boxes teachers can obtain more details about groups, e.g., names of the group members, answers to be voted in a given group, students participate in the chat and the messages posted so far. Teachers were also facilitated to intervene in group chat by posting predefined messages to groups in real-time.

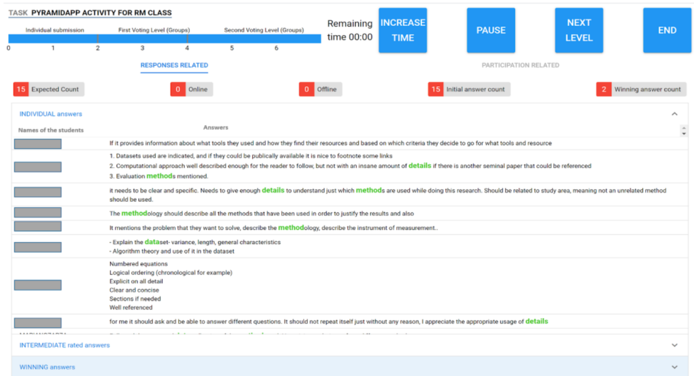

Fig. 3. Information presented in the response related tab of the dashboard.

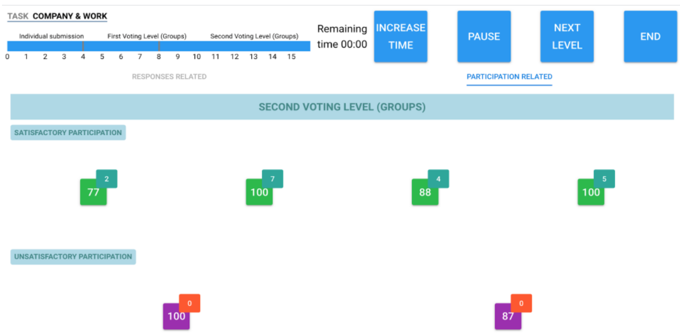

Fig. 4. Information presented in the participation related tab of the dashboard.

A timeline visualisation and a remaining time countdown were added in the dashboard to make teachers aware of the real-time progression of the activity and the remaining time (see Figure 3 top left). Four controls were added in the dashboard as buttons to allow teachers to modify the script manually during the runtime of the activity (see Figure 3 top right). For instance, *the increase time* button allows teachers to increase time for the currently active pyramid level, *pause* button allows to pause and resume activity at any moment, *next level* button allows to skip intermediate group levels in the pyramid and the *end* button allows to stop the progression of the activity whenever teacher wishes. Teachers' dashboard actions (that were taken by using control buttons or as a response to a dashboard warning) were communicated to the students as a notice appearing on top of the PyramidApp user-interface. All dashboard actions conducted by teachers were automatically logged.

Study participants and experimental design

Following a within-subjects design, six higher-education teachers (3 females) from the Engineering School of a public university in Spain participated in our study. Teachers were introduced to the functionalities and features of the PyramidApp and dashboard before the experimental sessions. Each teacher conducted three different collaborative learning sessions addressing the three conditions that we were interested in (see Table 2). The design of each collaborative learning activity varied based on the teacher's requirements to conduct CSCL activities in their classrooms and the time available (see Table 2). As shown in Table 2, teacher A, B and C followed the following order: no dashboard condition, mirroring condition and guiding condition while teachers D, E and F followed the following order: no dashboard condition, guiding condition and mirroring condition. The total time allocated for each activity, the number of students participated and the questions proposed by the teachers for different activities are presented in Table 2.

Table 2. A summary of collaborative learning activities conducted, reflecting the order of activities

Teacher ID	Order of sessions and details			Question given to students in all three sessions
	No Dashboard Condition	Mirroring Condition	Guiding Condition	
A	Time: 9 mins Students: 30	Time: 9 mins Students: 71	Time: 9 mins Students: 48	Share knowledge about IT companies and jobs
B	Time: 6 mins Students: 36	Time: 6 mins Students: 31	Time: 6 mins Students: 28	Share knowledge about research writing
C	Time: 6 mins Students: 17	Time: 6 mins Students: 16	Time: 6 mins Students: 19	Share knowledge about presentation skills
Teacher ID	Order of sessions and details			Question given to students in all three sessions
	No Dashboard Condition	Guiding Condition	Mirroring Condition	
D	Time: 13 mins Students: 31	Time: 13 mins Students: 24	Time: 13 mins Students: 19	Share knowledge about ethics in IT
E	Time: 9 mins Students: 7	Time: 9 mins Students: 21	Time: 9 mins Students: 51	Share knowledge about video production
F	Time: 15 mins	Time: 20 mins	Time: 20 mins	Share knowledge about

	Students: 13	Students: 19	Students: 12	distributed systems & ethics

Data Collection

All experiments were video-recorded. Apart from logging the teachers' dashboard actions, we also collected screen-captured data (audio and video) from the dashboard tablet. A researcher transcribed the video recordings to create a dataset that included timestamped information on teachers' actions. Transcribed video data and screen-captured data were then merged along the timestamps to create a single dataset that described each teacher's actions during each collaborative learning session. At the end of each experimental session teachers were also asked to score their perceived cognitive load reflecting the mental effort of orchestrating collaboration on a scale from 1 to 20 (1 low and 20 high). Figure 5 shows the technical setup used for experimentation.

Fig. 5. A teacher using the dashboard (top) and data collection in a classroom session (bottom).

Coding teachers' actions

In order to analyse the behavioral data collected we defined a coding scheme (following iterative refinements) to code teacher´s actions. At first, we came up with a detailed coding scheme that consisted of nineteen codes to code teachers' actions. However, we realised that some of those codes, e.g., reflection, are not directly observable in our video recorded data and are more related to cognitive aspects. As we did not collected data to interpret such cognitive aspects we improved the initial coding scheme eliminating such codes and including only the codes that reflected teachers' observable behaviours. Moreover, instead of defining detailed codes to capture minute details of teachers' actions we defined summarized codes that captured a number of minute actions (see Table 3). This simplified our coding scheme to contain only seven codes in total that captured teachers' observable behaviors when orchestrating collaboration.

The codes shown in Table 3 were used to code the data obtained from all three experimental conditions (e.g., no dashboard, mirroring and guiding conditions). The codes shown in Table 4 were only applied to data collected during mirroring and guiding conditions, in which the teachers used the dashboard to orchestrate collaboration. Two researchers coded the dataset using 1's and 0's indicating the presence and absence of the codes. There was high agreement between the coders (Cohen's kappa = 0.96, $p < 0.005$), and any disagreements were resolved by discussion. We then applied ENA techniques to model the structure of connections between coded elements in discourse data.

Table 3. Codes defined to describe teachers' actions in all three experimental conditions

Code	Definition
Teacher Individual Interaction	Teacher responds/answer to specific questions raised by individual students (unidirectional)
Teacher Class Interaction	This code captures the bidirectional interactions between teachers and the whole class. Examples: - Teacher requests information from the class (Surveying) - Teacher provides directions to the class on how to use the PyramidApp or describes the task (Giving directions) - Teacher discusses the finally selected answers at the end of the class (Debrief) - Teacher provides comments to the class to change student behavior from non-acceptable to acceptable pattern (Criticize)
Announcements to Class	Teacher makes announcements to the class regarding: - Time available - Phase transitions of the script - Student participation in the activity
Teacher Perception	This includes the following two behaviors: - Teacher is looking at individual student devices (e.g., mobile or desktop monitors) - Teacher is looking at the task projection

Table 4. Codes defined to describe teachers´dashboard actions in the mirroring and guiding conditions

Code	Definition
Check Responses Tab	This code summarises the following actions by the teacher within the *Responses* Tab of the Dashboard: - Scrolling answers received from individual students - Scrolling highly rated answers at the group level - Checking other statistics presented in the "Response Tab" (e.g. online & offline counts, number of answers etc.)

Check Participation Tab	This code summarises the following actions by the teacher within the *Participation* Tab of the Dashboard: - Checking information related to satisfactory and unsatisfactory voting participation of groups - Opening a particular group box and scrolling the chat messages posted by the students - Opening a particular group box and checking the names of the group members
Dashboard Interventions	This code summarises the following dashboard interventions by the teacher: - Opening a particular group box and posting messages to groups - Rating on behalf of student groups - Use of *Next Level* button to move to the next level of the activity - Use of *Increase time* button to increase the time for the activity - Use of *End* button to end the collaborative learning activity before reaching the end of planned time - Use of *Pause* button to pause the script

Modelling teacher´s actions using ENA

ENA is a statistical tool that aids in modeling connections among elements in qualitatively coded datasets (Shaffer et al. 2016; Shum et al. 2019). ENA quantifies the connections among codes in discourse and visualises the structure of connections using dynamic network models (Shaffer et al. 2016). ENA provides a cotemporal technique that takes into account the temporality in discourse data (Saint et al. 2020; Csanadi et al. 2018).

Recent studies have emphasized that temporal information in educational data is not well used although the temporal nature of learning is central in LA research (Knight et al. 2017; Reimann 2009). For instance, frequency-based measures do not capture sequential and temporal co-occurrences associated with learning processes (Saint et al. 2020). Csanadi et al. (2018) has shown that ENA which model temporal co-occurrences of learning data to be beneficial in modeling social interactions as traditional frequency-based measures, i.e., coding-and-counting strategies do not take into account the temporal dynamics of the discourse and produce limited (e.g., absence of how actions related to one another) yet potentially misleading insights.

In the context of CSCL, ENA has been applied for a variety of modelling purposes, ranging from models of students' actions in collaborative learning settings (Sung et al. 2019, Oshima et al. 2019), contributions within collaboration discussion spaces (Ma et al. 2019) to generating visualisations to support teachers interventions (Herder et al. 2018) and feedback in co-located collaborative situations (Shum et al. 2019).

In ENA network models, the nodes represent the codes and the weights of the network edges reflect the relative frequency of co-occurrences between two codes. The thicker edges represent stronger connections between nodes and thinner, less saturated edges represent weaker connections. In ENA a network model is generated for a given unit of analysis considering the co-occurrences of the codes within a defined conversation. Conversations include lines of data in which we need to identify connections for a given unit of analysis. Based on the given conversation variable, the input dataset will be divided such that it will not count connections between units that did not interact with one another.

In our study, ENA has been used to model teachers actions captured in collocated CSCL situations. During the modeling process, teachers who conducted collaborative sessions across the three different experimental conditions (e.g., no dashboard, mirroring and guiding) were set as the unit of analysis. The experimental conditions were set as the conversation variable. We also used the moving stanza window method to specify how far back within a given conversation ENA requires to identify connections. Basically, the moving stanza window method moves over data and counts the connections between codes that occur within the size of the given window. This connection accumulation phase is repeated for each unit of analysis resulting in a matrix of adjacency vectors that represent units in rows and connections in columns. For our analysis, we choose a window size of three. A dimensional reduction of the data is then performed via spectral value decomposition (SVD) to determine a set of new dimensions that preserves maximum variance among the units. ENA also calculates a centroid for a given network model which is the arithmetic mean of the edge weights. Hence centroid summarises network as a single point and provides a summarised visualisation for each unit's network in the projection space.

We believe that ENA is appropriate for our modeling task due to several reasons. First ENA takes into account the temporality of teachers' actions and provides insights into how different actions relate to one another. Visualisation of the structure of co-occurrences facilitates the meaning-making of behavioral data by facilitating the identification of action patterns. Second, ENA allows us to quantitatively compare the action differences between different conditions.

Results

We applied ENA to model teachers' actions across the three conditions that we are interested in, i.e., no dashboard, mirroring and guiding conditions. Following a mixed-methods approach we triangulated quantitative (log data) and qualitative data (post-activity questionnaire responses from teachers) to contextualize and produce results about the three conditions. Figure 6 shows the mean networks generated for the six teacher's actions in the three different conditions. To show the distribution of teachers' actions in detail across the three conditions we also plotted Figure 7.

A visual inspection of the structures of the mean networks presented in Figure 6 shows there is a difference between teacher actions in the no dashboard condition when compared to the mirroring and guiding conditions. The mean networks generated for mirroring and guiding conditions have similar network structures (see Figure 6(b) and 6 (c)). However, the connection strengths (co-occurrences) between nodes are different.

In the no dashboard condition strong connections between the following codes are visible: *teacher perception* and *teacher class interactions*, *teacher class interactions*, and *teacher individual interactions* (see Figure 6(a)). Missing connections with a node that represents *announcements to class* code in the ENA diagram shows that in the no dashboard condition teachers did not make announcements to the class. High teacher perception activities (see Figure 7) further confirms this finding. As described in Table 3 the code *announcements to class* constituted announcements related to time available, phase transitions of the script and student participation.

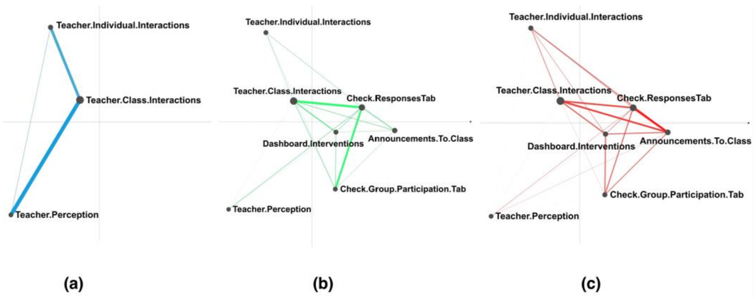

Fig. 6. Mean networks of teacher's actions in the (a) no dashboard, (b) mirroring condition and (c) guiding conditions.

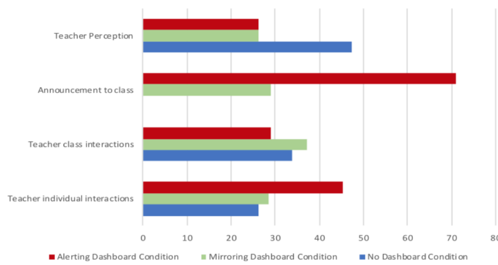

Fig. 7. Teachers' actions across the three conditions

As it can be seen in Figure 7, *teacher class interactions* were somewhat frequent in the no dashboard condition (see Figure 7). To further our understanding of *teacher class interactions* we plotted Figure 8 which shows the distribution of different types of teacher class interactions (see Table 3 for details on this code). As it can be seen in Figure 8 in the no dashboard condition surveying activities were more frequent when compared to the other two conditions. This indicates that teachers try to understand collaboration via surveying.

The post-activity questionnaire responses collected from the teachers also confirmed the above results. Teachers mentioned that in the no dashboard condition it became impossible to follow the activity evolution over time "*I had to ask students several times if they had finished the activity*". Teachers had problems in focusing on the epistemic aspects of the learning activity *"I was not aware whether students have problems in formulating answers. They all were silent. I couldn't make sure they were engaged in the task or they were doing something else",* and they felt out of control "*Very difficult to obtain the whole picture. I was stressed. I felt I did not have control over the activity".*

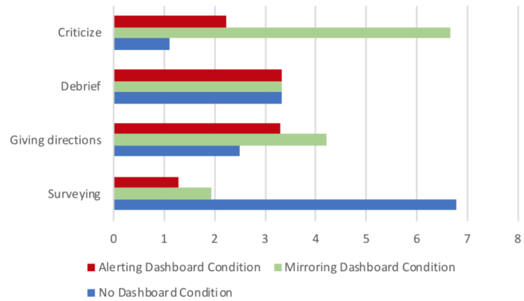

Fig. 8. Teacher-class interaction details.

To disentangle the differences between the mirroring and guiding conditions, we generated a difference network by subtracting the mean connection strengths for teachers' actions in the guiding condition from the mean connection strengths for teacher actions in the mirroring condition (see Figure 9). Each line in Figure 9 was colored to indicate which of the two networks contains stronger co-occurrence.

The difference network shows that there are three strong connections between the following codes in the mirroring condition: *teacher class interactions* and *check responses tab, teacher class interactions* and *check group participation tab, check responses tab* and *check group participation tab*. Screen-captured data from the dashboard tablet indicated that in the mirroring condition teachers looked at information presented in the dashboard 137 times (response tab was selected 80 times and participation tab was selected 57 times) which is higher than the number of times they looked at the information in the guiding condition which was 95 times (response tab was selected 53 times and participation tab was selected 42 times). This suggests that in the mirroring condition teachers frequently explored the information in an attempt to understand and evaluate the learning situation.

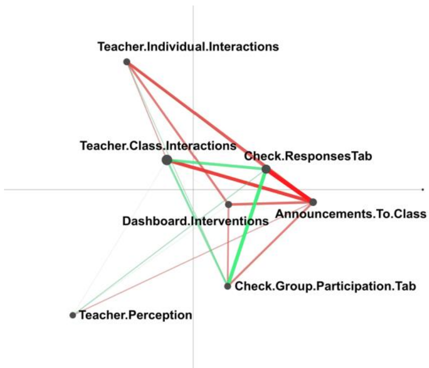

Fig. 9. Difference network for mirroring (in green) and guiding conditions (in red).

As shown in Figure 7 in the mirroring condition teachers were seen to engage in more class interactions when compared to the guiding condition. As shown in Figure 8 a majority of these class interactions constituted criticizing participation (6.6%) and providing directions to the class (4.2%).

The post-activity questionnaire responses collected from the teachers also confirmed the above findings. Regarding the mirroring condition teachers mentioned that they were mostly concentrating on one aspect of collaboration, e.g., evaluating the content, and missed the chances of reacting to other aspects of the activity, e.g., changing activity duration, *" In occasions I was concentrated on one aspect (e.g. reading their answers), I could not pay attention to other aspects in the dashboard (progress in the participation), so I missed elements to which I could have reacted, like adding more time in some phases".*

As shown in Figure 9 the strong co-occurences observed in the guiding condition are very different from the strong co-occurences observed in the mirroring condition. The strong co-occurences observed in the guiding conidion are the following: *teacher class interactions* and *announcements to class, check response tab* and *announcements to class, dashboard interventions* and *announcements to class, check group participation tab* and *announcements to class, dashboard interventions* and *check group participation, dashboard interventions* and *teacher individual interactions, check response tab* and *teacher individual interactions*.

Figure 7 shows that in the guiding condition teachers made a high number of announcements when compared to the mirroring condition. However, as shown in Figure 7 teachers engaged in less class interactions but more individual interactions in the guiding condition when compared to the other two conditions. As shown in Figure 8 teacher class interactions in guiding condition has dropped due to less surveying and criticism actions when compared to the other two conditions.

We analysed log data to understand the aforementioned differences and it was seen that in the guiding condition teachers posted more messages to groups (14 times) when compared to the mirroring condition (4 times). The following pre-defined messages were posted to the groups, *"Please rate the answers to finish the* *activity"* (6 times), *"I see that you're not discussing answers with your fellow group members"* (7 times), *"Have you already discussed your rating decisions with the fellow group members?"* (1 time). We interpret that lack of criticism and surveying in the guiding condition occurred as teachers engaged in direct communication with problematic groups by posting messages. This may have reduced the overall teacher class interactions in the guiding condition when compared to the mirroring condition. However, targeted interactions were seen to be enhanced, at the individual level (see Figure 7) and at the group level by posting messages. Although the overall teacher class interactions have reduced in the guiding condition due to such targeted interventions (at the individual and group level), teachers have not reduced the essential classroom guidance in the form of directions for collaboration in the guiding condition (see Figure 8).

Further, a strong connection between *announcements to class* and *check response tab* and comparatively less stronger connections between *announcements to class* and *check group participation tab, announcements to class* and *dashboard interventions, announcements to class* and *teacher perception* are also visible in Figure 9. This suggests that in the guiding condition teacher announcements were mostly informed by the information presented in the response tab of the dashboard and somewhat informed by the information presented in the group participation tab of the dashboard, dashboard interventions and perceptions.

We analysed the log data to understand the aforementioned connections. According to the log data, five teachers received *increase answer submission time* alert due to lack of answers submitted by students during the pre-defined submission time. One teacher also received *no keywords detected* alert and as a result, the teacher paused the activity during the answer submission stage of the pyramid script. Due to teachers' reactions to those alerts, the answer submission time of the script has increased. Teachers used this increased time to read answers submitted by students and to check other statistics, e.g., online-offline counts presented in the response tab of the dashboard. While checking this information teachers made announcements related to remaining time and activity participation aspects to the class. This has resulted in a strong connection between *announcements to class* and *check response tab* in Figure 9. Table 5 provides an excerpt that exemplifies such connections.

Further, one teacher also received a time alert in the first voting stage and three teachers received timing alerts in the second voting stage of the pyramid script. All teachers have reacted to these alerts. Teachers made announcements to the class e.g., remaining time and phase transitions, as a result of their reactions to alerts, and also based on information presented in the group participation tab of the dashboard, e.g, comments about activity participation. This has resulted in creating the strong connections between the following codes in the difference network presented in Figure 9: *announcements to class* and *check group participation tab, announcements to class* and *dashboard interventions* in the guiding condition. The connection between *announcements to class* and t*eacher perception* also reveals that some announcements were also influenced based on perception. In total teachers made 54 announcements during the guiding condition which constituted 10 announcements about time, 11 about script phase transitions and 33 about student participation. However, in the mirroring condition teachers only made 22 announcements in total which constituted 5 announcements about time, 10 about script phase transitions and 7 about participation.

In the post-activity questionnaire, teachers mentioned that receiving alerts in the dashboard made necessary script changes (critical moments) upfront and put them in control, *"I really felt I was in control. I could concentrate on those elements that interested me more (reading students' answers to identify misconceptions or issues of interest for later discussion). Even if I was not paying attention to activity participation and progression, the dashboard alerted me of critical moments in this respect"*, *"The alerts shown by the system are very quick to read and do not disturb my tasks, they are helpful to react to certain moments of the activity"*. However, teachers also mentioned that reacting to these alerts depended on the constraints of the classroom *"I decided to react to some of them, depending on other aspects of the context (like the overall time I could use for this activity). It is surprising that this happened to me even in a small group class. So, I guess this would be even more critical in larger classrooms".* Moreover, in some situations teachers mentioned that receiving alerts about known information did not add value *"sometimes, I was carefully paying attention to dashboard information about activity progression, and I felt the alerts were a bit annoying – as offering information I already knew"*.

Table 5. Excerpt from coded data in the guiding dashboard condition

Line	Teacher's observable behavior	Code
1	Teacher is scrolling and reading the answers submitted by the individual students to himself	Check.Response.Tab
2	"*Think about the message given in the case study before submitting answers to the question*"	Teacher.Class.Interaction
3	Lack of keywords detected alert appeared on the dashboard and teacher paused the activity	Dashboard. Intervention
4	*"Okay, the activity is paused"*	Announcements.To.Class
5	Teacher provided more hints/instructions on how to write better answers to the given task	Teacher.Class.Interaction
6	*"Okay, now I will resume the activity"*	Announcements.To.Class
7	Teacher is scrolling and reading the answers submitted by the individual students to himself	Check.Response.Tab
8	Teacher again provided more hints/instructions on how to write better answers to the given task	Teacher.Class.Interaction
9	Teacher is scrolling and reading the answers submitted by the individual students to himself	Check.Response.Tab
10	*"One minute left and we have only four answers so far"*	Announcements.To.Class

The differences between guiding and mirroring conditions can also be described based on other dashboard interventions. Table 6 provides a summary of dashboard interventions conducted by the six teachers across the two conditions. As can be seen in Table 6 in total teachers conducted more dashboard interventions in the guiding condition (33 in total) when compared to the total interventions made at the mirroring conditions (16 in total). It should be noted that some of these interventions were guided by the alerts, e.g., time and pause actions. However, overall in the guided condition, the self-directed interventions were also seen higher than the mirroring condition.

We also asked teachers opinions regarding the criteria used to generate alerts. Teachers highlighted some ideas that were not evaluated in the present study but proposed suggestions for future studies *"I wonder if it is valid for activities where time expected for discussing and rating is long. In this case, half of the time allocated would not work but maybe ¾ of the time allocated, or this can be a parameter modifiable by the teacher"*. All six teachers agreed that alerts provided guidance to act and were useful to manage the activity. Teachers also mentioned they felt confident to react to alerts and the number of alerts shown in the dashboard was adequate (did not disturb orchestration).

Table 6. Dashboard Interventions

Intervention	Guiding condition	Mirroring condition
Posting messages to groups	14	4
Rating on behalf of low participating groups	1	1
Next level action	4	3
Increase time action	10 (9 based on alerts and 1 self-directed)	5
End action	2	3
Pause action	2 (1 based on alerts and 1 self-directed)	0

Finally, the differences between the three conditions were also evaluated based on the perceived cognitive load of the teachers. On average, in the guiding condition teachers reported a high cognitive load of 6.2 (SD=3.27). In the no dashboard condition teachers reported a cognitive load of 5.6 (SD=5.54) and the lowest value was reported for the mirroring condition which was 5.4 (SD=2.7). In summary, teachers experienced a much higher cognitive load in the guiding condition and the lowest cognitive load was experienced during the mirroring condition.

Discussion

The results of the study showed that teachers had less awareness over the collaborative learning activity in the no dashboard condition. ENA results and subjective responses of the teachers confirmed that in this condition teachers were out of control and they could not make announcements to the class regarding time, phase transitions and students' participation during the activity.

However, when compared to the no dashboard condition, in both mirroring and guiding conditions teachers mentioned that having access to the dashboard became useful as it provided awareness regarding collaboration "*Design of the dashboard itself is user-friendly and intuitive. I had the opportunity to see all answers. Overall picture of collaboration is provided"*. However, mirroring and guiding support has influenced teachers' orchestration actions differently as illustrated using ENA.

In the mirroring condition, teachers mostly engaged in checking the information presented in the dashboard. The new knowledge gained by making sense of the information presented in the dashboard lead teachers to take actions (Verbat et al. 2013) mostly in the form of teacher class interactions. When compared to the guiding condition in the mirroring condition teachers conducted less number of orchestration actions. A possible explanation for this behavior is that in the mirroring condition teachers focused more on the epistemic facet of the learning situation, e.g., reading students' answers, and they missed the chances of performing necessary script adaptations, which was also confirmed using the post-activity questionnaire responses provided by the teachers. The observed behaviours are in alignment with our expectations about the condition (see Introduction).

However, when compared to the mirroring condition teachers conducted overall a high number of orchestration actions in the guiding condition. Some of these actions were guided using the alerts, e.g., modification of time allocated to different script phases. Some of the actions were self-directed, e.g., posting messages to groups. The automatic alerts may have influenced and enhanced teachers' confidence to use dashboard controls to conduct more self-directed actions. Moreover, as a result of reacting to alerts and self-directed actions, students were given more time to submit answers (during the answer submission phase of the script) and to evaluate answers from peers (during the voting phases of the script) creating a fruitful collaborative learning situation. Teachers also used this additional time to check activity participation within groups (e.g., voting and discussion), to provide comments regarding the quality of the students' answers (as a result of reacting to no keywords detected alert) and to intervene in less participating groups by sending messages or sometimes performing voting on behalf of the less participating groups. The additional information presented using alerts may have increased teachers' awareness of the collaboration process which also led to made more announcements to the class regarding the time available, quality of students' answers and script phase transitions.

These findings seem to indicate that guiding support is beneficial in orchestrating collaboration when compared to the mirroring support. In the post-activity questionnaire responses teachers perceived that the alerts helped to upfront critical moments associated with collaboration and guided to take actions, i.e., script adaptations. The aforementioned differences between the conditions are also in alignment with our expectations (see Introduction).

When considering the cognitive load teachers indicated that they experienced a high cognitive load in the guiding condition. Although we expected that teachers may experience the lowest cognitive load in the guiding condition, teachers indicated a different opinion. In contrast to our expectations teachers reported the lowest cognitive load in the mirroring condition. The recorded cognitive load can be understood by referring to different facets of the orchestration load together with the actions teachers performed in each condition. In the following we propose three different facets of the orchestration load namely *situation evaluation, goal formation* and *action taking* that allowed us to shed light on the differences of the teacher's perceived cognitive load.

As described above, in the mirroring condition teachers often attempted to evaluate the learning situation based on the information presented *(situation evaluation)*. Although teachers may had an overall picture of the learning situation in the mirroring condition, they were not supported explicitly as in the guiding condition to take action (*action taking*). Because of this, they had to constantly evaluate the learning situation and to formulate goals (*goal formation*). As they employed their cognitive resources for situation evaluation and goal formation this might have reduced their ability to detect necessary orchestration actions. This has resulted in an overall less amount of orchestration actions in the mirroring condition when compared to the guiding condition. We interpret that the less amount of orchestration actions teachers engaged in has resulted in a less cognitive effort which is reported as a low cognitive load.

The perceived cognitive load was higher in the guiding condition. Although we expected that alerts may provide an additional support for situation evaluation, goal formation and action-taking, the results were contradictory. One way to explain this is that disregard the additional support provided by the alerts for evaluating situation, goal formation teachers were also directed to take more orchestration actions when compared to the mirroring condition. By informing teachers to take more actions, alerts may have increased the cognitive load experienced by the teachers as more actions means more workload for the teachers.

Another way to explain this situation is based on the epistemic aspect of the learning activity. In orchestrating collaboration teachers not only engage in performing orchestration actions. But they also require to evaluate the content produced by the students. We referred to the workload created by content evaluation as *content load*. The content load can be seen as a competing load to the orchestration load yet is equally important in orchestrating collaboration. Teachers may have experienced the content load both in the mirroring and guiding conditions. However, in the guiding condition, when teachers were focusing on the content they were also informed to take orchestration action. Showing alerts in the dashboard, while they were checking the content may have taken their attention away. Focusing both on the content and the recommended actions at the same time may have created a scenario which is cognitively demanding. The competing nature of content load and orchestration load together with the high number of orchestration actions may have resulted in a high cognitive load for the teachers in the guiding condition.

Limitations of the study

There are several limitations to our study. First, the sample size of our study is low which was limited to six teachers. Although conducting research studies with a limited number of teachers is common in teacher-oriented studies (Martinez-Maldonado, 2019; Wise and Jung, 2019) due to practical constraints, we acknowledge that the lower sample size reduces the generalizability of the results presented. Further, we have not used any eye-tracking software to track the exact information the teacher is looking at while using the dashboard. Although we have come up with codes such as *checking responses tab* and *check group participation tab*, for instance, teachers may have also been looking at the time-related information or the dashboard controls presented at the top of the dashboard (not within a specific tab). We assumed that by switching tabs the teacher is mainly observing the information presented within the particular tabs, not the information presented in the common space. However, incorporating eye-tracking software could have provided more precise details on teacher exploration of the dashboard information.

Another limitation is that our collaborative learning activities were scripted according to the pyramid pattern. This limits the generalizability of the findings of the study to other structures of learning activities and requires further research.

Moreover, researchers helped the teachers to design the activities as teachers were not familiar with the activity authoring user interface. Allowing the teachers to design the activity by themselves would have also reflected the effort from the design stage of the activity although it is not the main aim of the study. Similarly, we have not evaluated how teachers reflected their experience to design their own future collaborative learning activities in a similar context. An evaluation of the teachers' reflections and further studies would have provided insights on how different types of support influenced existing practices.

Finally, we have not reported how teachers' actions affected students' activity engagement. Students' perception of teachers orchestrating collaboration would have provided a complete picture of the collaborative learning situation by closing the loop effectively (Clow 2012). This will be addressed in future work.

Conclusions

CSCL is a widely adapted pedagogical practice that facilitates students' productive learning in classroom learning situations. Research has explored the conditions under which group collaboration can be effective (e.g., group size, type of the learning task) and has shown that the quality of student interactions occur during activity enactment is one of the major attributes that facilitate the achievement of productive collaborative learning outcomes (Dillenbourg 1999). Teachers can foster such beneficial collaborative learning interactions among students during CSCL situations. Orchestration of collaboration is seen as an important teacher activity that can foster such beneficial collaboration interactions (Dillenbourg and Jermann 2010).

LA can facilitate teachers to make data-informed decisions (Martinez-Maldonado 2019). Teacher-facing dashboards are one of the main applications that tend to deliver LA information directly back to the teachers (Verbert et al. 2020) By providing information about student participation, LA can help teachers to understand where deviations occur and how to adapt scripts according to the requirements of the learning situation (van Leeuwen et al. 2019b). However, designing impactful LA solutions is known to be a difficult task (Knight et al, 2020). Recent research has shown that following a human-centered learning analytics approach could facilitate the generation of impactful solutions (Shum et al. 2019). To this end, this study aimed to understand how teacher's orchestration actions were influenced by different types of support provided, i.e., mirroring and guiding support.

The findings of the study suggest that provisioning of teacher-facing dashboards are useful for teachers in orchestrating authentic classroom collaborative learning situations. As we have elaborated in the discussion without having access to the dashboard teachers lack control over the learning activity and were driving blind without knowing what is happening in collaboration. When considering the mirroring and guiding support it was observed that different types of support influenced teachers' orchestration actions differently. In the mirroring support teachers mostly engaged in situation evaluation, whereas in the guiding support teachers were more directed to take actions. Moreover, in the guiding condition teachers reported they had good control over the learning activity. Hence, in terms of orchestration actions guiding support was seen more beneficial for the teachers.

However, in terms of perceived cognitive load, teachers experienced relatively a high cognitive load in the guiding condition when compared to the mirroring condition. We have disentangled this by deconstructing the orchestration load into different facets and also by identifying the competing loads teachers may experience during orchestration of collaboration. We studied the notion of orchestration load as a multifaceted construct that can be deconstructed into different facets namely *situation evaluation, goal formation* and *action-taking.* These facets were derived based on the behavioral analysis we have conducted. *Content load* which emerges as teachers engaged in evaluating the content produced by students in real-time can be seen as a load that is essential yet competes with the orchestration load in real-time. We think that deconstructing orchestration load to elaborate teacher's perceived cognitive load is an important contribution of our work as most of the exisiting studies refer to orchestration load as a high-level concept without drilling into details.

The findings and the limitations of the study have proposed interesting further research directions. First, teachers who have participated in our experiments were computer literate. All teachers have experience in using technology for their day-to-day teaching activities. However, it would be interesting to conduct further studies to explore how teachers with different backgrounds would use these types of tools in authentic settings. Recent studies have pointed out that teacher's data literacy, trust in technology may affect their use of LA tools (Verbert et al. 2020). Hence, conducting evaluation studies with teachers from different backgrounds can enhance our understanding of the impact of the proposed orchestration technology and to elicit useful design guidelines for impactful solutions.

Second, the type of task and time allocated for collaboration can also impact teachers' orchestration actions. In our study, the tasks were mostly related to sharing knowledge on certain aspects related to computer science. It would be interesting to conduct further studies to explore how different types of tasks proposed in different course domains could affect teachers' actions. Thirdly, regarding the activity duration, our collaborative learning activities were planned for shorter durations. We assume that conducting learning activities that are planned for longer durations may also influence teachers' actions. For instance, although teachers may value alerts in shorter timed activities due to a high workload, maybe this is different for activities that are planned for longer durations. In such activities teachers may have enough time to interpret and take action even without explicitly supported using alerts.

Finally, teachers also proposed the importance of customizing the criteria for generating alerts according to the unique needs of their sessions. We suggest that such preferences can be documented along with the learning design parameters which can be later translated to rules to generate personalised alerts that are tailored to the unique needs of particular learning situations. Not only the alerts but also the information presented in the teacher-facing dashboards can be customized to match with teachers' preferences, hence producing customized dashboards. In the future, we are planning to address the aforementioned research directions.

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5.2 Towards Teacher Orchestration Load-aware Teacher-facing Dashboards

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Towards Teacher Orchestration Load-aware Teacher-facing Dashboards

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ABSTRACT: In this workshop paper, we report a study conducted to investigate the use of tracking technologies to measure the teachers' orchestration load when conducting co-located collaborative learning activities. We distinguish the orchestration load experienced by the teachers in the absence and presence of teacher supporting tools, i.e. teacher-facing dashboards. Electrodermal activity (EDA) sensor and other multimodal data including observations, log data and subjective responses to questionnaires have been collected to measure the teachers' orchestration load in authentic collaborative learning scenarios. This workshop paper presents the study context, quantitative and qualitative data collection process undertaken and other considerations in detail.

Keywords: Computer-Supported Collaborative Learning, orchestration load, dashboards, MMLA, electrodermal activity (EDA).

1 INTRODUCTION

In the domain of Technology-Enhanced Learning (TEL) the notion of orchestration refers to "how a teacher manages, in real-time multi-layered activities in a multi-constraint context" (Dillenbourg, 2013). In the context of Computer-Supported Collaborative Learning (CSCL), orchestrating collaboration is an essential yet a challenging task which demands teachers' continuous monitoring, guidance and interventions across different social levels (e.g., individual, group and class level). On the other hand, the application of Learning Analytics (LA) tools in the context of CSCL has currently gained heightened attention (Jivet, Scheffel, Specht & Drachsler, 2018). By capturing, analyzing and visualizing data traces that represent students' collaborative interactions in real-time, LA offers the possibility for teachers to obtain a deeper understanding of the process of collaboration and student activity engagement (Jivet et al., 2018). Towards this end, teacher-facing dashboards have been deployed within CSCL environments as a supporting tool with objectives of building awareness and facilitating teachers' productive intervention towards groups that require immediate attention (van Leeuwen, 2015).

However, the number of studies that investigate whether the addition of teacher-facing dashboard applications influence orchestration load of the teacher is scarce. It is essential to study how the addition of such supporting tools contribute to the orchestration load of the teachers, as it will facilitate to elicit useful design guidelines that can guide the development of teacher support tools that may help reduce the orchestration load experienced. Towards this end, this workshop paper presents details of an experiment conducted to study how data collected in different modalities can be used as indicators to measure teachers' orchestration load in co-located CSCL settings.

2 STUDY DESIGN

2.1 Participants

Two female teachers from a Spanish University participated in the experiments. Teachers had prior experience in conducting collaborative learning activities and have used dashboard applications to orchestrate collaboration. Each teacher conducted three collaborative learning activities and students from the respective classes took part in the study with their informed consent. Each collaborative learning activity lasted around nine minutes.

2.2 Procedure

Before the classroom trials, to generate appropriate baseline data, teachers were asked to wear the EDA sensor for two hours for three days and mark the events of those days that were out of the ordinary working activities. The measurement of two hours per day, was taken during working hours when teachers conduct work activities outside of the classroom. In this way workload exists, but it is not affected by the teaching itself and the presence of students and tools used during lessons.

After collecting baseline data, collaborative learning activities were conducted in classroom sessions. A web-based tool called PyramidApp (Manathunga & Hernández-Leo, 2018). that implements the Pyramid pattern based on collaborative learning activities was used to design and deploy collaboration. In the experimental condition, teachers monitored and orchestrated the group activities using a teacher-facing dashboard; whereas the dashboard was not available in the control condition. The experimental condition was subdivided into two conditions based on the presence of certain warnings in the dashboard. For instance, in Dashboard condition I, the dashboard generated several warnings when; 1) students answers does not contain any keyword that was stated by the teacher during activity design time, 2) students skipped answer submissions, 3) students require more time for collaboration, 4) collaborative learning activity reaches the end. In the Dashboard condition II, the aforementioned warnings were turned off, but all the other features of the dashboard were available.

2.3 Data collection and analysis

At the beginning of each collaborative learning session we attached the Shimmer3 GSR+ sensor to the teacher by connecting two electrodes to the wrist and putting arm band that holds the sensor around the teacher's arm. The sensor is placed on the non-dominant hand to avoid discomfort to the teacher and reduce the noise produced by the movement (see Figure 1).

The sensor is mounted before the beginning of the activity and removed right after. Recording begins as soon as the sensor is removed from the docking station connected to the computer, so that the signal captured between this moment and the beginning of the activity, is being removed from the analysis. The same action is applied at the end of the recording. Signal captured between the end of the activity and connecting the sensor back to the docking station (end of recording) is being removed. Data transfer from the device was conducted immediately after the activity. Moreover, teacher's behaviour during every session was recorded either using a video camera or by a researcher taking observation notes based on the unique requirements of each classroom session. In the experimental sessions teacher's dashboard actions were automatically logged. Teachers' subjective measurements of the cognitive load experienced in both control and experimental sessions were also collected using NASA's TLX questionnaire (Hart & Staveland, 1988). Stimulated-recall interviews were also conducted with the teacher to better understand their orchestration requirements and pedagogical decision-making (see Figure 2).

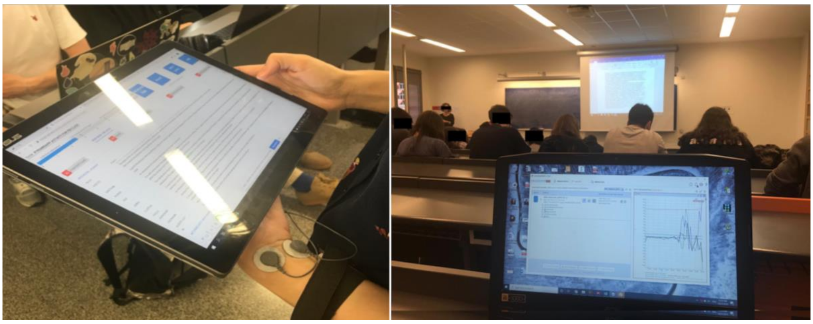

Figure 1: A teacher wearing the Shimmer3 GSR+ sensor during a classroom session (left) and data collection in a co-located collaborative learning setting (right)

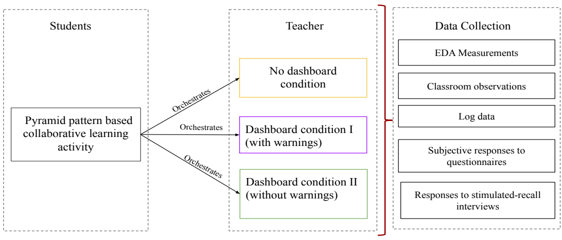

Figure 2: Different experimental conditions and data collection

3 CONCLUSIONS & FUTURE WORK

The addition of supporting tools to synchronous collaborative settings could facilitate teachers to diagnose collaboration (van Leeuwen, 2015). LA dashboards have been seen as a promising tool that can assist to raise teacher awareness, reflection and sense-making on peer learning activity engagement and to impact behavior (van Leeuwen, 2015). In this study we have collected qualitative and quantitative data in different modalities in order to measure orchestration load experienced by the teachers. A mixed-method approach will be used with the triangulation of quantitative and qualitative data to warrant results about the three conditions. We will analyse the collected data to explore how multimodal data can be used as indicators to measure teachers' orchestration load in order to propose orchestration load aware design guidelines for teacher-facing dashboards.

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Appendix A

INTELLIGENT GROUP FORMATION IN COMPUTER-SUPPORTED COLLABORATIVE LEARNING SCRIPTS

The content of this section was published in the following conference proceedings:

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Intelligent Group Formation in Computer Supported Collaborative Learning Scripts

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***Abstract*—Well-structured collaborative learning groups scripted based on Collaborative Learning Flow Patterns (CLFPs) often result in successful collaborative learning outcomes. Formulation of such learner groups based on instructor defined criteria promises potentially effective performance of participating students. However, forming student groups manually based on multiple criteria often fails due to its complexity and the time limitations of practitioners. Hence, an intelligent assistance which supports adaptive collaboration scripting based on instructor defined criteria, while adhering to CLFPs is presented. Constraint Optimization techniques have been used for learner group formation and preliminary tests revealed that the proposed approach could be utilized when formulating student groups while satisfying team formation criteria.**

***Keywords*—Computer Supported Collaborative Learning (CSCL); Collaborative Learning Flow Patterns (CLFPs); Jigsaw; Binary Integer Programming; Constraint Optimization**

I. Introduction

Collaborative learning is a pedagogical approach in which learners collaborate amongst peers towards achieving learning goals while constructing shared knowledge and understanding. In such contexts, collaboration could occur between a pair of students or within a larger group. Collaborative learning triggers significant individual cognitive processes which may often result in "socio-cognitive" conflicts among individual learners [1]. Resolving such conflicts via discussions with peers, cause individuals to achieve improved competence levels and knowledge gains. However, it is difficult to ensure that learning via interactions may occur in any situation [2]. Realization of success in collaboration settings often require adequate scaffolds [3].

When considering scaffolding strategies in the context of collaborative learning, "scripts" plays a significant role [1]. Effective interactions among learners could be fostered by adapting to Collaborative Learning FLow Patterns (CLFPs) which are derived from broadly accepted practice rather than from general learning theories [4]. This paper presents, a novel binary integer programming approach towards group formation in CSCL environments based on Jigsaw CLFP. Flexibility towards grouping based on instructor defined criteria is facilitated and the proposed approach was tested using real world datasets.

II. Learner Group Formation criteria

During the work presented in this paper, Jigsaw CLFP was adhered when formulating learner groups. It consists of three major phases known as task allocation, expert group formation and Jigsaw group formation. During task allocation each individual student is assigned to study a particular task, while in expert phase students who studied the same task work collaboratively. Finally, students who have studied different tasks are grouped together forming Jigsaw groups [4]. In the work presented in this paper, suggestions for task allocation and expert group formation are computed simultaneously and presented in Phase 01 while Phase 02 depicts Jigsaw group allocations. Further, CLFPs inherit a set of conditions commonly known as constraints which shape up the desired collaboration [5]. Intrinsic constraints are mandatory to be satisfied (see Table I) while extrinsic constraints are induced by contextual factors or arbitrary decisions [3].

TABLE I
Intrinsic constraints applied in Jigsaw CLFP

Phase	Intrinsic or Hard Constraints
Phase 01	Each student is allocated to study one sub problem
	Each task is allocated to a minimum number of students
Phase 02	A student can work only in one Jigsaw group
	There should be at least one student for each task within the Jigsaw group
	Each Jigsaw group should have a minimum number of students

III. Proposed Approach

When considering the nature of the problem being addressed where grouping is done adhering to different constraints, it was seen that constraint optimization could be adapted when formulating learner groups based on Jigsaw CLFP. A scenario with intrinsic constraints mentioned in Table I can be modeled as a constraint optimization problem, using the following mathematical notations.

A. Problem Formulation

Given a total set of T tasks, N students the problem is to assign tasks for each pair of students with the goal of minimizing the cost incurred during task assignment. The Phase 01 of the problem can be modeled as follows:

$$Minimize \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{T} X_{ik} X_{jk} C_{ij} \qquad (1)$$

subject to

$$\sum_{k=1}^{T} X_{ik} = 1 \quad \forall i \in \{1, ..., N\} \tag{2}$$

$$\sum_{i=1}^{N} X_{ik} \geq G \quad \forall k \in \{1, ..., T\} \tag{3}$$

where X_{ik} denotes assigning student i to task k, X_{j_k} denotes assigning student j to task k. For each pair of students i and j, the cost C_{ij} is included as a term in the objective function precisely when i and j are assigned to the same task k. Cost C_{ij} could take on any value larger than or equal to 0 depending on the extrinsic constraints applied in each learning scenario. Further constraint (2) ensures that each individual i can be assigned to only one task k. Constraint (3) guarantees that each task k is assigned to a minimum number of students G based on the practitioners' input on task allocation.

Similarly in Phase 02, we can formulate M number of total Jigsaw groups with the goal of minimizing the cost incurred when assigning students to groups. However, during this phase an additional constraint (4) has been added to the model to make sure that at least one student from each task (from phase 01) is presented in each Jigsaw group.

$$\sum_{i=1}^{N} B_{im} X_{ik} \geq 1 \quad \forall k \in \{1, ..., T\}, \forall m \in \{1, ..., M\} \tag{4}$$

B_{im} denotes assigning student i to Jigsaw group m, X_{ik} denotes the previous task assignment (during phase 01) of student i to task k.

During problem modeling, extrinsic constraints applied during a particular phase have been incorporated into the objective function parameters. Hence if, and based on the extent that, the conditions on the variables are not satisfied (intrinsic constraints) extrinsic constraints which have some variable values in the objective function would be penalized. The following example demonstrates how objective function parameters could be encoded depending on the requirement of formulating homogeneous and heterogeneous student groups.

Example: To the extent possible participants who are allocated to the same task during phase 01 are required to have similar knowledge levels and they should belong to different gender categories.

In this scenario extrinsic constraints are related to both homogeneity and heterogeneity of student data since, *similar knowledge levels* and *different gender categories* are considered. Based on the extrinsic constraints specified, cost term C_{ij} associated with a pair of students i and j could be defined as follows:

$C_{ij} = 0$, if both students have similar knowledge levels and if they belong to different genders

$C_{ij} = 2$, if both students have different knowledge levels and if they belong to similar genders

$C_{ij} = 1$, otherwise ($i.e.$ i and j differ in one parameter but not the other)

TABLE II
PHASE 01 RESULTS

Task 1	**Task 2**	**Task 3**	**Task 4**	**Task 5**
1	4	7	3	6
2	5	14	8	10
11	15	16	9	12
13	22	18	17	21
		19	20	

TABLE III
PHASE 02 RESULTS

Group 1	**Group 2**	**Group 3**	**Group 4**
2	1	3	4
5	7	10	6
8	12	13	11
9	14	18	17
16	15	22	19
21	20		

TABLE IV
PHASE 01 RESULTS

Task 1		Task 2		Task 3		Task 4	
LID	GD	LID	GD	LID	GD	LID	GD
8	1	3	2	1	2	6	2
9	2	4	1	2	1	11	2
10	1	5	1	7	1	13	1
12	1	16	1	17	2	14	1
19	1			18	1	15	1

IV. TESTING AND EVALUATION

The algorithm was deployed on a personal computer with Intel(R) Core(TM) i5-2430M CPU@ 2.40GHz X 4 having 4GB of RAM. Implementation was done using Python and SQLite database. Gurobi Optimizer [6] version 6.5 has been used to solve different problem instances using real world student data obtained from authors of [7].

A. Group Formation Design Analysis

Algorithm was evaluated in terms of intrinsic and extrinsic constraint satisfaction. Table II and Table III shows grouping results for 22 students (each number represents a student). Execution of the algorithm finished within a few seconds (0.005 sec. during Phase 01 and 0.010 sec. in Phase 02), providing optimal results for the given problem instance.

Table IV and Table V shows results of a sample scenario which considers extrinsic constraints. Heterogeneity of gender details (GD) was considered during phase 01 while homogeneity of language preferences for collaboration (LP) was considered in phase 02. Execution of the algorithm finished within a few seconds (1.222 sec. during Phase 01 and 0.275 sec. in Phase 02) providing optimal allocations.

It should be noted that based on the way that we have modelled the problem, the cost parameter which represents associated extrinsic constraints in a given problem instance is completely general, meaning that instructors could incorporate extrinsic constraints to the model depending on the learning context without any hard limits.

TABLE V
PHASE 02 RESULTS

Group 1		Group 2		Group 3		Group 4	
LID	LP	LID	LP	LID	LP	LID	LP
4	1	5	1	1	1	3	1
6	2	10	1	2	1	13	1
7	1	11	1	9	1	17	1
8	1	12	1	14	1	19	1
15	2	18	1	16	1		

B. Scalability and Performance Analysis

Based on a number of tests conducted, it was noted that the algorithm scale well, when extrinsic constraints were excluded. For instance, it took only 0.104 sec. during Phase 01 to allocate 5 tasks to 160 students (each task was allocated to 32 students) and 0.025 sec. during Phase 02 to allocate 160 students to 10 groups. However, obtaining optimal grouping results became harder with an increased number of learners and extrinsic constraints. Based on test results, it was concluded that when the problem is more constrained (i.e. three extrinsic constraints per phase, more learners) the algorithm takes more time to finish execution.

V. RELATED WORK

Different algorithms, frameworks, tools and techniques have been developed over time to address the learner group formation problem. However, most of the existing approaches model a fixed set of parameters [8] or are only able to handle a minor number of learner attributes when forming groups [9]. On the other hand work done by [10], [11] have adapted similar techniques to formulate learner groups. However, the problem modeling approach they have presented is different from our work and they have not adapted to CLFPs which result in formulating complex grouping structures. Nevertheless, many authors have evaluated the scalability of the suggested approaches considering fewer grouping parameters [12], [10], [13] while many have not provided test results although they argue that the suggested approaches scale well [14], [8].

VI. CONCLUSION

During the work presented in this paper a novel binary integer programming approach for group formation based on Jigsaw CLFP was proposed. The suggested approach could handle different grouping constraints defined with regard to a particular learning scenario hence it addresses the multiple criteria grouping problem. Cost function parameters could be effectively used when formulating groups incorporating a number of extrinsic constraints, without restricting grouping criteria using hard limits. Based on test results it was noticed that the algorithm formulates learner groups providing optimal grouping results within seconds based on intrinsic constraint specified. Further, it was determined obtaining near-optimal results via approximations (running algorithm as an any-time solution) would be advantageous in complex scenarios (i.e., different extrinsic constraints applied for grouping) due to limited computation time allowed in classroom scenarios. We have already modeled and conducted several tests on regrouping learners, which would support educators when adapting to constantly changing learning environments. However it was determined that further work is needed to achieve learner regrouping on the fly. As for future work, it is of importance to investigate on heuristics which could optimally solve complex problem instances. Moreover, implementation of a group formation service which provides grouping and regrouping recommendations offered by the algorithm would facilitate its application and adaption in real practise.

ACKNOWLEDGMENT

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Appendix B

COLLABORATIVE LEARNING DESIGNS USING PYRAMIDAPP

The content of this section was accepted to be published in the following conference proceedings:

Amarasinghe, I., Hernández-Leo, D., Manatunga, K., Beardsley, M., Bosch, J., Carrió, M., Chacón-Pérez, J., Jimenez-Morales, M., Llanos, D., Lope, S., Martinez-Moreno, J., Santos, P., & Vujovic, M. (in press). Collaborative learning designs using pyramidapp. *Proceedings of the 11th International Conference on University Teaching and Innovation (CIDUI): Beyond competencies: new challenges in a digital society*.

TITLE: **Collaborative Learning Designs using Pyramid App**

Subtitle: Computer Supported Collaborative Learning in Classroom Sessions

1. ABSTRACT

Designing effective collaborative learning activities for classroom is challenging. The PyramidApp is a tool that facilitates the implementation of the Pyramid pattern, shaping a collaboration structure that promotes the participation of all students and fruitful social interactions. This paper shows how this educational strategy can be applied to different types of tasks and subject matters, shedding light about how computer-supported collaborative learning can be incorporated in the classroom.

2. ABSTRACT:

Designing effective collaborative learning activities for classroom is challenging. The PyramidApp is a tool that facilitates the implementation of the Pyramid pattern, shaping a collaboration structure that promotes the participation of all students and fruitful social interactions. This paper shows how this educational strategy can be applied to different types of tasks and subject matters, shedding light about how computer-supported collaborative learning can be incorporated in the classroom.

3. KEYWORDS: 4-6

Aprendizaje Colaborativo Apoyado por Ordenador, CSCL, Scripts, patrón Pirámide

4. KEYWORDS: 4-6

Computer Supported Collaborative Learning, CSCL, Scripts, Pyramid pattern

5. FIELD OF KNOWLEDGE

Engineering and Architecture

6. SUBJECT AREA

ARCHITECTURE AND LEARNING SPACES

7. PREFERRED PRESENTATION CATEGORY

Oral Presentation

ISSN: 2385-6203

8. DEVELOPMENT:

1. Introduction

Computer Supported Collaborative Learning (CSCL) has emerged as a dynamic and interdisciplinary field of research which aims in studying how people can learn together with the help of computers (Stahl, Koschmann, & Suthers, 2006). In CSCL, collaborative learning scripts explicate the flow of pedagogical scenarios using different techniques such as role and group allocation (Dillenbourg, 2002) and have been shown to create positive effects on domain learning and collaboration skills (Radkowitsch et al., 2020).

Collaborative Learning Flow Patterns (CLFP) capture the essence of well-known collaboration scripts and facilitate to pre-structure collaboration, supporting collaborative learning practitioners to design learning tasks which will result in establishing productive social and cognitive interactions among learners (Hernandez-Leo et al., 2005). Pyramid pattern is an example for one such CLFP, that could be applied in collaborative learning scenarios in which a number of participants face the resolution of the same complex problem usually which does not have a unique solution (Hernández-Leo et al., 2006). At the initial stage of the CLFP, students require to provide individual solutions to a given problem. In the next levels, students are grouped into small groups to evaluate individual solutions. Small groups are then merged formulating larger groups in an iterative manner until a common consensus is reached. Such facilitated interactions nurture individual participation, accountability and balanced positive interactions (opinions of all members count) in a collaborative knowledge-oriented negotiation process (Manathunga & Hernández-Leo, 2018). Deployment of scripted collaborative learning activities in classroom learning situations and engaging learners in argumentative knowledge construction processes were seen to enhance the domain-specific knowledge acquisition of activity participants (Hermann & Dillenburg, 2003). A specific software implementation of the Pyramid CLFP scripts is PyramidApp (Manathunga & Hernández-Leo, 2018). The tool provides an automatic mechanism to enact the aforementioned Pyramid pattern via different activity phases.

The ACAD framework (Carvalho & Goodyear, 2014) has been proposed and used to analyze the design of arrangements that lead to successful learning activities and outcomes. The framework defines three elements that can be designed by educators: the epistemic tasks, the setting (space, place, tools, ...), and the social organization (dyads, teams, division of labor, …). Therefore, according the ACAD framework (Carvalho & Goodyear, 2014), PyramidApp offers a setting (the tool online space) and a social organization (pyramid structure) (see Graphic. 1). *The question is then to what extent the use of the tool is marginal, only valid to limited educational scenarios, or to what extent it can be applied to a wide range of subject matters and types of learning tasks.* To answer this question, this paper presents and analyzes a number of designs implemented using the PyramidApp. We hope these examples also shed light for those who seek to deploy similar CSCL activities in their own learning situations.

2. PyramidApp

PyramidApp is a web-based system which through an authoring tool (Graphic. 2) enables educators to create Pyramid CLFP-based activities (Manathunga & Hernández-Leo, 2018). The input parameters required to be configured include the task description, number of participants, number of levels, and group size.

Through the PyramidApp enactment tool, students can submit individual answers to the given task and discuss initial options in small groups (Graphic. 3). They agree upon a common option that will be propagated to the next level(s) where much larger groups are formulated and reach a consensus on one or few options at the global level. The tool comprises an option submission space, a voting feature to aid in reaching consensus along with an integrated discussion space.

3. Learning designs applying Pyramid App in the classroom

3.1. Participants

Teachers (N=11) were recruited to deploy CSCL activities using opportunity sampling, i.e. the tool was offered for use to naturally accessible groups in essentially the Engineering School but also the Communication and Human Biology faculties and a Design School associated to the university. After knowing the mechanisms of Pyramid CLFP and the PyramidApp, teachers were free to design tasks appropriate for their respective classes.

3.2. Methods

Graphic. 5 outlines learning designs used by the teachers in eight different subject areas. The learning objectives specified for CSCL activities (Graphic. 5 column 3) were analysed based on the cognitive skills proposed in the Bloom's taxonomy (Bloom, 1956), which describes skills and abilities teachers expect as outcomes of their students. The taxonomy consists of six levels namely knowledge, comprehension, application, analysis, synthesis and evaluation.

Knowledge is referred to as one of the most common educational objectives that describes the amount and kind of knowledge a student possesses as a result of completing an education unit (Bloom, 1956). Knowledge emphasizes the "remembering, either by recognition or recall, of ideas, material, or phenomena" (Bloom, 1956, p. 62). *Comprehension* explains learner's ability to make use of material or ideas which has

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already been communicated (Bloom, 1956). Comprehension can be more demanding than remembering information and will facilitate learners to grasp meaning and intent of the material (Bloom, 1956). This will guide learners to *application,* in which learners may apply knowledge in appropriate situations to which a solution is not specified. The next level *analysis* refers to the breaking of the material into its constituent parts (Bloom, 1956). During *synthesis*, learners may put together or reconfigure elements and parts to constitute a pattern or structure which has not been there before (Bloom, 1956). Finally, during *evaluation*, students make quantitative or qualitative judgements which involves a combination of the previously stated behaviors (Bloom, 1956). A summary of how the educational objectives proposed for CSCL activities map with specific cognitive skill levels proposed in the Taxonomy are shown in graphic. 4. As shown in graphic. 4, three activities map with *knowledge*. Three activities map with *comprehension*. One activity map to *Application*. Two activities map with *Analysis*. Three activities map to *synthesis* and one activity maps with e*valuation*.

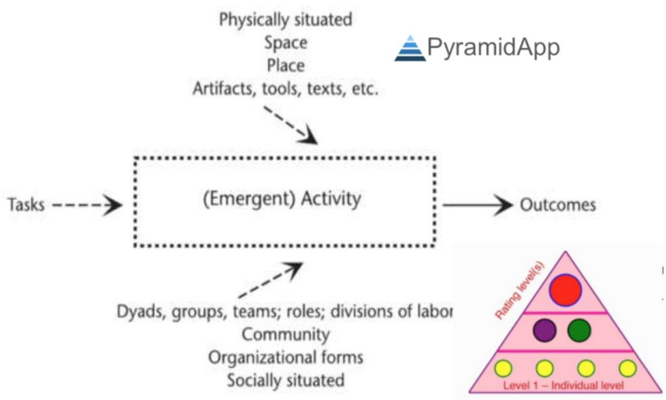
4. Summary

In summary this study presents how eleven teachers have used the PyramidApp tool to implement pyramid pattern based collaborative learning activities in their classrooms. Graphic. 5 outlines the details of the activities carried out by the teachers. The activities proposed by the teachers were analysed in accordance to the cognitive skills proposed in Bloom's taxonomy to set examples and to reflect the wide range of possibilities that the proposed pyramid mechanism provides.

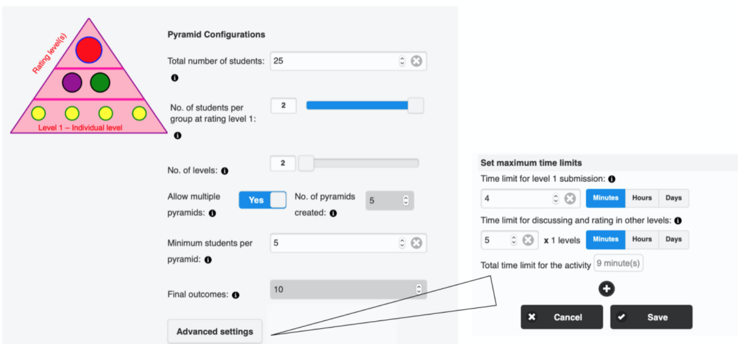
5. Conclusions

This study presents in detail scripted collaborative learning sessions conducted by eleven teachers in eight different courses. The objectives of the proposed CSCL activities have been analysed using cognitive skills specified in Bloom's Taxonomy which focuses on the development of students' intellectual aspects of learning. The results of the analysis revealed that the CSCL activities proposed in different courses can be aligned into different cognitive skills. Even within the same course, teachers were seen to deploy CSCL activities that aimed to address different cognitive skills of students. The aforementioned activities have been enacted in both small and large group contexts. Results suggest that the Pyramid pattern based CSCL activities can be designed and deployed to achieve different cognitive skills of students, in diverse types of epistemic tasks, across different course domains while scaling up the activities to the requirements of different classroom sessions.

8.1. GRAPHIC OR TABLE 1



8.2. GRAPHIC OR TABLE 2



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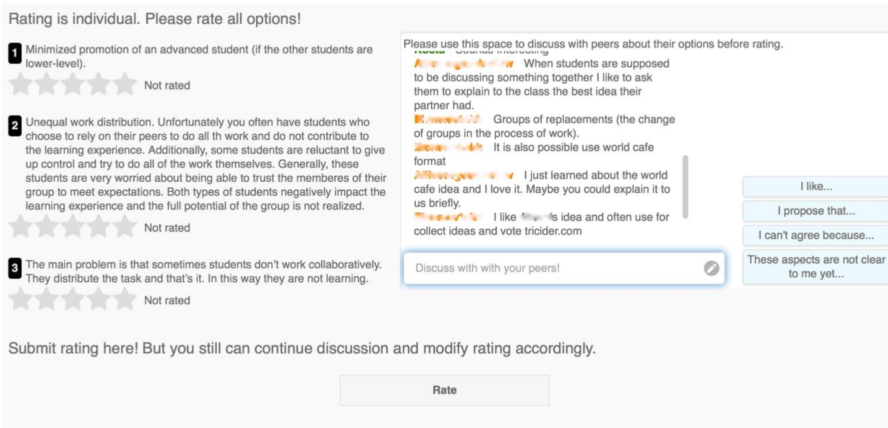
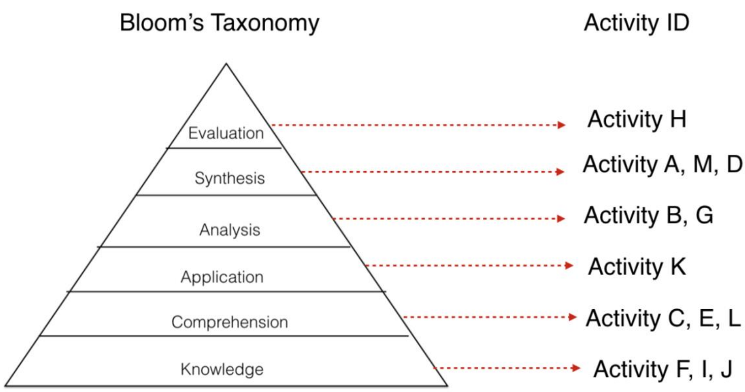
8.3. GRAPHIC OR TABLE 3



8.4. GRAPHIC OR TABLE 4



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8.5. GRAPHIC OR TABLE 5

Name of the Course	Activity ID	Educational objective of the task	Task Description	Number of Students participated
Introduction to ICT Engineering studies (Undergraduate program)	A	Reflecting about the potential of data to infer relevant characteristics for analytical models leading to practical applications.	Considering the following proposed header for a service similar to whatsapp, define a user profile oriented towards financial risk with the most relevant characteristics that are possible to obtain from those events. Choose the 4 characteristics you believe are more important and argue why those are related to financial risk.	12
	B	To help students reflect and discuss key concepts in the lesson.	Students are asked to analyse different cases dealing with ethics and how computing professionals should make decisions regarding professional and social conduct. Students have to read the corresponding cases carefully and identify which ethical principles have been committed or violated in the particular case.	24-30
	C	To help students practice generating questions; to nudge students to pay attention to peer presentations; and to facilitate student understanding of peer presentations.	Students are asked to generate a question about a presentation that has just finished. Students are then asked to review the questions of their peers and select the ones they most want to hear the answers to. The selected questions are then asked to the presenters.	16-19
	D	To help students understand key concepts in the lesson; to have students practice retrieval learning.	Students are asked to pause for 1 minute and think about how to explain a concept (e.g. distributed practice) to a peer. They are then asked to write down their explanation; review and rate the explanations of peers considering keywords (e.g. active forgetting, spacing effect); and then rewrite their explanation of the concept.	54
	E	To motivate students to ask questions and think more about the presentations and topics that are presented. Also, the idea was to initiate a discussion based on the questions selected, choose questions that were not selected and explain the benefits of asking questions, going through them and discussing.	Each student should submit one question regarding the topic that was previously presented.	16
	F	To open minds with open questions before introducing a topic to generate some initial debate on the topic of increasing the interest on the session content.	Students had to answer an open question about a topic at the beginning of the sessions. Answers were then voted by students to come to the ones with more consensus in the group. After this, the selected top answers were discussed and commented in class as introduction to the session topic	33-50
Distributed Applications (Undergraduate program)	G	To practice the analysis of non-functional requirements for distributed applications. To clarify concepts.	Read the description of a scenario that requires the development of a distributed application. Explain which are non-requirements especially relevant for the given case.	18-25
Network Protocols (Undergraduate program)	H	To practice the recognition of the mechanisms of transport layer networking protocols in real network traffic. Learning from failure: identifying common failures in students' problem-solving when addressing these types of tasks	Recognize and explain which TCP protocol mechanisms for flow and congestion control can be seen operating in the following network traffic capture file.	25-60
Research Methods (Postgraduate program)	I	To recall guidelines on how to write a paper.	List the key aspects that need to be considered when writing an Introduction section for a research paper.	19-28
Academic uses and specific terminology in English - Prototyping with Arduino (Undergraduate program)	J	To recall arduino components	Task A: Students were shown an image with an electric schematic of Arduino board, sensors and actuators and a programming code (with errors) for using the components. Students were then asked to write down a solution for solving all the errors. During Pyramid phases students discuss about the proposed solutions to agree in the most complete solution. Task B: Students were shown an image including 12 different arduino components. Then, students are asked to write down the names of all the components they are able to recognize. During Pyramid phases students discuss about the proposed solutions to agree in the most complete solution	12-27
Fundamentals of Television Production (Undergraduate program)	K	To understand the basis of TV and new audiovisual formats productions and developing television programmes at a small scale.	Task A: Recognising the different *mise en scène* models when working with a television multi-camera system. Task B: Debating different technical solutions for a TV production after the close reading of an article and the screening of several examples. Task C: Suggesting alternative for new television formats in the current audiovisual scenario.	21-67
Introduction to University (Undergraduate program)	L	To co-construct a definition about Responsible Research and Innovation (RRI)	After a short lecture on RRI, students are asked to write their own definition of what they consider to be responsible in the field of biomedical research. They then share their individual definitions through pyramid activity, discuss and vote the definitions of their classmates. At the end, the most voted definitions are commented with the whole class.	2 groups of 60 students
Foundations of science teaching and learning (Postgraduate program)	M	To synthesize the key ideas of a classroom	After the classroom, students had to write individually the take-home message of the session. Through the pyramid activity, they were selecting the key ideas that better represented the content of the classroom. Then, the teacher facilitated a reflection about what they have learned and she used this for introducing the next class.	2 groups of 30 students

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Hernández-Leo, D., Villasclaras-Fernández, E. D., Asensio-Pérez, J. I., Dimitriadis, Y., Jorrín-Abellán, I. M., Ruiz-Requies, I., & Rubia-Avi, B. (2006). Collage, a Collaborative Learning Design Editor Based on Patterns Special Issue on Learning Design. Journal of Educational Technology and Society, International Forum of Educational Technology and Society, 9(1), 58-71.

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Appendix C

TOWARDS DATA-INFORMED GROUP FORMATION SUPPORT ACROSS LEARNING SPACES

The content of this section was published in the following workshop proceedings:

Amarasinghe, I., Hernández-Leo, D., & Jonsson, A. (2017). Towards data-informed group formation support across learning spaces. In L. P. Prieto, R. Martinez-Maldonado, D. Spikol, D. Hernández-Leo, M. J. Rodríguez-Triana & X. Ochoa (Eds.), *Joint proceedings of the sixth multimodal learning analytics (MMLA) workshop and the second cross-lak workshop co-located with 7th international learning analytics and knowledge conference (LAK 2017), vol. 1828* (pp. 31–38). Aachen: CEUR. Available: http://ceur-ws.org/Vol-1828/paper-05.pdf

Towards Data-Informed Group Formation Support Across Learning Spaces

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Abstract. Learning via collaboration has gained much success over past few decades given their learning benefits. Group composition has been seen as a relevant design element that contributes to the potential effectiveness of collaborative learning. To support practitioners in this context this paper addresses the problem of automatic group formation implementing policies related to well-known collaboration techniques and considering personal attributes in across-spaces contexts where multiple activities, places and tools are involved in a learning situation. Analytics of contextual and progress-in-activity information about learners presented as a summary would support practitioners to obtain a comprehensive knowledge about them to subsequently facilitate formation of effective collaborative groups to face forthcoming activities. The paper discusses a work in progress web based architecture of a group formation service to compute groupings which also assists in recommending grouping constraints via learning analytics which will facilitate practitioners in the adaptive set-up of the group formation design element across-spaces.

Keywords: Learning Analytics, Computer Supported Collaborative Learning, Collaborative Group Formation, Jigsaw, Social Learning.

1 Introduction

Over the past few decades research conducted in different disciplines have confirmed active collaborative learning is an effective means of instruction which can be utilized in both traditional and online educational environments that would result in long-term effects in education [1]. Group work conducted under proper conditions provides an opportunity for students to clarify and refine their understanding of concepts through discussions and rehearsals with peers [2, 3]. However, learning via interactions does not occur in every situation [4]. Careful consideration over the design of collaboration is as key to achieve desired learning goals.

With the advancements in web technologies and social media students collaborate with each other not only in the physical classroom spaces defined by the formal educational contexts, but also across different digital spaces. In such a context computer supported collaborative learning (CSCL) could effectively mediates interactions among distant learners and co-present learners via computer-based scripts supporting uninterrupted collaboration irrespective of learner's physical location. Or students can engage in flows or sequences of pedagogically-interconnected collaborative learning activities, each proposing a different group formation policy and supported using a different digital collaboration tool [5].

However, designing and implementing interconnected flows of activities using different learning spaces are not straightforward. For instance in online learning spaces like MOOCs where thousands of students get registered for a particular course or in large classroom cohorts with, for example, over a hundred (or even less) students it becomes difficult and time-consuming for practitioners to go through each learner's profile or / and actions in previous activities in the flow in order to decide which grouping parameter, or combination of parameters, are pedagogically interesting to be considered in group formation policies and calculate the groupings accordingly [6, 7]. Hence researchers have been investigating several techniques to automate the process of group formation via Computer Supported Group Formation (CSGF) [6, 7] which provides computational support to complete group formation task successfully. However, existing approaches do not focus on solving across-spaces learning situations where parameters for group formation policies come from constraints depending on the pedagogical method behind the flow of activities but also from students' characteristics and their monitored behavior and performance during the flow.

Considering these across-spaces learning situations needs, in this paper we describe a work-in-progress web based architecture of a group formation service called "IGroups" which automates learner group formation and employs methods from learning analytics to provide glimpse towards understanding what occurs in different learning spaces to facilitate the identification of relevant parameters for group formation for forthcoming activities in a flow of pedagogically interconnected tasks and tools. This will aid practitioners not only to overcome time consuming group formation tasks but also to design and monitor the space of collaboration.

2 Related Work

Many studies have pointed out that formation of well-structured collaborative learning groups as the starting point of CSCL [4, 8]. One major approach of forming student groups is based on considering different factors related to student profiles [5, 9]. Grouping learners with different learning profiles results in heterogeneous groups while members who are similar to one another can be grouped together forming homogeneous groups [10]. Further, multiple constraints defined by an educator towards a collaboration task or constraints inherited from a Collaborative Learning Flow Pattern (CLFP) behind a pedagogical method may also become important when formulating student groups [5]. Groups formed without careful consideration often causes problems such as disproportionate participation of individuals, demotivation and resistance to group work in future activities [4, 10]. There has been an increasing number of prior works in the field of CSGF. Different algorithmic approaches have been suggested over time to formulate student groups using different approaches [8, 7, 11, 12, 13]. Among some of the efforts towards in which authors describes initial efforts towards web-based group formation systems include DIANA [13], OptAssign [14] and groupformation.org [15]. In DIANA [13] learner group formation was carried out prioritizing student's personal tendencies and attitudes associated when using their own skills to formulate heterogeneous groups. In OptAssign [14] group formation was modeled as a family of assignment problems. They have reported the evaluation results but have concluded highlighting the requirement of better analytical tools to investigate the quality of the solutions obtained. Moreover, in groupformation.org [15] student information was gathered via a preliminary survey and a preference survey which was then used to create student profiles. Further, homogeneous and heterogeneous student groups based on instructor defined criteria was facilitated. However, authors have not provided experimental results of the suggested approach.

2.1 Requirements towards an across-space data informed group formation support

During the literature review it was noticed that aforementioned systems do not appear to be deployed for real classroom usage for practitioners. Existing systems do not take the advantage of connecting heterogeneous data sources which will provide significant insights towards how learning occurs across different spaces. Although in many situations practitioners have access towards an enormous amount of student data, knowledge which could be extracted from this data is left untouched due to barriers in technical expertise. In some situations, learner data spread across heterogeneous sources (e.g., log files, form responses, assessment marks, survey results, lab/library attendance data, demographics etc.) might require a considerable amount of time to process manually.

On the other hand, it was noticed that different authors suggest [15] to carry out preliminary surveys to capture student data with respect to different criteria before forming collaborative learner groups. In our perspective, this will create an additional burden on instructors since they have to design and share additional surveys prior group work. If students' responses are delayed grouping activity will also be delayed and it was noticed that authors have not discussed how to incorporate incomplete survey results and its effect towards grouping criteria. Surprisingly it was noticed that these systems do not take the full advantage of the digital age meaning that they do not incorporate already collected data and automatically tracked data rightly available across different digital spaces rather they wait and restrict the systems to a preliminary survey. In such a context, it is of importance to leverage powerful learning analytics which would be advantageous for practitioners during different phases of collaborative sessions as follows.

Firstly, during the design phase of a collaborative learning activity, learning analytics could provide a broader insight towards learners as a summary. These types of analytics for instance would help practitioners when deciding which pedagogical approaches will best suit for students in a particular learning environment. Further, clustering algorithms such as K-Means can be used to partition student's data, providing practitioners hints towards deciding extrinsic/soft constraints which best fits for group formation in a particular context. Secondly, during the run time of a collaborative learning task, learning analytics could provide insights towards engagement and behavioral patterns of individual students. Further, it could also help in identifying students who are having less engagement or problems during collaborations. This information will make aware practitioners about students who require personalized support and assistance. Finally, after finishing a collaborative learning task, learning analytics could provide reflections [16] on learning occurred supporting better decision making in future sessions.

3 IGroups System Architecture

The IGroups system will be implemented adapting to common three-tier web architecture including presentation, logic and data tier. Main objectives of this system development are twofold; firstly, it automates the process of assigning students to collaborative groups based on different policies (heterogeneity, homogeneity, CLFPs), secondly it provides useful and significant insights in determining possible factors that will guide collaboration towards success via learning analytics module.

Formulation of collaborative learner groups was implemented using constraint optimization techniques using a novel binary integer programming approach [17] adhering to CLFPs (i.e., Jigsaw, Pyramid) which will pre-structure collaboration [18] based on constraints defined for group formation [5]. Further, regrouping of students while adapting to changes occur in the learning environments are also facilitated.

Since, the learning analytics module will be implemented to obtain the maximum advantage of using student data which spans across heterogeneous sources it was determined to integrate "IGroups" system to other existing third party software systems via application programming interfaces e.g., REST API. These third-party software systems may include well known and widely used educational platforms such as Moodle LMS, social media platforms or other tools supporting the activities in a learning flow.

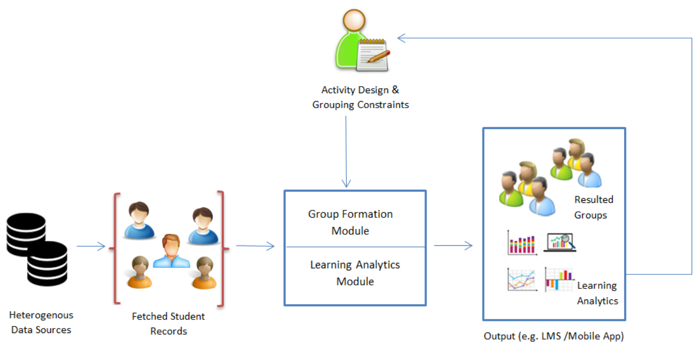

Fig. 1. IGroups System high-level design

Student data spread across heterogeneous sources will be processed and presented for practitioners. Computation of designed groupings according to the decided parameters will be also presented for practitioners for their refinement, if required, and accessible via another API for the automatic setup of grouping configurations in tools to be used in forthcoming activities. Investigation of which types of learning analytics as well as visualizations might be of interest in day today teaching practices to support learning design is another research area yet to be explored [19], as a first step we decided to provide learning analytics using easy to interpret visualizations. These visualizations would provide useful hints and guidance towards practitioners on deciding criteria for group formation on demand using readily available information. This information will not be limited only towards basic knowledge which could be extracted via learner's profiles such as demographics but will also include summarized information on their previous performance levels, collaborative behavior during past peer interactions, social communication and interactions across different digital spaces.

3.1 Data informed group formation support in across-spaces example

This example demonstrates how practitioners could carry out design and implementation data informed collaborative learning activities via "IGroups" system. Assume a scenario that the instructor wants to carry out a collaborative learning activity in a research methods course at a master's program class. Major objectives of this collaborative task is to familiarize students with the existing research groups in the University with the goal of helping students to identify faculty members who could guide and collaborate during their master thesis. The time duration given to finish the collaborative task was limited to three weeks. Since it is important to consider student's research interests before allocating them to study a particular research group instructors may decide to use learning analytics module in the IGroups system. At this point system will extract individual student's interests from profile records available in the LMS database and will be presented towards practitioner supporting them to make data driven decisions on how to allocate students to study a particular research group at the University.

Further, instructor may also consider students previous research experiences since mixing of less / no experienced students with experienced students will promote helping among themselves. Research experiences could be extracted via information publicly available in student's LinkedIn profiles. This information will then be presented as statistical summaries towards practitioner which will be useful on deciding feasibility towards formulation of balanced groups based on previous research experiences.

After deciding on grouping criteria instructor will also decide on a CLFP to carry out collaborative tasks. Assuming the instructor would like to formulate collaborative groups based on widely adopted Jigsaw CLFP given its benefits he/she will utilize the group formation functionality implemented in the IGroups system. Based on Jigsaw CLFP at the expert phase instructor wants to allocate students who are having similar research interests to study the same research group which matches best with their interests. It is also decided to mix student's based on previous research experience levels given its benefits. And at the next stage of Jigsaw CLFP it is decided to allocate students who have studied different research groups to the same Jigsaw group, hence sharing knowledge within Jigsaw groups will enhance each other's awareness towards different research groups at the University. After deciding on the aforementioned grouping structures instructor could utilize the functionality implemented in the IGroups system for calculating optimal student groups based on the criteria specified. Group allocations will be then communicated to students via Moodle LMS.

During expert phase of Jigsaw CLFP students who are allocated to study on a particular research group will meet with faculty members to get to know their ongoing research and research focuses. Students are advised to share knowledge gathered via discussions in the group twitter account using a particular hash tag. Students in the same group can comment on interesting research carried out by different faculty members or re tweet peer's posts which they think is important. While students are engaged in the collaborative activity instructors can monitor student's engagement and interactions during the task with the help of learning analytics module in the IGroups system which will provide analytics after analyzing tweets that matched the specified hash tag. For instance, instructors could revisit student’s weekly participation in the collaborative task based on analytics generated considering total number of tweets, retweets and comments made. These analytics could also be shared with students providing information on how other groups are engaged in the collaborative task. This type of sharing could increase student motivation and engagement. Further, instructors will also be presented with student clusters based on group performance. Easy to understand visualizations which also facilitates some interactivity which demonstrates how changing of group structures would affect performance levels would provide hints for instructors to decide on grouping criteria (based on performance during expert phase) which needs to be adhered during Jigsaw phase.

Instructor will then input grouping criteria to formulate Jigsaw groups to the IGroups system and Jigsaw group allocations will be communicated to the students. At the end of the Jigsaw activity each student will rate their interests towards working with a particular research group during their master thesis via a Moodle mobile application. This data will then be processed and presented via learning analytics module of IGroups system providing insights on whether collaborative activity has resulted in fruitful outcomes.

4 Conclusions

This paper describes work in progress architecture of a web based group formation system which supports educational practitioners when formulating collaborative learner groups while taking into account existing student's data spans across heterogeneous tools and sources. It is an architecture with open programming interfaces for its integration with data sources (academic systems, educational tools, etc.) and collaboration tooling relevant to support learning activities. Adaptive collaboration is supported via flexible computerized scripts which enables practitioners when handling changes occur in the collaborative space. Further, learning analytics incorporated into group formation service will provide practitioners useful insights during different stages (at the beginning, progress-in activity, post activity) of a collaborative task. Such insights would help practitioners to make data driven decisions towards more potentially effective student's groupings for the setting up of different tools supporting multiple tasks involved in a flow of collaborative learning activities.

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Appendix D

TOWARDS ESTIMATING ORCHESTRATION LOAD USING PHYSIOLOGICAL AND SUBJECTIVE MEASURES

In Appendix D we present the use of physiological - EDA (also known as galvanic skin response - GSR) and subjective measures (questionnaire responses) to estimate the orchestration load experienced by a teacher when orchestrating scripted collaborative learning activities under different conditions: no dashboard condition, mirroring support condition and guiding support condition. The details of the different experimental conditions were described in Chapter 5 of the dissertation.

Towards estimating orchestration load using physiological and subjective measures

Physiological measures using EDA

Fig. 1 below shows the graphs that were plotted using EDA data collected from a teacher while she was orchestrating CSCL sessions under no dashboard condition, mirroring condition and guiding conditions.

As can be seen in Fig. 1-a, the presence of peaks in graphs imply changes in the affective state of the teacher. In other words, the teacher's affective state is changing as a reaction to the activity. Moreover, by visual inspection of signal change during the activity it can be seen that there are some differences between the three conditions. For instance, in the no dashboard condition - signal shows an increase in the number of peaks and skin conductivity towards the end of the activity. In the mirroring condition (see Fig. 1-b) signal implies that the physiological state was not constant during the whole activity. According to the peaks, teachers' physiological state changes over time, where less arousal can be noticed towards the end. Also, this physiological response declines towards the end of the activity. In the guiding condition (see Fig. 1-c) the signal was more constant and shows that there was physiological response (according to the peaks), but that state remained more-less constant during the whole activity.

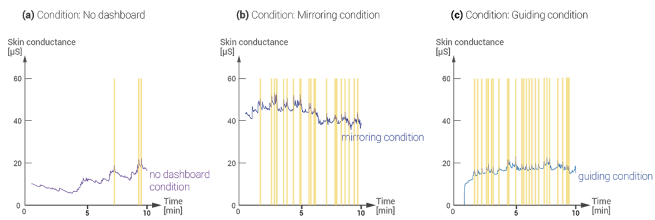

Fig. 1. EDA signal (peaks) in three conditions

Subjective measures using questionnaire responses

In the no dashboard condition the teacher mentioned she was frustrated and felt discomfort for not knowing what is happening (e.g. “Very difficult to obtain the whole picture. I was stressed regarding the planned time as some students were taking more time and frustrated for not having means to control the script progressions”.) We infer that EDA signal shows that arousal which could be related to frustration increases towards the end of the activity.

In the mirroring condition the teacher expressed that thinking and making decisions to take orchestration actions became somewhat demanding in real-time (e.g. “I am more relaxed when I use the dashboard and I can monitor the progression of the activity, but thinking and decision making was somewhat demanding”.) However towards the end of the activity the physiological response declines which means less arousal, and the teacher mentioned that she felt more control of the activity and became more calm over time.

In the guiding condition the teacher mentioned that she felt comfortable and was in control due to the automatic guidance provided by the dashboard warnings to take orchestration actions (e.g. “I really felt I was in control, alerts were very helpful, I could relax and read on student’s submissions, discussions etc.”.) We infer that this state remained more-less constant during the whole activity.

Findings and Future Work

According to the above results, we can conclude that differences between the three conditions are clear and this research provides some promising first findings. Based on the physiological measurements collected using EDA and subjective measurements collected using questionnaires indicate that the teacher was less comfortable in mirroring condition and was much comfortable in the guiding condition. In the future, we are planning to enrich our analysis further with a bigger sample of teachers. The study findings will guide us to reflect on subjective and objective measurements and also to propose orchestration load aware design guidelines for teacher-facing dashboards.