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Learning Analytics for Natural User Interfaces

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ABSTRACT: The continuous advancement of natural user interfaces (NUIs) allows for the development of novel and creative ways to support collocated collaborative work in a wide range of areas, including teaching and learning. The use of NUIs, such as those based on interactive multi-touch surfaces and tangible user interfaces (TUIs), can offer unique opportunities for learning, for automatically capturing digital traces of students' multimodal interactions, and for facilitating multi-user exploration of student data. We used a composite framework to characterize our first-hand experiences and a small number of related deployments. The dimensions of analysis considered include the orchestration activities involved, the phases of pedagogical practice supported, the target actors, the iteration of the LA process, and the levels of impact of the LA deployment. Results from our analysis helped us identify the current trends, gaps, challenges, and pedagogical opportunities of the application of LA and the use of NUIs for supporting learning.[1]

Keywords: Design, groupware, visualizations, design, dashboard, NUIs, awareness, face-to-face

1 INTRODUCTION

There has been a growing interest in the potential of learning analytics (LA) for supporting mobile and online learning activities. However, to a large extent, student learning still happens in face-to-face (f2f) environments (Bowers & Kumar, 2015). The development of effective f2f communication and collaboration skills are key 21st century competencies for employability and lifelong learning (Lee, Tsai, Chai, & Koh, 2014). Blended learning strategies and massive online courses have become popular targets for LA solutions (Kay, Reimann, Diebold, & Kummerfeld, 2013; Picciano, 2014), but they are primarily, or wholly, focused on the non-f2f online part of student engagement in learning activities. This is in part because it is easier to capture the logs of student interactions when the activity and communication are mediated by computers. By contrast, logging traces of student activity in collocated f2f settings, such as

[1] An earlier, shorter version of this paper (Martinez-Maldonado et al., 2016b) is the foundation for this article, which has been extended in light of feedback and insights from LAK '16.

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traditional classrooms, can impose several practical and technical challenges (Martinez-Maldonado, Clayphan, Ackad, & Kay, 2014).

Collaboration demands the development of a number of skills that are important not only in educational settings but also to tackle real-world challenges (Scheuer, Loll, Pinkwart, & McLaren, 2010). Collaborative tasks typically require brainstorming, deliberation, negotiation, and argumentation, usually in the service of some form of artefact design that can embody the knowledge of the group (Stahl, 2006). These forms of collaborative work can be powerful vehicles for authentic learning and typically have a major f2f element (Olson, Teasley, Covi, & Olson, 2002). In short, collaboration between students has the potential to greatly enhance learning (Roschelle & Teasley, 1995) and LA methods can provide an alternative way for researchers to visualize learning processes in their full complexity (Siemens & Baker, 2012) — not just in online learning environments, but also in co-located settings.

The continuous advancement of natural user interfaces (NUIs) allows for the development of novel and creative ways to support collocated collaborative work in a wide range of areas. A NUI is a system for human–computer interaction that the user operates through intuitive actions related to natural, everyday human behaviour and that impose fewer barriers between the user and information (Wigdor & Wixon, 2011). Emerging technologies such as gesture recognition, object tracking, multi-touch screens and tangible interfaces allow for the deployment of novel NUIs that are generating a shift in human–computer interaction. The proliferation of NUIs is also opening a broader range of possible applications to facilitate and enrich f2f activities in educational contexts (Dillenbourg & Evans, 2011). This is of high significance from a LA perspective, since these technologies can make visible group processes that until recently have remained invisible or unquantifiable. Increasingly over the last two decades, these technologies have been moving from research to commercial applications (Ardito, Buono, Costabile, & Desolda, 2015; Evans & Rick, 2014).

In this paper, we focus on multi-user *interactive surfaces* and *tangible interfaces* — devices designed to enable simultaneous interaction by one or more users. Examples of these include interactive tabletops, interactive whiteboards (IWB), tangible interfaces, and smaller-scale devices such as tablets, which can allow transitions between individual and group work (Scott, Grant, & Mandryk, 2003). Interactive surfaces and tangibles provide more flexibility in creating NUIs when compared with desktop computers that commonly offer a mouse and a keyboard to interact with the interface (Steinberg, 2012). This is because they allow the interaction with content and applications using touch, stylus, gestures, pressure, and other ways to provide input. Functionalities of interactive surfaces also commonly include the provision of a work space that offers multiple direct inputs, so users can manipulate digital content with fingers or through physical, trackable objects (e.g., pens, gloves, fiducial markers) while they communicate via speech, facial expression, and gesture (Ardito et al., 2015). Less explored functionalities of these devices include the unique opportunity to automatically capture students' digital footprints that can be analyzed to make normally ephemeral f2f interactions persistent and (once rendered in appropriate form) "visible." Their intrinsic multi-user capabilities can assist in enhancing collocated exploration, discussion, and sense-making of LA indicators. Furthermore, Oviatt's (2013)

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research argues for the critical role of creative sketching in learning, placing renewed emphasis on digital pens and surfaces.

These underexplored opportunities motivate the need to define key dimensions of a new design space, where surface technology and LA tools can meet to address f2f learning challenges. We propose that the articulation of such an explicit design space should be helpful for both researchers and designers. Firstly, a design space serves as an instrument for making sense of past research, coordinating future research by identifying potential uses of the technology and challenges, and avoiding unintended duplication of effort. Secondly, a design space should provide conceptual guidance for the development of new LA tools by clarifying the scope (e.g., target audience; desired functionality) or by targeting unmet needs and underexplored teaching and learning areas that the design space highlights. Designing and deploying LA tools using interactive surfaces and tangible devices requires a comprehensive understanding of interaction design and the possibilities that these technologies offer, not just for learning and teaching, but also for LA. A design space should also consider the pedagogical underpinnings, the different target actors, the teaching strategies, data sources, the potential impact on authentic scenarios, and the degree of maturity of research and development in this area.

This paper presents a synthesis of conclusions drawn from an empirical analysis of current research and development, exploring ways to deploy LA innovations utilizing interactive surfaces and tangible interfaces in novel and creative ways. To describe the design space in this emerging area, we use a composite analytical framework, drawing principles from five sources: 1) a framework of classroom orchestration (Prieto, Dlab, Gutiérrez, Abdulwahed, & Balid, 2011); 2) a framework to support the implementation of teaching practices in the classroom (Kaendler, Wiedmann, Rummel, & Spada, 2015); 3) the *actors* commonly targeted by LA tools (Siemens, 2012); 4) the *iterative process* they commonly follow to use and respond to LA tools (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013); and 5) the *impact* of the LA deployment (Santos, 2016). We analyze the technological and educational aspects of our first-hand experiences as researchers/designers, and the small number of authentic deployments of LA utilizing different types of interactive surfaces that we have been able to identify. In parallel, our approach allows us to analyze the maturity of multi-user interactive surface technology and LA solutions by drawing a contrast between interesting pieces of research conducted in controlled lab conditions and authentic classroom deployments. The contribution of this paper is the discussion of our analysis results that helped us identify current trends, gaps, challenges, and pedagogical opportunities offered at the intersection of the applications of LA and the use of NUIs for supporting learning.

The rest of the paper is structured as follows. The next section provides an overview about touch and tangible interaction, and a definition of orchestration technology and its links with LA. Section 3 presents the theoretical underpinning of our composite framework. Section 4 discusses case studies associated with the use of LA tools and techniques to NUI-based learning scenarios. This section also describes the cases using the framework, making an emphasis on particular orchestration challenges, pedagogical uses, and advantages of using interactive surfaces and tangible interfaces for LA purposes. Section 5 discusses the application of our framework, the maturity, opportunities, and needs in this area. Section

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6 concludes with a discussion of alternative uses of the framework and possible avenues of future work in the area of LA using surfaces and tangibles.

2 BACKGROUND

2.1 Touch and Tangible Surfaces in Education

Surface computing is still a maturing technology, which has become a more *natural* alternative to traditional mouse and keyboard input by enabling multi-touch interaction using fingers, hands, or special pens (Brown, Wilson, Gossage, Hack, & Biddle, 2013). Similarly, tangible interfaces offer the additional advantage of allowing users to manipulate physical objects and thus receive haptic feedback, which is more naturalistic for tasks that require the experience of textures, modelling realistic spatial representations, or mastering visual-motor skills (Evans, Drechsel, Woods, & Cui, 2010; Schneider & Blikstein, 2015a; Schneider, Jermann, Zufferey, & Dillenbourg, 2011). This shift in input technology has opened the interaction space, allowing a wide range of new collaborative and ubiquitous applications, especially for tasks more effectively performed face-to-face (Olson et al., 2002).

Multi-touch and tangible interfaces often allow learners to interact directly with objects instead of using indirect input devices such as the keyboard, the mouse, or pointers. Performing physical actions on physical or digital objects allows students to be more easily aware of what others are doing. Additionally, students can combine the advantages of the physical setting provided by traditional f2f meetings with the possibilities that a digital environment can offer (Higgins, Mercier, Burd, & Hatch, 2011). Some example tasks that have been supported by multi-touch and tangible interfaces include group planning (Jermann, Zufferey, & Dillenbourg, 2008), diagramming (Frisch, Heydekorn, & Dachselt, 2009), designing (Martinez-Maldonado, Goodyear, Kay, Thompson, & Carvalho, 2016a), data exploration (Abad, Anslow, & Maurer, 2014), brainstorming (Clayphan, Martinez-Maldonado, Tomitsch, Atkinson, & Kay, 2016), knowledge building (Baraldi, Del Bimbo, & Landucci, 2008), and information curation (Apted & Kay, 2008). However, whilst advancements in hardware have been rapid (e.g., through gaming products sensing movement and gesture as well as tablet technology), application software for large surface devices is still in its early stages compared with (for instance) the market of mobile devices.

In terms of educational contexts, there has been great interest in using large interactive surfaces for supporting collaborative learning pedagogies (Higgins et al., 2011). Interactive white boards (IWBs) have been used to conduct whole class activities (Clayphan et al., 2016; Evans & Rick, 2014), both vertical and horizontal large touch screens have been used to conduct small group work (Kharrufa, Martinez-Maldonado, Kay, & Olivier, 2013), and multiple tablets have been interconnected to support tasks in pairs (Wang, Tchounikine, & Quignard, 2015), or to show a user interface just for the teacher (Kharrufa et al., 2013). Moreover, the use of tangible objects on surface interfaces has been regarded by practitioners and researches as a particularly important feature for the cognitive development of young students' coordination and 3D orientation (Dillenbourg & Evans, 2011). Tangible interfaces are promising for tasks that require the manipulation of objects, which is not possible in flat displays; examples have included narrative, biochemistry, and simulation systems (Dillenbourg & Evans, 2011).

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There is increased interest in the digital affordances of surface devices to support handwriting and sketching (Oviatt, 2013). These are often more fluid ways for students to communicate and generate ideas, compared with the use of mice, and physical or on-screen keyboards. Another use of large surface devices has been collaborative data visualization, mostly for geospatial datasets (Abad et al., 2014), but there has been little attention to date on the processes of collaborative sense-making around educational data visualizations.

In short, surface-based devices (and to a lesser degree tangible devices) are now mainstream products. However, compared to the massive investment in analytics from systems that mediate interaction between remote participants, there is little work exploiting surface and tangible analytics. Not surprisingly, the complexity of capturing, disambiguating, and interpreting f2f user actions makes this quite challenging. As with all analytics applications, the goal is not to try to record everything; rather, were it possible to capture and render persistent traces from normally ephemeral f2f interaction, what would be appropriate and desirable data to log? It is timely to consider the potential enhancements that LA could provide to f2f learning.

2.2 Technology for Classroom Orchestration

The metaphor of classroom *orchestration* was originally defined in terms of the real-time management of classroom resources, learning processes, and teaching actions (Dillenbourg & Jermann, 2010). This metaphor takes into account the variability and complexity of classrooms and the key role of teachers in adapting the available pedagogical and technological resources to help students achieve their intended learning goals (Dillenbourg et al., 2011; Roschelle, Dimitriadis, & Hoppe, 2013; Twiner, Coffin, Littleton, & Whitelock, 2010). Orchestration in the classroom can be defined as a loop of awareness and regulation: the teacher monitors the state of the classroom, compares it to some desirable scenario, and performs actions to reach a more productive state (Dillenbourg et al., 2011). This loop is very similar to the one described by Soller, Martinez, Jermann, & Muehlenbrock (2005) applied to fully computer-mediated learning systems and the analysis of student data. In both cases (for computer-mediated and f2f learning) there is scope for producing indicators of learning processes to analyze and provide support, or enhance awareness of the learning processes.

Importantly, the metaphor has been further embraced by other researchers to explain several other activities that need to be attended to before and/or after the actual deployment of learning tasks, not only in the classroom, but also in online or blended learning scenarios (Prieto et al., 2011). The community has also defined the mechanisms and technologies to support the orchestration activities (Tchounikine, 2013). *Orchestration technology* may support the management of the orchestration or some part of it. This includes, for example, systems that help teachers manage the class workflow (Martinez-Maldonado, Clayphan, & Kay, 2015a), enhance their awareness (Gutiérrez Rojas, Crespo García, & Delgado Kloos, 2012), track student progress (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2014), or provide informed feedback (Gutiérrez Rojas, Crespo García, & Delgado Kloos, 2011). Other orchestration approaches have been focused on supporting teachers to deploy their learning designs (Dimitriadis, Prieto, & Asensio-Perez, 2013), guiding reflection sessions (Do-Lenh, 2012),

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re-designing after the activity is completed (Martinez-Maldonado, Kay, Yacef, Edbauer, & Dimitriadis, 2012; Roschelle et al., 2013), and providing tools that can be flexibly re-configured by the teachers themselves to serve specific orchestration purposes (Tchounikine, 2013).

The metaphor of classroom orchestration also promotes the use of data to support state awareness and workflow manipulation. According to Dillenbourg et al. (2011), the technology itself does not need to perform complex analysis or automated actions; instead, it should provide just the key information about the classroom state, leaving the diagnosis of such data to the teacher. This coincides with some of the objectives of LA innovations aimed at bringing human judgement into the analysis loop (Siemens & Baker, 2012). Moreover, the metaphor has also been extended by the notion of distributed orchestration (Sharples, 2013), considering that other actors of the learning process besides the teacher can also be responsible for part of or all the orchestration tasks. Thus, orchestration may be applicable to self-managed learning scenarios where students are responsible for orchestrating key aspects of their own learning experience (Roschelle et al., 2013).

The orchestration metaphor empowers teachers as drivers of classroom activities and advocates for the use of simple technologies that may have important effects. The effectiveness of orchestration and the extent to which teachers can respond to the ways students perform their tasks is critical because it directly impacts student activity, and therefore, their learning. Our work takes an approach based on orchestration because it is a dynamic perspective that considers authentic issues arising in the classroom, usually affected by unanticipated processes and contingencies. In contrast with learning theories that focus on cognitive aspects, orchestration is concerned with practical issues and tasks not directly linked with learning but that can shape learning. This makes orchestration very relevant for deploying LA tools in authentic learning settings: LA could play a key role in supporting f2f and blended learning activities. To achieve this, a clear understanding of orchestration activities is needed to create effective LA solutions in those f2f settings where teachers or students need to adapt quickly to unexpected problems.

3 THE COMPOSITE FRAMEWORK

The composite framework we used to analyze the current research and deployments that combine LA tools and interactive surfaces is defined by five dimensions: a) a set of *orchestration activities* to which the LA tools provide support, b) the *phases of the pedagogical practice* that are supported, c) the *target actors* of the LA, d) the *level of impact* of the LA innovation, and e) the *extent of iteration* of the LA and pedagogical processes (see Figure 1). The composite framework is a 5-dimensional matrix that can categorize a wide variety of LA deployments. Each of these dimensions, and their theoretical underpinnings, are described in the rest of this section.

3.1 Orchestration Activities

Prieto, Dimitriadis, Asensio-Pérez, and Looi (2015) developed a framework that identifies four orchestration activities. For the first dimension of our analysis framework, we considered these four

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orchestration activities that either teachers or students perform (see Figure 1, a). LA solutions can be created to support the actors in performing such activities. The four orchestration activities are design, management, adaptation, and awareness.

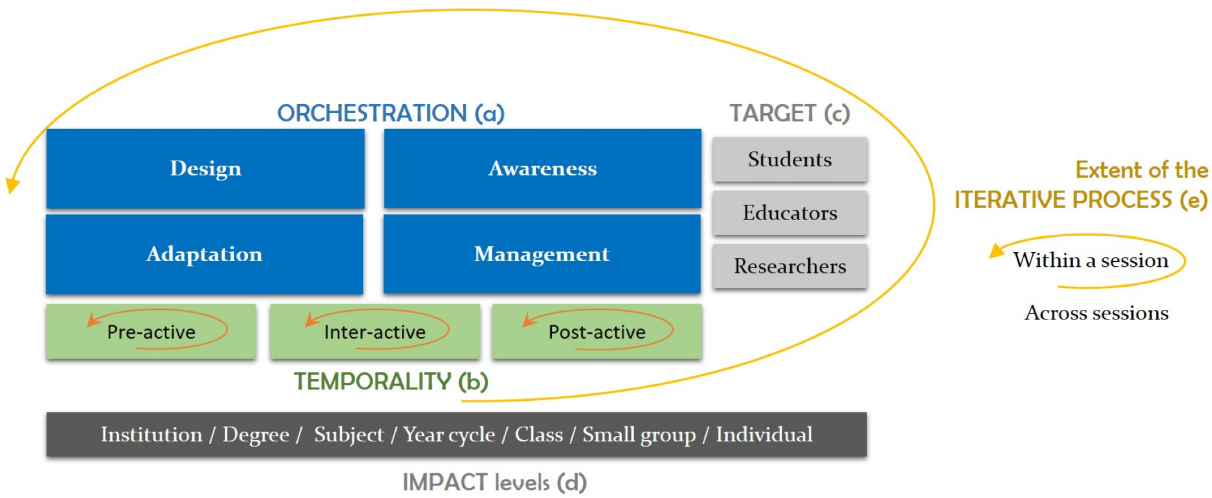

Figure 1: A combination of frameworks creates this 5-dimensional framework, which we used to analyse the current state of learning analytics applied in contexts where interactive surfaces and

3.1.1 Design

Learning design includes the preparation of educational materials, pedagogical approaches, social dynamics, tasks, scripts, strategies, and any other resources needed to create learning opportunities for students (Goodyear & Retalis, 2010). Teachers commonly have a crucial role in learning design and co-design (Ertmer, Parisio, & Wardak, 2013; Tracey, Hutchinson, & Grzebyk, 2014). There may also be other actors specialized in learning design, particularly in higher education (Tracey et al., 2014). Alternatively, students can also design or co-design their own learning tasks (Goodyear & Ellis, 2007). The design process is not necessarily linear, as design and planning can co-occur while the actual activity unfolds or after it is completed (Prieto et al., 2011). In terms of LA, awareness and/or analytical tools may support fine-tuning of learning designs by providing visualizations of student data, indicators about how planned tasks actually occurred, or insights from the community of practice. In short, although learning design is an activity that commonly occurs before the actual learning activity, it can also co-occur while the student's activity unfolds (Goodyear & Dimitriadis, 2013). As a result, LA tools can provide support to teachers before, during, or after the learning activity for them (or instructional/learning designers) to revise the enactment of the design in runtime or make more permanent, substantial changes to the learning design that can have an impact on future learning sessions.

3.1.2 Management

Management refers to the coordination of the ongoing teaching process and/or the self-regulation during the enactment of the learning activity (a learning session). This includes the management of time for each student's task (e.g., the class duration), task distribution, and social arrangements. In short, this

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activity is focused on the coordination of the workflow of the learning activity. For the case of f2f learning activities, the management is commonly performed at a classroom level. But this could also be virtual classroom management for online/blended activities. This regulation can be performed through social interaction (e.g., the teacher directing the flow of the class or students managing their own workflow based on feedback from LA systems) or be partly handed over to some computer controlled mechanism (Prieto et al., 2011). LA tools can support the actors responsible for the management of the learning processes by providing, for example, key information about the execution of the workflow so it can be modulated or reconfigured according to the demands of the activity. A LA tool could also be designed to support reflection for teachers so they can understand what went well and what went wrong during the enactment of the learning activity in order to modify its management for future sessions.

3.1.3 Adaptation

Adaptations or interventions are often needed for the designed learning activities and the original plan in order to respond to unforeseen or extraneous situations (for example, technology breaking down, students not arriving on time). Adaptations to the original plan may also be needed to take advantage of emergent learning opportunities (for example, when the teacher modifies the order of the tasks or skips some tasks because of the status or overall progress of the class). When the learning activity depends on the learning technology, the adaptation can be strongly influenced by the capacity of that technology, the class script, or the learning activities to be flexibly adapted to unexpected events and the emergence of new tasks (for example, some tools do not allow making changes to the script or design on the fly).

Adaptation can also include the actors creating improvised tasks or adapting the planned tasks during the enactment, even in cases where the technology does not provide an elegant solution. Similarly, the systems can offer flexible functions to handle those adaptations. LA tools can support this process by providing teachers or students with key information that would allow them to manually intervene or adapt specific learning tasks, or for the learning system to automatically adapt the tasks to particular student's needs or provide automated interventions to tune the order or the approach to the tasks. Other analytics approaches such as predictive modelling or clustering could be applied to provide hints to the students or teacher before an unforeseen event occurs. For example, LA tools could automatically warn the teacher in case some unexpected event in the classroom is detected. As a response, the system may be able to propose optimal ways of group formation depending on the students in the class, automatically detect disengagement so the teacher can vary the tasks, or detect when a group has finished a task so they can advance to the next tasks.

3.1.4 Awareness

Awareness, along with formative/summative assessment tools, is clearly critical for orchestrating learning and relevant for visual LA innovations. Awareness includes the process aimed at getting insights about what is happening in the learning situation. While "awareness" of different sorts pervades all sense-making activity around data (Verbert et al., 2013), for this activity we focus on those awareness mechanisms particularly linked to the students' learning activity. Examples of learning activity data

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include information about learning progress, student's logged actions, and formative and summative assessment results.

Awareness support tools can, for example, enhance student awareness about their own work (self-awareness), about their collaborative work (group awareness), about the outcomes of others (peer assessment), or provide key information to the facilitators (teacher's awareness). LA tools may provide key insights into students' learning processes so actors can modify their teaching strategies, the provision of feedback, the pedagogical approach, or the students' learning strategies. These can be simple tools such as basic visualizations of group progress, more complex student modelling, or predictive approaches.

3.2 Temporality: Phases of Pedagogical Practice

The second dimension is derived from the Implementing Collaborative Learning in the Classroom (ICLC) framework by Kaendler et al. (2015) pointing to teacher competencies needed across the implementation phases of learning strategies in classroom sessions. It defines five teacher competencies: *planning, monitoring, supporting, consolidating,* and *reflecting*, which span three phases of teaching practice: *pre-active, inter-active,* and *post-active* (Figure 1, b). The authors map planning to the pre-active-phase; monitoring, supporting, and consolidating to the inter-active phase; and reflecting to the post-active-phase. Although teacher competencies could be matched with the orchestration activities described above, the metaphor of orchestration is not only concerned with the ability of the teacher to perform tasks according to professional knowledge. Rather, it is concerned with how different types of technology can support teachers, or students themselves, to manage multi-layered activities in a multi-constraint context (Dillenbourg et al., 2011). Additionally and very importantly is the idea that almost all orchestration activities can be relevant before, during, or after the activity (Prieto et al., 2011). For example, planning and learning design commonly occur in the pre-active phase, but it can be that a teacher has to adapt the intended design on the fly, or accomplish some re-designing work in the post-active phase.

In summary, by combining both frameworks, we can map surface and tangible-based LA in terms of *what* orchestration support they provide and *when*. We have not yet specified *for whom*, which is considered next.

3.3 Target Actors

LA solutions can be oriented towards different actors of the learning process, including students, teachers, intelligent agents, administrators, etc. (Chatti, Dyckhoff, Schroeder, & Thüs, 2012). At the same time, LA studies can be conducted for research, or prototype system-design purposes, without being deployed in authentic learning scenarios. LA can also support learning designers to make informed decisions based on evidence about changes that the course may require. Therefore, to understand the design space of LA in a specific area, and its degree of maturity in terms of real deployments, we should differentiate the actors being targeted as end-users of the LA tools.

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Based on the users targeted by the current deployments covered in our analysis (e.g., who will make use of the LA outputs), we divide the target users into three groups (Figure 1, c): *students, educators* (including lecturers, tutors, learning designers), and *researchers* (including individuals and the community of research).

3.4 Impact Levels of Learning Analytics

The previous dimension referred to the actors who are the actual users of the LA tools. But LA can produce an indirect benefit in other aspects of the educational process (Verbert et al., 2013). For example, a dashboard can be targeted to teachers but the impact of using the dashboard can be translated into an improvement of student learning, or prompt the modification of the learning design of the following course (making a wider impact on the course or other students and teachers). As a result, the *impact* dimension refers to the different levels on which the LA tool can have an impact. Buckingham Shum (2012) defined three layers of LA impact. The first layer covers most of the case studies discussed in this paper, focused mostly on classrooms and small learning communities, where teachers and students are the main stakeholders. Buckingham Shum (2012) referred to this layer of LA research as the micro-layer. The meso-layer is focused on the institution (e.g., making an impact at a program level or adopting some LA framework by a whole institution), whereas the macro-layer looks at the broader society (for example, at a level of the entire educational system within a country).

Nonetheless, it is not only challenging to define the boundaries between layers but also to isolate the impact of a tool on specific stakeholders. Given that the purpose of our framework is to understand the design space and the maturity of a specific area in LA, we are interested in narrowing down the intended levels that the LA tool may have an impact on to specific levels of stakeholders. Based on the layers identified by Buckingham Shum (2012) and the current deployments covered in our analysis, we divide the levels of impact of LA into six groups (Figure 1, e): individual, small group, class, which are associated with the micro-layer; subject (one edition of one subject), year cycle (including multiple editions of the same subject), which can be in between the Micro and Meso layers; course and institution, which are associated with the meso-layer.

3.5 Extent of the Iterative Process

The fifth and last dimension introduces the notion of iteration at two extents: *within a (learning/analytics) session* and *across sessions* (Figure 1, e). We will use the word *session* to refer to the continued learning activity that students perform either face-to-face or online. Examples of f2f sessions can be a classroom tutorial, a lecture, a small-group meeting, or an experimental trial. As a result, *iteration within* one session refers to the iterative process of LA support within each pedagogical phase. This has been described by Verbert et al. (2013) as the process users follow to have access to data (1. *awareness*); ask questions and assess the relevance of the data (2. *reflection*); answer questions, getting new insights (3. *sense-making*); and induce new meaning or behavioural change (4. *impact*). This four-stage iterative process occurs while users interact with a LA tool in a given phase. *Iteration across* sessions is concerned with the workflow as the phases (*pre-active, inter-active,* and *post-active*) are

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repeated over multiple sessions. This is crucial so that LA tools can provide support activities spanning multiple sessions.

In summary, the composite framework considers that the pre-active, inter-active, and post-active phases form a linear workflow for one specific session (e.g., a classroom session, an experimental trial, an online task). Each orchestration aspect can be supported in any of these phases (e.g., planning is not restricted to the pre-active phase, but can occur in the inter-active and post-active phases). LA support can be targeted at different actors in each phase, and across phases or sessions. Finally, the LA tools can have a particular impact on other stakeholders at different levels, from the individual student to the whole institution.

4 ANALYSIS OF CASE STUDIES

In this section, we analyze a series of case studies of LA applications that use interactive surfaces or tangible devices to support different orchestration activities. Table 1 presents an overview of the design space defined by the dimensions of our framework. We have analyzed our own current R&D exploring LA associated with the use of interactive surfaces and tangible devices, and a small number of deployments by other researchers that we identified as relevant. As far as we are aware, our list of cases is the first joint effort to bring together LA innovations and NUI-based learning settings. The table maps the projects analyzed (column 1), the orchestration activities addressed (2–5), the pedagogical phases supported (6–8), and whether they involve certain levels of *iteration* (9–10). The actors targeted in each deployment are represented by letters: E for educators, teachers, tutors, and learning designers; S for students; and R for researchers. Beyond the dimensions of the composite framework, in the case studies we seek to identify the *forms* in which the data is communicated to the actors, such as whether it is presented in a raw format (e.g., statistics, algorithms results, patterns), through visual representations (e.g., dashboards, visualizations, alerts, notifications), or by direct automated actions. We also pay attention to the topology of LA tools classified by the *type of information* they offer, including information about 1) the task/class progress, 2) student interaction, 3) quality of the students' solution, and 4) learning (including conceptual change, learning to collaborate, or learning about the process).

In the following subsections, we provide a concise description of our first-hand experiences from seven case studies (the first seven rows in Table 1). These cases serve to illustrate how the dimensions of the composite framework are interwoven to help understand the technologies used and pedagogical aspects tackled by the LA solutions. To facilitate the presentation of the cases, these are grouped by the main actors targeted in each (teachers/learning designers, students, and researchers, respectively). Lastly, we briefly describe other LA applications where some sort of surface technology has been used (last four rows of Table 1).

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Table 1: Analysis of the Current Design Space of Learning Analytics Applications Utilizing Interactive Surfaces. Target Actors: E=Educators, S=Students, R=Researchers

Project	Orchestration Activities				Pedagogical Phases			Impact	Iteration	
	Design	Awareness	Adaptation	Management	Pre	Inter	Post		Within	Across
1- MTFeedback (Martinez-Maldonado et al., 2015b)		E				✓		Group & Class	✓	
2- Analytics for redesign (Martinez-Maldonado et al., 2012)	E	E		E	✓		✓	Year cycle		✓
3- CoCo design table (Martinez-Maldonado et al., 2015c)	E/R				✓			Subject	✓	
4- Navi surface (Charleer et al., 2013)		E/S				✓	✓	Individual & Subject	✓	✓
5- LARAe.TT (Charleer et al., 2015)		E/S		E/S		✓	✓	Individual & Subject	✓	✓
6- Co-located eye-tracking (Schneider et al., 2015)		R				✓		Individual & Group		
7- Motion sensors (Schneider & Blikstein, 2015)		R				✓		Individual		
8- Script awareness tool (Martinez-Maldonado et al., 2015a)			E	E		✓		Class	✓	
9- Tinker lamps (Do-Lenh, 2012)		E/S				✓		Group & Class	✓	
10- Monitoring tablets (Wang et al., 2015)		E				✓		Class	✓	
11- Learning catalytics (Schell et al., 2013)		E				✓		Subject	✓	✓

4.1 Supporting Awareness for Teachers

We start by describing two case studies of analytics support for enhancing teacher awareness.

4.1.1 MTFeedback: Helping teachers track and prioritize groups with targeted feedback

The first case study consisted of providing support to enhance teachers' classroom *awareness* and assessment on the fly (*inter-active phase*). The pedagogical intentions of the teachers were that students could engage in collaborative discussions and visually represent their proposed solutions to challenging problems. The teacher conducted this activity face-to-face to support students and provide direct feedback to promote verbal discussion and argumentation. The setting used was the MTClassroom (Figure 2, left). This is a multi-surface classroom environment composed of 4–5 large interconnected tabletops and three vertical displays. Each tabletop was enriched with a Kinect sensor that differentiates individual touches. This allows for the capture of an identified log of student actions at each table. Six teachers and more than 300 students were involved in a series of realistic studies conducted during three regular semester courses. Three types of tasks were facilitated by the tabletops: collaborative concept mapping, brainstorming, and scripted group meetings. All the tabletops and vertical displays were controlled by a teacher's tablet-based dashboard (Figure 2, right). This also showed visualizations that conveyed student information in two dimensions: individual participation and group progress. It also showed notifications from the MTFeedback subsystem. This analyzed student artefacts in the backend to generate both positive and negative notifications according to the groups' misconceptions or underperformance, automatically identified based on thresholds set by the teacher.

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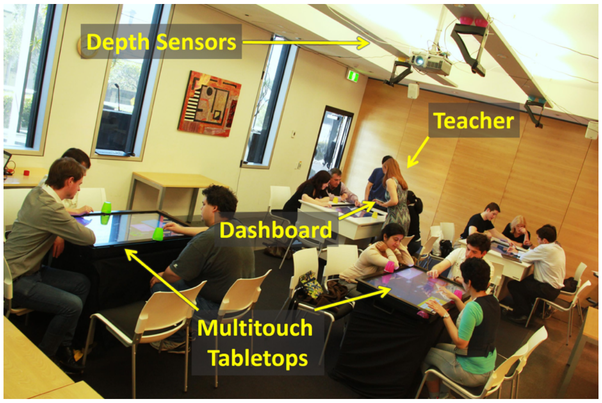

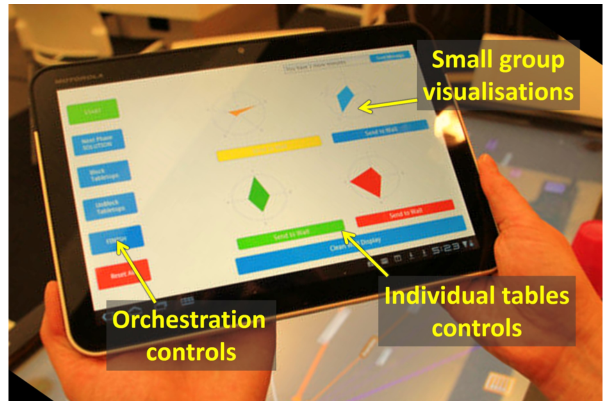

Figure 2: Left: An ongoing small-group session in the MTClassroom. The teacher is holding a tablet-dashboard while providing feedback to one team. Right: The dashboard showing visualizations of participation for four groups.

Empirical evaluations studied if the visualizations and notifications shown in the dashboard effectively supported teachers' *iterative LA process within a session* by enhancing their *classroom awareness* and thus allowing them to take more informed decisions when selecting the groups that required more attention (Martinez-Maldonado, Clayphan, Yacef, & Kay, 2015b). Results indicated that the system helped to capture traces of student activity seamlessly, thus allowing the generation of live visualizations and notifications for the teacher. The deployment of the teacher's dashboard on a tablet allowed free mobility to the teacher while having access to control and monitoring tools. The visualizations and notifications allowed teachers to attend to groups that needed immediate support and provide formative and/or corrective feedback, which translated into students' conceptual changes. This also made an impact on teacher awareness in terms of gaining insights about the status of the whole class. Table 1, row 1, presents an overview of how this case study can be described based on the different elements of the framework. Figure 3 and Table 1 (row 1) show how each element of the framework categorizes this case study.

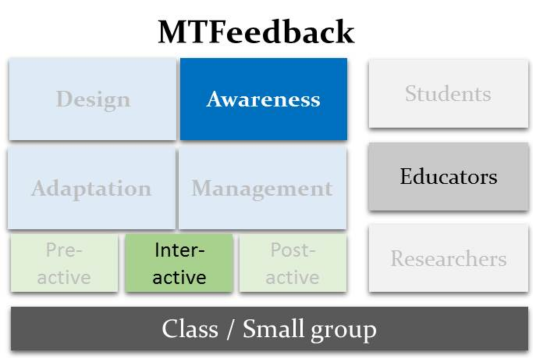

Figure 3: Representation for the case "MTFeedback" according to the elements of the framework. The teacher used the system to gain awareness about small group interaction in the classroom.

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4.1.2 Learning Analytics for Redesign

For the second case, the situation was also associated with the MTClassroom for conducting tutorials; however, this study focused only on one teacher designing and then re-designing 1-hour tutorials for two different subjects (business and management) in two consecutive university semesters. The study provided LA support in two forms, iterating *across two sessions* (Martinez-Maldonado et al., 2012). First, the teacher had access to a set of visual analytics in the *post-active phase* of a classroom session for semester 1 of an undergraduate subject. The aim of the visualizations was to enhance teacher *awareness* and helping her *assess* how the initial intentions played in the classroom. Second, in the *pre-active phase* of the next class session (semester 2), the visualizations provided insights into the aspects of the learning tasks that needed to be redesigned (see representation of the case according to the framework in Figure 4 and refer to Table 1, row 2). The first tutorial involved 236 students distributed in 14 classroom sessions. The second involved 140 students distributed in 8 sessions. The goals and the topic of both tutorials were similar: to promote discussion and deep understanding of political dynamics for students to learn how to address organizational issues. Both tutorials had a similar macroscript, which consisted of two small-group concept-mapping tasks. The captured data included application logs, snapshots of the evolution of each group's concept map, and teacher actions to advance the class according to her script.

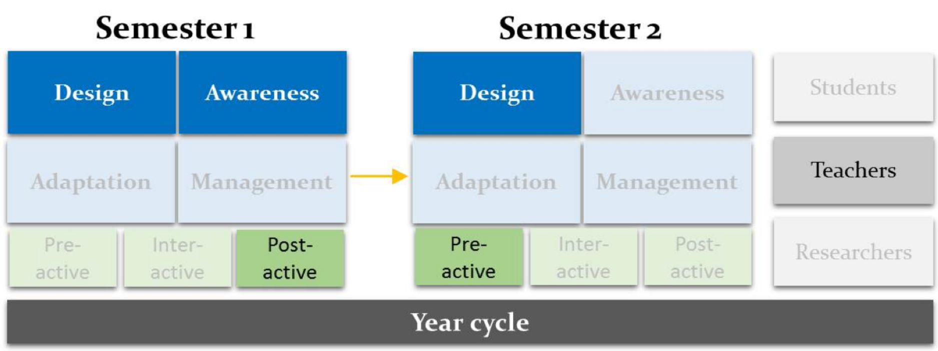

Figure 4: Representation of the Learning Analytics for Redesign case according to the elements of the framework.

Four semi-structured interviews were held with the teacher after the tutorials to capture their intentions and reflections. The first interview served to elicit the teachers' intentions that the information captured by the MTClassroom could inform about. These intentions were grouped into three categories: the class script progress (A), student participation (B), and student achievement (C) in all sessions. In the second interview, the LA support was presented to the teacher in the form of visualizations (graphs), workflow diagrams, and raw numerical results about each of the three pedagogical intention categories. This supported teacher reflection in the post-active phase of the first macro-level iteration of the LA cycle (Martinez-Maldonado et al., 2012). The next two interviews focused on capturing the teacher's re-design decisions as part of the pre-active phase of the next iteration.

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Regarding the class script (A), for example, the teacher was provided with a fuzzy workflow diagram (see Figure 5). She identified that in most tutorials, students spent too much time on the first task, not leaving enough time to complete the second task. Concerning student participation (B), a bar chart was shown to the teacher, indicating that within most groups participation had not always been equally distributed. A third example (for category C) is illustrated by the results from a correlation analysis, which suggested that a hierarchical concentric arrangement of student concept maps was associated with achieving better solutions. These insights were informative for the teacher in re-designing the tutorials. For the next tutorial sessions, the teacher provided an initial scaffolding solution for students to progress more quickly and focus on the subsequent higher-level tasks. The teacher also developed a strategy to encourage all students to use the tabletop, and to follow a specific concentric layout.

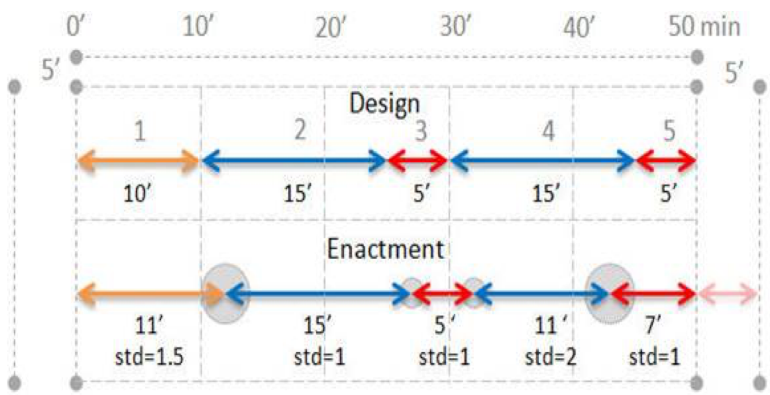

Figure 5. Planned time limits for 5 tasks (top row) and the enactment of the design for 14 tutorials (bottom row) (Martinez-Maldonado et al., 2012).

In this study, the surface devices allowed the automated collection of classroom evidence. The data was exploited to generate visual and non-visual information to help the teacher compare her planned intended goals with how they actually played in the classroom. This example illustrates the synergy between surface technology and LA to provide continued iterative support to teacher awareness and planning across sessions, which can make an impact on her whole year-long teaching cycle.

4.2 Analytics for Learning Designers

A recent report documents problems caused by a lack of mutual awareness among users of computer-mediated learning design systems (Nicolaescu, Derntl, & Klamma, 2013). One of the functionalities of using large surfaces is that they invite all team members to interact with the shared device, making their actions visible. The next subsection describes a case study of analytics support for learning design.

4.2.1 CoCoDes: Collaborative educational design

This case study consisted of supporting *design* in the *pre-active* phase using design analytics that can make an impact on learning designers while they design and plan the tasks for a whole *subject*. The specific goal of this study was to understand how surface technology and minimalist visual analytics can support high level *learning design*. Figure 6 and Table 1 (row 3) present how each element of the

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framework categorizes this case study. The setting was the Design Studio (Martinez-Maldonado et al., 2015c). Figure 7 shows this multi-surface space providing a set of digital and non-digital tools, including a tabletop, an IWB, tablets, a white-wall, a dashboard, and various paper-based materials. The tabletop and the IWB run an application called CoCoDes. It offers a large interface customized to support rapid construction of candidate designs as part of the conceptual design stage of university courses. The tool shows a flipped timeline where users can arrange learning tasks on a weekly basis. This allows the manipulation of iconic digital objects to configure spatiotemporal characteristics of learning tasks and their workflow.

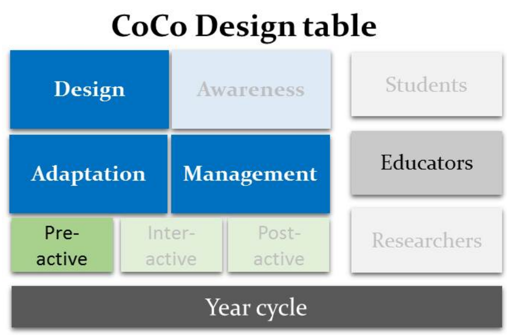

Figure 6: Representation of the CoCo Design Table case according to the elements of the framework. One iteration shows a number of teachers and learning designers redesign candidate subject designs and use an analytics dashboard to compare them back to back.

The dashboard shows live visualizations of the candidate designs created in the surface devices. This information includes a list of the learning tasks added to each candidate design, a pie chart that shows how students' time would be divided among learning spaces (face-to-face and online), and a histogram showing the student's weekly workload (see Figure 7, right). The goal of presenting a dashboard with visualizations of multiple candidate designs is to support teachers' high-level comparison and promote understanding of the impact of substituting certain learning tasks for equivalent tasks on students' workload and direct contact time.

Four teams of three teachers and learning designers participated in an observational lab study. The goal of each team was to produce two high-level candidate designs of a university course, satisficing some competing design goals. Results of the study showed that the dashboard was one of the features that was most valued by participants. It provided an overall view of the tasks within each design and helped most groups in keeping themselves on track toward their design goals by having continuous access to indicators of their designs. Moreover, participants valued the combination of large devices to have a view of the designs, smaller sized tablet devices to seek information as needed, and the dashboard to keep aware of the changes to their designs.

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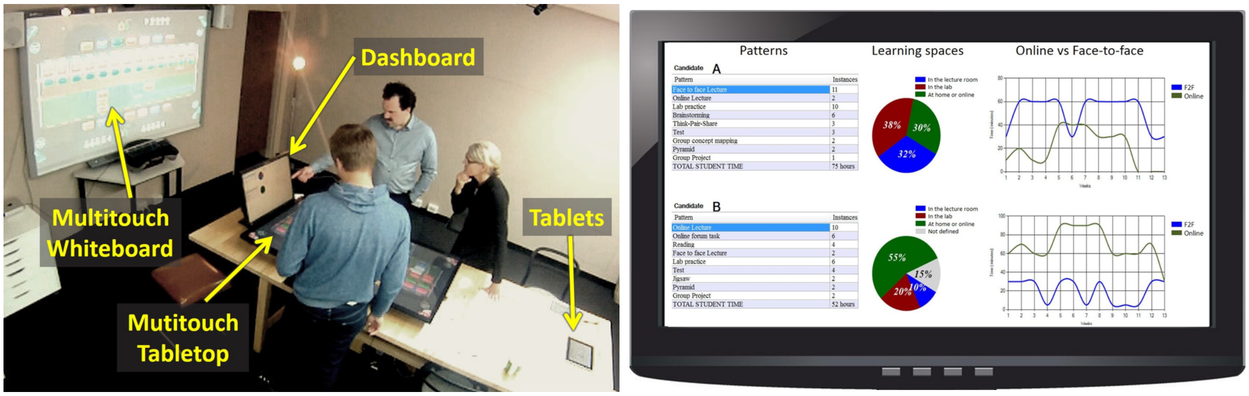

Figure 7. Left: A group of designers looking at the dashboard while designing two candidate designs (A and B) in the Design Studio. Right: The dashboard showing a) the tasks included in each design (left), b) the proportion of tasks by learning space (middle), and c) the weekly distribution of student time between online and f2f work (right).

4.3 Collaborative LA Data Exploration

Collaborative tools have been used to help small groups keep a shared view and articulate their insights more fluidly than with single-user displays. Surface devices can be used to support collaborative reflection on educational data. Next, we describe two case studies of collaborative LA exploration.

4.3.1 Navi Surface

This case study aimed to support students by enhancing their *awareness* about their achievements to help them self-*regulate* their own learning. The approach relies on a student dashboard that can be used in the *inter-active* and/or the *post-active* phases (see Figure 8). Figure 9 (left) and Table 1 (row 4) present how each element of the framework categorizes this case study. The third author and his colleagues used the notion of badges to create Navi Surface (Charleer, Klerkx, Odriozola, Luis, & Duval, 2013). Badges are used to abstract important aspects of student learning processes, including intended learning outcomes and produced artefacts such as blog posts and shared documents.

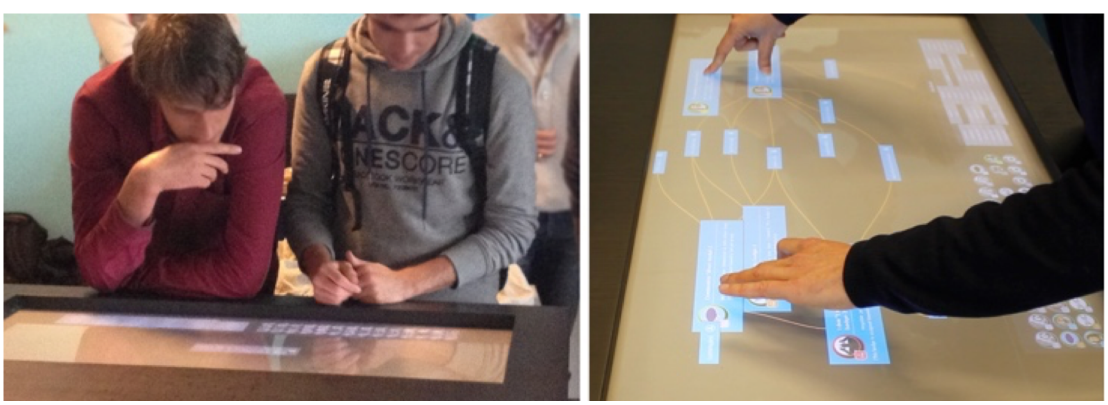

Figure 8: Students using Navi Surface in pairs to explore their achievements through a collaborative badge visualization.

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Navi Surface is a tabletop-based tool that allows teachers and students to navigate student achievements for a university course. Users can navigate through the tool to get more information about how and why badges were awarded to which students, based on the learning traces captured during the course. Multiple items can be accessed simultaneously, enabling group interaction with the data. The teacher can guide the process, for example, by dragging relevant course goals onto the interface to promote discussion about what students have achieved, while students can also interact and steer the conversation.

Navi Surface was evaluated with 14 students (4 groups of 2, 3, and 4 members) who used the tool in groups and individually, and were able to access their badge data and that of others. Preliminary observations showed that the interface promoted engagement, group interaction, and evaluation of achievements. This can be explained as follows: Most dashboards provide a single-user experience, requiring motivation (either intrinsic or extrinsic) from a student to access the LA data. Interactive tabletops can create a more inviting environment and facilitate a shared experience for students and their teachers. The tabletop played a key role as a catalyst for discussion, and participants reported the approach as a fun way to interact collaboratively with LA data. By contrast, when students used the tabletop alone, a more hesitant interaction with the LA data was observed. These observations suggest that the collaborative nature of the tabletop device promoted social discourse for the exploration of student data. Future work is required to test if this increases the chances of constructive reflection by students about their achievements. The setup supports awareness and reflection about personal achievement during the *inter-active* (during course sessions) and *post-active* (for evaluation purposes) phases. Sessions can be repeated during the course to increase awareness of student progress and achievements across sessions.

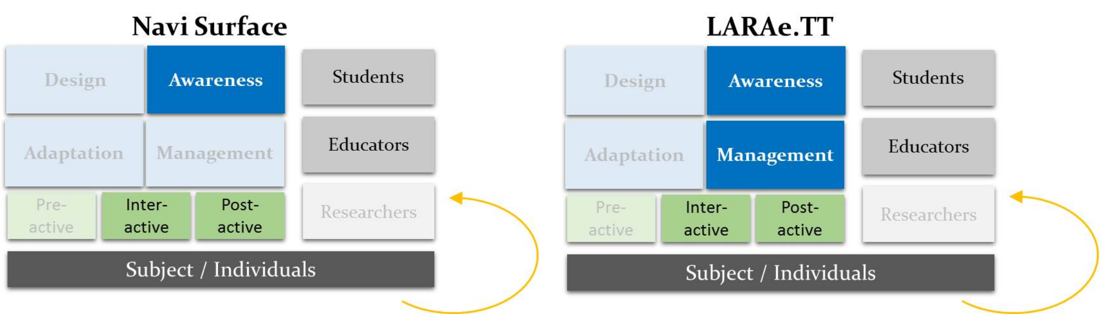

Figure 9. Representation of the Navi Surface and LARAe.TT cases according to the elements of the framework. In both cases, the systems enhanced reflective discussion among students and teachers using large displays for several sessions.

4.3.2 LARAe.TT

The second case study in this section includes the use of LARAe.TT (Charleer, Klerkx, & Duval, 2015). Similar to Navi Surface, this tabletop tool aims to support student *awareness* and reflection in the *inter-active* and *post-active* phase, particularly for inquiry-based learning (IBL) activities. In IBL, teachers encourage learners to pose questions and formulate hypotheses about a given topic, accomplishing independent investigations to support their conclusions. LARAe.TT visualizes the paths that students follow through their inquiry-based learning activities. The tool is grounded on an IBL process model,

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which distinguishes six phases: problem identification, operationalization, data collection, data analysis, interpretation, and communication. Thus, students assume an active role in regulating their own learning as they follow their individual paths. LARAe.TT allows students and teachers to discuss and retrace individual steps taken by students. They can look up related content such as hypotheses formulated, evidence gathered, and so forth.

Figure 10 shows the LARAe.TT interface, with the visual representations of student learning paths in the centre. The application provides a series of drop zones that allow students and teachers to drag activities to see more detail in the form of text or pictures that evidence student activity for a particular IBL phase. Dragging a student name into a personal drop zone (the coloured squares in Figure 10) allows students to explore and filter their data according to the positions of participants at the tabletop.

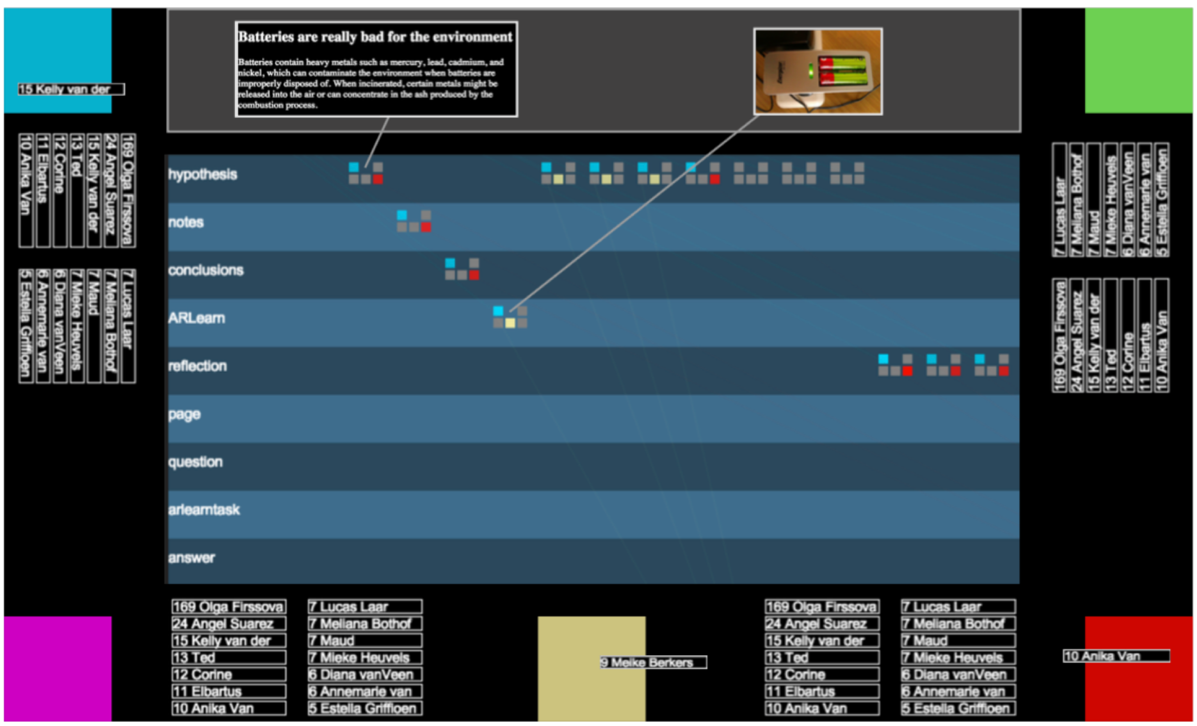

Figure 10. LARAe.TT activities are shown in the centre of the screen. The top drop zone lets users expand an activity to get more detail. Each user has a coloured, personal drop zone for highlighting activities.

LARAe.TT was presented to and evaluated by 15 participants (teachers, students, and researchers) at a workshop. The evaluation explored how the tabletop application can assist both students and teachers during the IBL process. It showed potential to facilitate students assessing their own progress and managing the distribution of their work. LARAe.TT can not only help students explore personal achievements, but can also let them compare, reflect on, and learn from the activities of their peers. Teachers, on the other hand, can invite students to the tabletop to initiate a discussion, intervene, discuss progress, ask for clarification and reasoning, assess activities, and point out peer activities for

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comparison and inspiration. As such, teachers and students can use the tabletop system during evaluation sessions to visualize the history of individual student activities across the entire course. Thus, LARAe.TT can provide support for teachers and students to gain better understanding of their individual learning paths at a *subject level*, from the initial sessions to the final evaluations. Figure 9 (right) and Table 1 (row 5) present how each element of the framework categorizes this case study.

Overall, Navi Surface and LARAe.TT illustrate a very particular orchestration use for interactive surfaces to support reflection and post hoc assessment. The physicality of the tabletop and the design of the interface provide a unique opportunity to support collective f2f exploration of student data with the purpose of facilitating discussion between students and their teacher.

4.4 Multi-Modal Learning Analytics for Researchers

The previous case studies suggest that interactive surfaces provide opportunities to support students' f2f interactions and teachers' orchestrations. At the same time, they also provide researchers with a wealth of information to better understand the nature of social learning in the inter-active and post-active phases: researchers can use many data collection tools to capture student interactions as they learning new concepts by using cameras, microphones, motion sensors, mobile eye-trackers, galvanic skin response sensors, and emotion detection tools. We see interactive surfaces as environments where rich learning episodes can occur, which makes them ideal devices for using multi-modal sensors. We illustrate this idea with the two examples below.

4.4.1 Mobile eye-trackers and joint visual attention

This case study is about capturing a fundamental building block of student interaction: joint visual attention (JVA), known by developmental psychologists and learning scientists to be a pre-requisite for any kind of high-quality collaboration because it allows a group to build common ground to solve a problem effectively. The third author and his colleagues (Schneider et al., 2015) have developed innovative ways to capture JVA around interactive surfaces to provide measures about *individual* and *group* strategies and performance. Their methodology involves using fiducial markers (Figure 11) to remap student gaze onto a ground truth. Since the fiducial markers are part of the tangible interface, the interactive surface becomes an essential part of being able to collect and meaningfully analyze the eye-tracking data. Having both gazes on the same physical plane allowed the researchers to determine whether students were jointly looking at the same location at the same time. They found that the number of times that JVA is achieved is not only correlated with students' quality of collaboration, but also reflects higher performance on the problem-solving task as well as higher learning gains. This kind of data stream allows researchers to generate reliable footprints of collaboration quality, and separate productive from less productive groups of students. This data could potentially be collected in real-time to help teachers decide which groups need attention and which ones do not need help.

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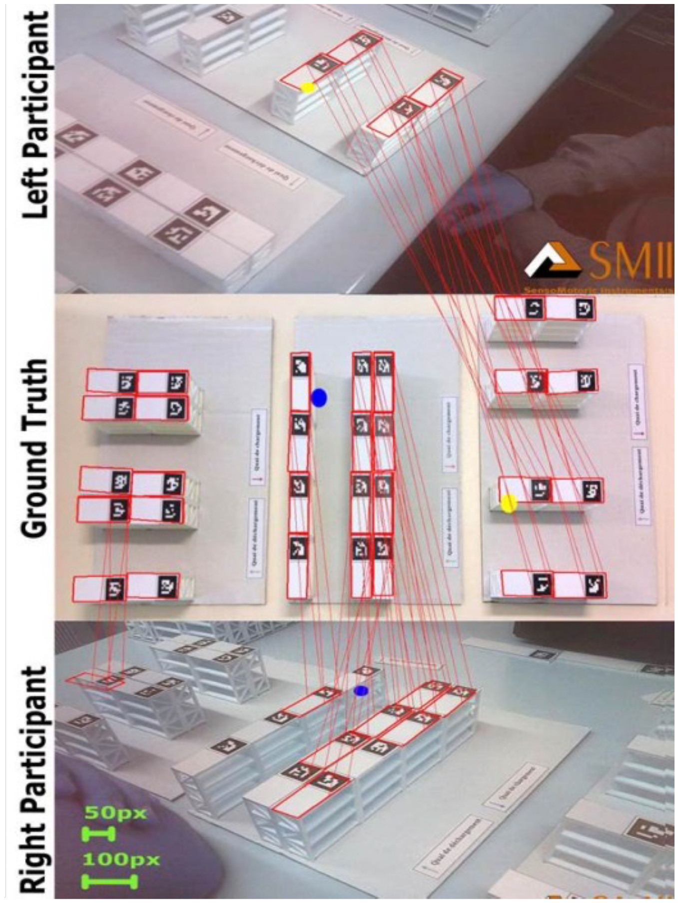

Figure 11: Two students analyzing a static version of a tangible interface. Red lines show the points used for remapping student gazes onto a ground truth (middle figure).

For instance, those authors were able to identify different collaborative interactions by looking at the eye-tracking data in more depth (Schneider et al., 2016). For each moment of JVA, they identified which student was at this particular location first (i.e., who initiated it) and who was there with some lag (i.e., who responded to it). Thus, students in each dyad had a score (in percentage) describing how many moments of JVA they initiated and responded to. By taking the absolute difference of those scores, they obtained a measure (between 0 and 1) describing how groups distributed the responsibility of initiating moments of JVA. Groups with a score of 0.0 were perfectly balanced, while groups with a score closer to 1.0 were imbalanced. This measure ended up being a significant predictor for the group's learning gains, and was found to represent (non-)productive collaborative dynamics in the transcripts. Imbalanced groups were more likely to have passive students who would generally agree with their partners, while balanced groups were more likely to have students who would challenge their partners and negotiate new knowledge in rich ways.

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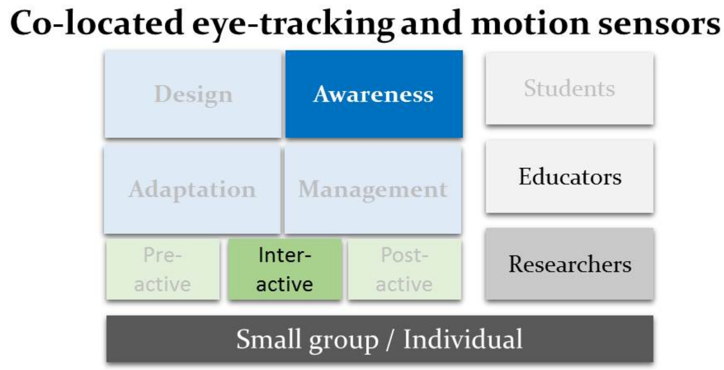

Figure 12. Representation of the Co-located Eye Tracking and Motion Sensors cases according to the elements of the framework. In both cases, the systems helped researchers gain an understanding of small group and individual performance while students collaborate face-to-face.

This last example shows that one interesting aspect of multi-modal sensors is that they allow researchers to more easily go back and forth between qualitative and quantitative data, helping them more easily generate new measures at the sample level. The next step of this line of research is to look at videos augmented with gaze information (Figure 6 shows one frame of this kind of video) to support qualitative analysis of student interactions. This kind of analysis was previously difficult to conduct since it required researchers to position multiple cameras around a group to infer whether two students were simultaneously looking at the same location. Sensors can now provide this information to researchers, which can speed up the pace of qualitative work. Figure 12 and Table 1 (row 6) present how each element of the framework categorizes this case study.

4.4.2 Motion sensors and students' physical mobility

This last case study is about capturing another key aspect of f2f interactions: students' ability to use their physical body to express ideas and manage collaborative processes. These movements can be manually coded or captured using a motion sensor. For example, Schneider and Blikstein (2015b) used a Kinect sensor to collect data from a study conducted with 38 students interacting with a tangible interface, resulting in 1 million data points describing their body postures. They then fed this matrix into a simple clustering algorithm to obtain the following prototypical body positions (active, semi-active, and passive; see Figure 13).

Not surprisingly, they found that the time spent by students in the "active" posture (left graph of Figure 13) was positively associated with their learning gains while the "passive" posture (right graph) was negatively correlated with them. More interestingly, they found that the number of times students transitioned from one posture to another was the strongest predictor for learning. This suggests that the most successful students were the ones who not only acted, but also systematically stepped back to reflect on their actions and think about their next steps. With traditional qualitative approaches, it would have taken months to identify and code this kind of behaviour. Using sensors and unsupervised machine learning, it took a fraction of the time to isolate this productive learning behaviour.

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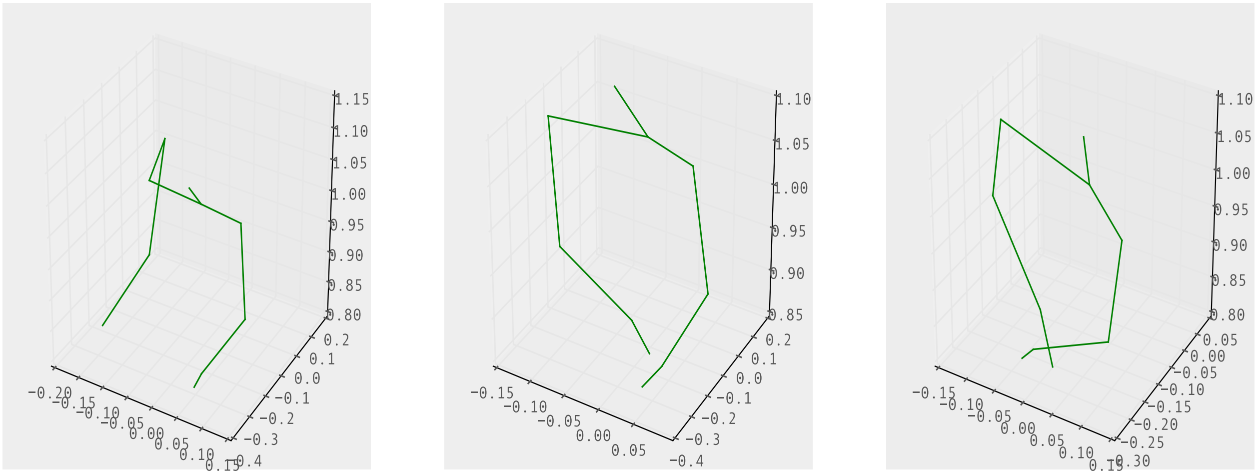

Figure 13: The results of the clustering algorithm on students' body posture. The left centroid is active, with both hands on the table; the middle one is semi-active, with one hand on the table; the right one is passive, with both arms crossed.

In the same study, researchers were also able to identify productive collaborative dynamics. After manually coding each student in the dyad as being the driver or the passenger of the group (i.e., the driver is the person who talks the most, decides what the group does next, and is generally more active; by default, the other person is the passenger), they found that drivers tend to use both hands equally (Figure 14, bottom graph) while passengers tend to use their dominant hand more (Figure 14, top left). Being able to identify roles was important in this study because the composition of the group was associated with different learning gains (Figure 14, top right). The authors created four groups by doing a median split on student grade point average (GPA).

Not surprisingly, groups with two high-GPA students did well on the learning test (first boxplot) and groups with two low-GPA students did poorly (last boxplot). Interestingly, groups with a low-GPA driver did almost as well as groups with two high-GPA students (second boxplot). This is because more proficient students would be less pro-active in this situation, and would give the opportunity to low-GPA passengers to engage themselves intellectually. The high-GPA passenger would guide this process by gently suggesting ideas and by discriminating between fruitful and non-fruitful directions, which benefited both participants. Finally, groups with a high-GPA driver did almost as poorly as groups with low GPA-students (third boxplot): in this case, the high-GPA driver would do all the work in a very quick and efficient way, which would discourage the passenger and create a free-rider effect. This result shows ways to identify collaborative dynamics with sensors automatically, and suggests productive ways to engineer collaborative groups.

In conclusion, results suggest that surface devices, augmented with multi-modal sensors, provide researchers with rich opportunities to collect massive datasets about student learning experiences.

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Those datasets can then be mined using machine-learning algorithms, or used to augment videos and facilitate qualitative analyses of student interactions. Figure 12 and Table 1 (row 7) present how each element of the framework categorizes this case study.

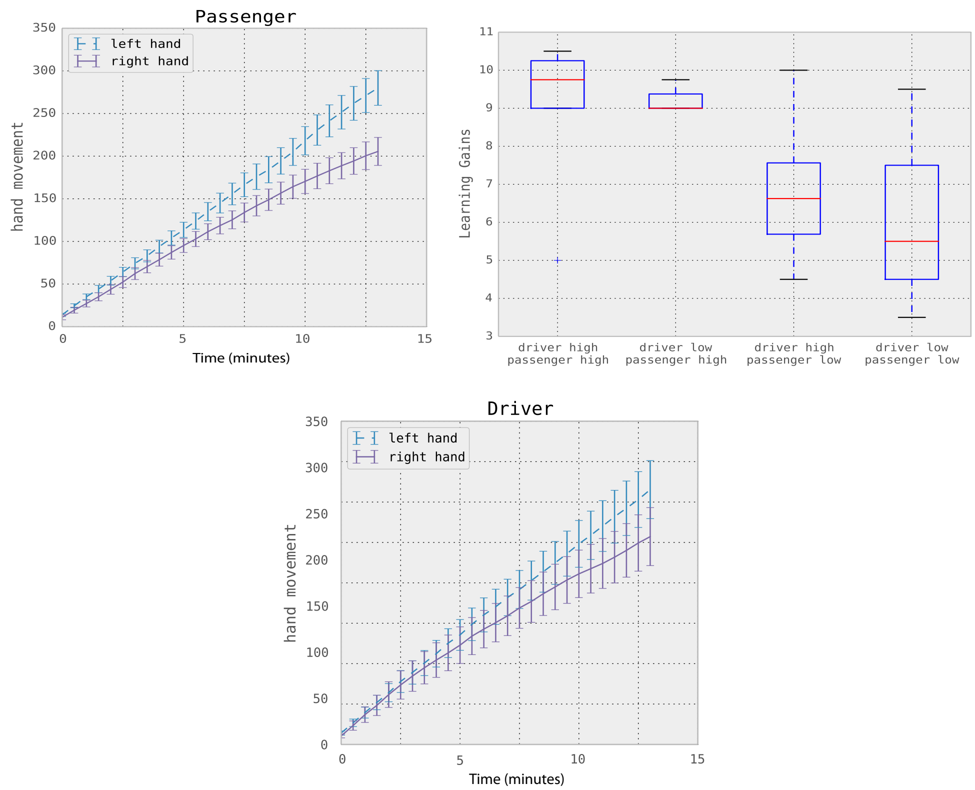

Figure 14: Left side: averaged amount of movement generated by students' hands. Top right: Boxplots of the four kinds of dyads: driver/passenger with high/low GPA. The Y-axis shows the average learning gains of the dyads.

4.5 Other Cases

We also analyzed several other case studies. The first author and colleagues investigated the impact of showing the teacher visualizations about the enactment of the macro-script during a class session through a script awareness tool (Martinez-Maldonado et al., 2015a). This is the only example we are aware of that directly supported the orchestration activities of *adaptation* and *flexibility* to enhance the *management* of the workflow of a multi-surface classroom (see Table 1, row 8).

Do-Lenh's (2012) work was very similar to the first case study described above. His system captured from each small group using multiple tangible tables in a classroom. Next, a public dashboard was displayed on an IWB for all students and their teacher to track their progress on the task, compared with the other groups (see Table 1, row 9).

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Recent work by Wang et al. (2015) proposed similar visualizations of the progress of the task for students working with and sharing tablets (instead of tabletops) (see Table 1, row 10). Similar cases of LA applied to interactive surfaces are slowly emerging to support BYOD (bring your own device) strategies. An example is Learning Catalytics (Schell, Lukoff, & Mazur, 2013), which provides some visual analytics to teachers about student progress and their misconceptions while collaborating in the classroom using tablets or mobiles. The visualization tools offered by this system allow the teacher to keep their students on track throughout the duration of the class (see Table 1, row 10).

5 DISCUSSION

This synthesis of results identifies the degree of maturity, challenges, and pedagogical opportunities of LA and interactive surfaces. We discuss different aspects of the case studies presented above, the implications of defining this design space, the particular affordances of surface devices, and the kinds of analytics that look promising in supporting f2f collaborative learning challenges.

A basic affordance of large surfaces is that (used well) they more readily support the ergonomic (perceptual, physical, cognitive, social) characteristics of groups than small surfaces. Therefore, it is not surprising that group work is a common denominator in most of the cases reviewed, but with the difference in some cases that they support novel kinds of interactivity, and critically, make them traceable. The case studies illustrate varied ways to capture student interactions, enabling teachers to provide enhanced feedback while orchestrating a classroom and permitting the collaborative exploration of student data. The combination of these technologies has the potential to open up new lines of research by allowing automatic processing and mining from large amounts of heterogeneous traces of f2f data (such as physical actions, gaze, body mobility, speech, etc.). Critically, these technologies are not only analytics tools for researchers, but show promise for providing real-time feedback on activity to students and educators. The people who constitute the learning system are provided with data about their own process whereas before they were the object of study by researchers, who were the only people with the tools to capture and render such data. Manually analyzing this kind of f2f data through more conventional video coding and observational approaches is time-consuming. As surface analytics matures, real-time analytics could become practical in authentic classroom settings at runtime.

In the cases reviewed, interactive dashboards and visualizations were the most common ways to show educational data to educators and students. The focus was on providing *information about the task* (Charleer et al., 2015; Charleer et al., 2013; Do-Lenh, 2012; Martinez-Maldonado et al., 2015b; Wang et al., 2015) and *activities of the class* (Martinez-Maldonado et al., 2015a) progress (Case 1), *students' interaction with the shared device* (Case 2) (Martinez-Maldonado et al., 2015b; Martinez-Maldonado et al., 2012; Schneider & Blikstein, 2015b), *the class design* (Martinez-Maldonado et al., 2015c; Martinez-Maldonado et al., 2012), and, to a lesser extent, the *quality of the students' solution* (Case 3) (Martinez-Maldonado et al., 2012). Only two studies provided *notifications* (Martinez-Maldonado et al., 2015b; Schell et al., 2013) to the teacher during the inter-active phase to aid the decision making of the teacher

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in the classroom. Finally, detailed and more complex analytics that give information about more abstract aspects of learning such as *achievement* (Charleer et al., 2013) and *collaboration* (Schneider et al., 2015) have mostly been lab studies (Case 4).

The most suitable tasks for surface technology seem to be those that involve a combination of talk, discussion, manipulation of digital or physical objects in a spatiotemporal representation plane, and/or that require larger sized displays. The tasks in the case studies included collaborative concept mapping (Martinez-Maldonado et al., 2015b; Martinez-Maldonado et al., 2012), brainstorming (Martinez-Maldonado et al., 2015b), team meetings (Martinez-Maldonado et al., 2015b), data exploration (Charleer et al., 2015; Charleer et al., 2013), logistics training (Do-Lenh, 2012; Schneider et al., 2015), and a physiology challenge (Schneider & Blikstein, 2015b). The use of dashboards and visualizations in the classroom is still in its infancy. With the increasing use of digital surfaces in the classroom (e.g., tablets), it will be very common in the near future to see more implementations of systems that visualize key aspects of student activity and/or performance or simply visualize or notify them for cases where students are disengaged, underperforming, or not collaborating with their peers. This information could also be helpful for the students themselves to self-regulate their interaction and learning activities. The use of LA to support learning design is also an underexplored area of application.

The data captured by interactive surfaces and the orchestration technology can also be valuable to facilitate teachers' reflections on their designs (Martinez-Maldonado et al., 2015c; Martinez-Maldonado et al., 2012), even if the time constraints of the class make it challenging to make big changes on the original plan, they can re-design for the following sessions. One case study (Martinez-Maldonado et al., 2012) illustrated how orchestration support can be provided by LA at a macro level of iteration (across sessions), showing analytics about the planned curriculum compared to how it actually occurred. Regarding more complex, multi-modal analytics approaches, the challenge is to feed these data back to students (and teachers) to help them make better informed decisions and to support student collaboration. Gaze awareness tools where students in a remote collaboration can see the gaze of their partner in real time on the screen can be highly beneficial to students. This allows them to monitor the visual activity of their partner and anticipate their contributions, which leads to higher quality collaboration and higher learning gains (Schneider et al., 2015). Visualizations of individual learner traces on shared surface devices can help in bootstrapping dialogue between teacher and students. On the one hand, they allow learners to gain insight into the learning activities of themselves and their peers and the effects these have, while allowing teachers to stay aware of the subtle interactions in their course. In addition, teachers and students can jointly agree on appropriate learning strategies to follow, based on collaborative discussion around real factual data (Charleer et al., 2015).

Table 2 presents an overview of the orchestration activities, actors, and pedagogical phases currently addressed by the analyzed case studies. Emphasis has been placed on supporting the orchestration activities of *awareness* and *assessment* and in the inter-active and post-active phases of the learning activities (rows 2 and 3). By contrast, other cells are empty or populated just by 1–2 exemplars. The empty cells in the table mean that the analyzed cases have not addressed certain orchestration

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activities, targeted some actors, or provided support in some pedagogical phases. For example, the orchestration aspect that refers to *adaptation, flexibility,* and *intervention* has barely been explored in the analyzed cases. Thus, there is potential innovation in developing solutions that, for example, can perform automatic or semi-automatic interventions in student activities. There may be still under-attended actors as well. For example, providing LA tools to enhance student awareness or other orchestration activities in the physical classroom has not been deeply explored. Table 1 (columns 9 and 10) also shows that there is potential to provide iterative support at a macro level. This can include providing continued LA support across sessions — bridging the physical world where interactive surfaces can capture some traces of f2f activity, with the digital remote access to resources. An alternative indicator of the maturity of this area of application is to observe to what extent the LA solutions can be readily deployed in authentic classrooms. Most of the examples analyzed describe lab-based scenarios, indicating that this area is rapidly growing but is still exploratory. The only examples of LA classroom tools mostly supported the orchestration aspect via the teacher's or public dashboards.

Table 2: Maturity of Learning Analytics Applications Utilizing Interactive Surfaces. E=Educators, S=Students, R=Researchers, ^{n}=number of studies

Orchestration activities	Pedagogical phases		
	Pre-active	Inter-active	Post-active
Adaptation		E	
Management		E^2, S^2	E^2, S^2
Assessment	E	R^2, E^4, S^3	E, S
Design	E^2, R		E

Through the data gathered in the *Learning Analytics for Redesign* and *LARAe.TT* case studies, a large historical database regarding activities and achievements can be gathered. This can provide further benefit to teachers to evaluate, plan, and redesign their courses based on collective knowledge accumulated and curated by other teachers from the f2f learning experiences. As a result, the data captured in the micro-layer (e.g., in the classroom) can be valuable in the meso-layer (e.g., for course coordination and learning design of other subjects). By deploying these types of LA tools across different courses, this large LA knowledge database can provide a richer and more accurate, overarching view on courses and students. This can also help institutions improve the synergy between courses, redesigning educational strategies with a global vision. Alongside, historical data can help support students in planning their learning career, while personal progress and achievement information across courses and semesters can facilitate more accurate feedback. Deploying LA surface and tangible tools at a larger scale and performing longitudinal studies may, in the near future, help measure the impact of our approaches to support f2f learning in the meso-layer and eventually also in the macro-layer.

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6 CONCLUSION

This paper has presented a description of the orchestration activities, challenges, and pedagogical opportunities of applying LA solutions utilizing interactive surfaces to facilitate a range of f2f tasks. As illustrated in Tables 1 and 2, this area of research is still immature as the technology is co-evolving alongside pedagogical practices that are beginning to recognize the value that these pervasive devices may offer. Our analysis framework helped to characterize the design space in terms of orchestration activities that need to be addressed, along with the pedagogical phases that teachers or students need to accomplish in order to prepare for classroom sessions. This framework is promising to help decompose other LA deployments, especially for those scenarios that can be complex, involving iterative support across different classroom sessions, and considering different tools, and multiple sessions, LA target users, and orchestration activities.

The paper points to the future work needed to support students directly, exploit further unexplored affordances of interactive surfaces (such as sketching), and also support other orchestration activities, such as adaptation, flexibility, intervention, management, design, and planning. Besides, most LA support through interactive surfaces has focused on providing visualizations and dashboards. Other analytics techniques look particularly promising for surface tools, given the activity data they are able to capture. These may include multi-modal analytics (e.g., traces of physical actions, or LA approaches for tasks that require handwriting and sketching using interactive surfaces), analytics from heterogeneous sources of data (e.g., coming from different devices or education software), and the provision of (semi) automated system interventions, alarms, or feedback.

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REFERENCES

Abad, Z. S. H., Anslow, C., & Maurer, F. (2014). Multi-surface interactions with geospatial data: A systematic review. *Proceedings of the 9th ACM International Conference on Interactive Tabletops and Surfaces* (ITS '14), 16–19 November 2014, Dresden, Germany (pp. 69–78). New York: ACM. https://dx.doi.org/10.1145/2669485.2669505

Apted, T., & Kay, J. (2008). PhoTable: Enhancing the social interaction around the sharing of digital photographs. Paper presented at the CHI '08 Workshop on Collocated Social Practices Surrounding Photos, 5–10 April 2008, Florence, Italy.

Ardito, C., Buono, P., Costabile, M. F., & Desolda, G. (2015). Interaction with large displays: A survey.

ACM Computer Surveys, 47(3), 1–38. https://dx.doi.org/10.1145/2682623

Baraldi, S., Del Bimbo, A., & Landucci, L. (2008). Natural interaction on tabletops. *Multimedia Tools and Applications, 38*(3), 385–405. http://dx.doi.org/10.1007/s11042-007-0195-7

Bowers, J., & Kumar, P. (2015). Students' perceptions of teaching and social presence: A comparative analysis of face-to-face and online learning environments. *International Journal on Web-Based Learning & Teaching Technologies, 10*(1), 27–44. http://dx.doi.org/10.4018/978-1-5225-0783-3.ch073

Brown, J., Wilson, J., Gossage, S., Hack, C., & Biddle, R. (2013). Surface computing and collaborative analysis work. *Synthesis Lectures on Human-Centered Informatics, 6*(4), 1–168. http://dx.doi.org/10.2200/S00492ED1V01Y201303HCI019Buckingham Shum, S. (2012). *Learning analytics*, *policy briefing*. Institute for Information Technologies in Education, UNESCO.

Charleer, S., Klerkx, J., & Duval, E. (2015). Exploring inquiry-based learning analytics through interactive surfaces. *Proceedings of the Workshop on Visual Aspects of Learning Analytics* (VISLA '15), 17 March 2015, Poughkeepsie, NY, USA (pp. 1–4).

Charleer, S., Klerkx, J., Odriozola, S., Luis, J., & Duval, E. (2013). Improving awareness and reflection through collaborative, interactive visualizations of badges. *Proceedings of the 3rd Workshop on Awareness and Reflection in Technology-Enhanced Learning held at EC-TEL '13*, 17 September 2013, Paphos, Cyprus (pp. 69–81).

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5), 318–331. http://dx.doi.org/10.1504/IJTEL.2012.051815

Clayphan, A., Martinez-Maldonado, R., Tomitsch, M., Atkinson, S., & Kay, J. (2016). An in-the-wild study of learning to brainstorm: Comparing cards, tabletops and wall displays in the classroom. Computer Human Adapted Research Group (CHAI), University of Sydney. https://dx.doi.org/10.1093/iwc/iww001

Dillenbourg, P., & Evans, M. (2011). Interactive tabletops in education. *International Journal of Computer-Supported Collaborative Learning, 6*(4), 491–514. http://dx.doi.org/10.1007/s11412-011-9127-7

Dillenbourg, P., & Jermann, P. (2010). Technology for classroom orchestration. In M. S. Khine & I. M. Saleh (Eds.), *New science of learning0* (pp. 525–552). New York: Springer. http://dx.doi.org/10.1007/978-1-4419-5716-0_26

Dillenbourg, P., Zufferey, G., Alavi, H., Jermann, P., Do-Lenh, S., Bonnard, Q., Cuendet, S., & Kaplan, F. (2011). Classroom orchestration: The third circle of usability. *Proceedings of the 9th International Conference on Computer-Supported Collaborative Learning* (CSCL 2011), 4–8 July 2011, Hong Kong, China (pp. 510–517). International Society of the Learning Sciences.

Dimitriadis, Y., Prieto, L. P., & Asensio-Perez, J. I. (2013). The role of design and enactment patterns in orchestration: Helping to integrate technology in blended classroom ecosystems. *Computers & Education, 69*, 496–499. http://dx.doi.org/10.1016/j.compedu.2013.04.004

Do-Lenh, S. (2012). *Supporting reflection and classroom orchestration with tangible tabletops.* PhD dissertation. École Polytechnique Fédérale de Lausanne, Switzerland: CRAFT group, School of Computer Science. http://dx.doi.org/10.5075/epfl-thesis-5313

(2017). Learning analytics for natural user interfaces. *Journal of Learning Analytics*, *4*(1), 24–57. http://dx.doi.org/10.18608/jla.2017.41.4

Ertmer, P. A., Parisio, M. L., & Wardak, D. (2013). The practice of educational/instructional design. In R. Luckin, S. Puntambekar, P. Goodyear, B. Grabowski, J. Underwood, & N. Winters (Eds.), *Handbook of design in educational technology* (pp. 5–19). New York: Routledge.

Evans, M. A., Drechsel, E., Woods, E., & Cui, G. (2010). Multi-touch tabletop computing for early childhood mathematics: 3D interaction with tangible user interfaces. In K. Gomez, L. Lyons, & J. Radinsky (Eds.), *Learning in the Disciplines: Proceedings of the 9th International Conference of the Learning Sciences* (ICLS ’10), Vol. 2, Short Papers, Symposia, and Selected Abstracts, 29 June–2 July 2010, Chicago, IL, USA (pp. 274–275). International Society of the Learning Sciences.

Evans, M., & Rick, J. (2014). Supporting learning with interactive surfaces and spaces. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 689–701). New York: Springer. http://dx.doi.org/10.1007/978-1-4614-3185-5_55

Frisch, M., Heydekorn, J., & Dachselt, R. (2009). Investigating multi-touch and pen gestures for diagram editing on interactive surfaces. *Proceedings of the 4th ACM International Conference on Interactive Tabletops and Surfaces* (ITS ’09), 23–25 November 2009, Calgary, AB, Canada (pp. 149–156). New York: ACM. https://dx.doi.org/10.1145/1731903.1731933

Goodyear, P., & Dimitriadis, Y. (2013). In medias res: Reframing design for learning. *Research in Learning Technology, 21*, 1–13. http://dx.doi.org/10.3402/rlt.v21i0.19909

Goodyear, P., & Ellis, R. (2007). Students’ interpretations of learning tasks: Implications for educational design. In R. J. Atkinson, C. McBeath, S. K. A. Soong, & C. Cheers (Eds.), *ICT: Providing Choices for Learners and Learning* (ASCILITE 2007), 2–5 December, Singapore (pp. 339–346). Australasian Society for Computers in Learning in Tertiary Education. http://www.ascilite.org/conferences/singapore07/procs/goodyear.pdf

Goodyear, P., & Retalis, S. (2010). Learning, technology and design. In P. Goodyear & S. Retalis (Eds.), *Technology-enhanced learning: Design patterns and pattern languages* (pp. 1–28). Rotterdam: Sense Publishers. http://dx.doi.org/10.3402/rlt.v21i0.19909

Gutiérrez Rojas, I., Crespo García, R., & Delgado Kloos, C. (2011). Orchestration and feedback in lab sessions: Improvements in quick feedback provision. In C. Kloos, D. Gillet, R. Crespo García, F. Wild, & M. Wolpers (Eds.), *Towards ubiquitous learning* (pp. 424–429). Berlin Heidelberg: Springer. http://dx.doi.org/10.1007/978-3-642-23985-4_33

Gutiérrez Rojas, I., Crespo García, R., & Delgado Kloos, C. (2012). Enhancing orchestration of lab sessions by means of awareness mechanisms. In A. Ravenscroft, S. Lindstaedt, C. Kloos, & D. Hernández-Leo (Eds.), *21st century learning for 21st century skills* (pp. 113–125). Berlin Heidelberg: Springer. http://dx.doi.org/10.1007/978-3-642-33263-0_10

Higgins, S., Mercier, E., Burd, E., & Hatch, A. (2011). Multi-touch tables and the relationship with collaborative classroom pedagogies: A synthetic review. *International Journal of Computer-Supported Collaborative Learning, 6*(4), 515–538. http://dx.doi.org/10.1007/s11412-011-9131-y

Jermann, P., Zufferey, G., & Dillenbourg, P. (2008). Tinkering or sketching: Apprentices’ use of tangibles and drawings to solve design problems. In P. Dillenbourg & M. Specht (Eds.), *Proceedings of the 3rd European Conference on Technology Enhanced Learning: Times of Convergence: Technologies Across Learning Contexts* (EC-TEL 2008), 17–19 September 2008, Maastricht, The Netherlands

(2017). Learning analytics for natural user interfaces. *Journal of Learning Analytics*, *4*(1), 24–57. http://dx.doi.org/10.18608/jla.2017.41.4

(pp. 167–178). Springer-Verlag. http://dx.doi.org/10.1007/978-3-540-87605-2_19

Kaendler, C., Wiedmann, M., Rummel, N., & Spada, H. (2015). Teacher competencies for the implementation of collaborative learning in the classroom: A framework and research review. *Educational Psychology Review, 27*(3), 505–536. http://dx.doi.org/10.1007/s10648-014-9288-9

Kay, J., Reimann, P., Diebold, E., & Kummerfeld, B. (2013). MOOCs: So many learners, so much potential. *IEEE Intelligent Systems, 3*, 70–77. https://dx.doi.org/10.1109/MIS.2013.66

Kharrufa, A., Martinez-Maldonado, R., Kay, J., & Olivier, P. (2013). Extending tabletop application design to the classroom. *Proceedings of the 8th ACM International Conference on Interactive Tabletops and Surfaces* (ITS '13), 6–9 October 2013, St Andrews, United Kingdom (pp. 115–124). New York: ACM. https://dx.doi.org/10.1145/2512349.2512816

Lee, K., Tsai, P. S., Chai, C. S., & Koh, J. H. L. (2014). Students' perceptions of self-directed learning and collaborative learning with and without technology. *Journal of Computer Assisted Learning, 30*(5), 425–437. http://dx.doi.org/10.1111/jcal.12055

Martinez-Maldonado, R., Clayphan, A., Ackad, C., & Kay, J. (2014). Multi-touch technology in a higher education classroom: Lessons in-the-wild. *Proceedings of the 26th Australian Computer–Human Interaction Conference* (OzCHI 2014), 2–5 December 2014, Sydney, Australia (pp. 189–192). New York: ACM. https://dx.doi.org/10.1145/2686612.2686647

Martinez-Maldonado, R., Clayphan, A., & Kay, J. (2015a). Deploying and visualising teacher's scripts of small group activities in a multi-surface classroom ecology: A study in-the-wild. *Computer Supported Cooperative Work, 24*(2), 177–221. http://dx.doi.org/10.1007/s10606-015-9217-6

Martinez-Maldonado, R., Clayphan, A., Yacef, K., & Kay, J. (2015b). MTFeedback: Providing notifications to enhance teacher awareness of small group work in the classroom. *IEEE Transactions on Learning Technologies, 8*(2), 187–200. https://dx.doi.org/10.1109/TLT.2014.2365027

Martinez-Maldonado, R., Goodyear, P., Dimitriadis, Y., Thompson, K., Carvalho, L., Prieto, L. P., & Parisio, M. (2015c). Learning about collaborative design for learning in a multi-surface design studio. *Proceedings of the 11th International Conference on Computer Supported Collaborative Learning* (CSCL 2015), 7–11 June 2015, Gothenburg, Sweden (pp. 174–181). International Society of the Learning Sciences.

Martinez-Maldonado, R., Goodyear, P., Kay, J., Thompson, K., & Carvalho, L. (2016a). An actionable approach to understand group experience in complex, multi-surface spaces. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI '16), 7–12 May 2016, San Jose, CA, USA (pp. 2062–2074). New York: ACM. https://dx.doi.org/10.1145/2858036.2858213

Martinez-Maldonado, R., Kay, J., Yacef, K., Edbauer, M.-T., & Dimitriadis, Y. (2012). Orchestrating a multi-tabletop classroom: From activity design to enactment and reflection. *Proceedings of the 7th ACM International Conference on Interactive Tabletops and Surfaces* (ITS '12), 11–14 November 2012, Cambridge/Boston, MA, USA (pp. 119–128). New York: ACM. https://dx.doi.org/10.1145/2396636.2396655

Martinez-Maldonado, R., Schneider, B., Charleer, S., Buckingham Shum, S., Klerkx, J., & Duval, E. (2016b). Interactive surfaces and learning analytics: Data, orchestration aspects, pedagogical uses and challenges. *Proceedings of the 6th International Conference on Learning Analytics and Knowledge* (LAK '16), 25–29 April 2016, Edinburgh, UK (pp. 124–133). New York: ACM.

(2017). Learning analytics for natural user interfaces. *Journal of Learning Analytics*, *4*(1), 24–57. http://dx.doi.org/10.18608/jla.2017.41.4

https://dx.doi.org/10.1145/2883851.2883873

Nicolaescu, P., Derntl, M., & Klamma, R. (2013). Browser-based collaborative modeling in near real-time. *Proceedings of the 9th International Conference on Collaborative Computing: Networking, Applications and Worksharing* (Collaboratecom), 20–23 October 2013, Austin, TX, USA (pp. 335–344). IEEE. https://dx.doi.org/10.4108/icst.collaboratecom.2013.254111

Olson, J. S., Teasley, S., Covi, L., & Olson, G. (2002). The (currently) unique advantages of collocated work. In P. J. Hinds & S. Kiesler (Eds.), *Distributed work: New research on working across distance using technology* (pp. 113–136). Cambridge, MA: MIT Press.

Oviatt, S. (2013). *The design of future educational interfaces*. London: Routledge.

Picciano, A. G. (2014). Big data and learning analytics in blended learning environments: Benefits and concerns. *International Journal of Artificial Intelligence and Interactive Multimedia, 2*(7), 35–43.

Prieto, L. P., Dimitriadis, Y., Asensio-Pérez, J. I., & Looi, C.-K. (2015). Orchestration in learning technology research: Evaluation of a conceptual framework. *Research in Learning Technology, 23*. http://dx.doi.org/10.3402/rlt.v23.28019

Prieto, L. P., Dlab, M. H., Gutiérrez, I., Abdulwahed, M., & Balid, W. (2011). Orchestrating technology enhanced learning: A literature review and a conceptual framework. *International Journal of Technology Enhanced Learning, 3*(6), 583–598. http://dx.doi.org/10.1504/IJTEL.2011.045449

Rodríguez-Triana, M. J., Martínez-Monés, A., Asensio-Pérez, J. I., & Dimitriadis, Y. (2014). Scripting and monitoring meet each other: Aligning learning analytics and learning design to support teachers in orchestrating CSCL situations. *British Journal of Educational Technology, 46*(2), 330–343. http://dx.doi.org/10.1111/bjet.12198

Roschelle, J., Dimitriadis, Y., & Hoppe, U. (2013). Classroom orchestration: Synthesis. *Computers & Education, 69*, 523–526.

Roschelle, J., & Teasley, S. (1995). The construction of shared knowledge in collaborative problem solving. In C. O'Malley (Ed.), *Computer Supported Collaborative Learning* (pp. 69–97). Berlin Heidelberg: Springer. http://dx.doi.org/10.1007/978-3-642-85098-1_5

Santos, J. L. (2016). *Exploring learning analytics and learning dashboards from a HCI perspective.* PhD dissertation. KU Leuven, Faculty of Engineering Science.

Schell, J., Lukoff, B., & Mazur, E. (2013). Catalyzing learner engagement using cutting-edge classroom response systems in higher education. *Cutting-edge Technologies in Higher Education, E6*, 233–261. http://dx.doi.org/10.1108/S2044-9968(2013)000006E011Scheuer, O., Loll, F., Pinkwart, N., & McLaren, B. (2010). Computer-supported argumentation: A review of the state of the art. *International Journal of Computer-Supported Collaborative Learning, 5*(1), 43–102. http://dx.doi.org/10.1007/s11412-009-9080-x

Schneider, B., & Blikstein, P. (2015a). Flipping the flipped classroom: A study of the effectiveness of video lectures versus constructivist exploration using tangible user interfaces. *IEEE Transactions on Learning Technologies, 9*(1), 5–17. http://dx.doi.org/10.1109/TLT.2015.2448093

Schneider, B., & Blikstein, P. (2015b). Unraveling students' interaction around a tangible interface using multimodal learning analytics. *International Journal of Educational Data Mining, 7*(3), 89–116.

Schneider, B., Jermann, P., Zufferey, G., & Dillenbourg, P. (2011). Benefits of a tangible interface for collaborative learning and interaction. *IEEE Transactions on Learning Technologies, 4*(3), 222–

(2017). Learning analytics for natural user interfaces. *Journal of Learning Analytics*, *4*(1), 24–57. http://dx.doi.org/10.18608/jla.2017.41.4

232. https://dx.doi.org/10.1109/TLT.2010.36

Schneider, B., Sharma, K., Cuendet, S., Zufferey, G., Dillenbourg, P., & Pea, R. (2016). Detecting collaborative dynamics using mobile eye-trackers. *Proceedings of the 12th International Conference of the Learning Sciences* (ICLS '16), 20–24 June 2016, Singapore (pp. 1346–1349).

Schneider, B., Sharma, K., Cuendet, S., Zufferey, G., Dillenbourg, P., & Pea, R. D. (2015). 3D tangibles facilitate joint visual attention in dyads. *Proceedings of the 11th International Conference on Computer Supported Collaborative Learning* (CSCL 2015), 7–11 June 2015, Gothenburg, Sweden (pp. 158–165). International Society of the Learning Sciences.

Scott, S. D., Grant, K. D., & Mandryk, R. L. (2003). System guidelines for co-located, collaborative work on a tabletop display. *Proceedings of the 8th European Conference on Computer Supported Cooperative Work* (ECSCW 2003), 14–18 September 2003, Helsinki, Finland (pp. 159–178). Springer.

Sharples, M. (2013). Shared orchestration within and beyond the classroom. *Computers & Education, 69*(1), 504–506. http://dx.doi.org/10.1016/j.compedu.2013.04.014

Siemens, G. (2012). Learning analytics: Envisioning a research discipline and a domain of practice. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (LAK '12), 29 April–2 May 2012, Vancouver, BC, Canada (pp. 4–8). New York: ACM. https://dx.doi.org/10.1145/2330601.2330605

Siemens, G., & Baker, R. S. J. d. (2012). Learning analytics and educational data mining: Towards communication and collaboration. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (LAK '12), 29 April–2 May 2012, Vancouver, BC, Canada (pp. 252–254). New York: ACM. https://dx.doi.org/10.1145/2330601.2330661

Soller, A., Martinez, A., Jermann, P., & Muehlenbrock, M. (2005). From mirroring to guiding: A review of state of the art technology for supporting collaborative learning. *International Journal of Artificial Intelligence in Education, 15*(4), 261–290.

Stahl, G. (2006). *Group cognition: Computer support for building collaborative knowledge*. Cambridge, MA: MIT Press.

Steinberg, G. (2012). *Natural user interfaces.* Paper presented at the SIGCHI Conference on Human Factors in Computing Systems (CHI '12), 5–10 May 2012, Austin, TX, USA. https://www.cs.auckland.ac.nz/courses/compsci705s1c/exams/SeminarReports/natural_user_interfaces_gste097.pdf

Tchounikine, P. (2013). Clarifying design for orchestration: Orchestration and orchestrable technology, scripting and conducting. *Computers & Education, 69*(1), 500–503. http://dx.doi.org/10.1016/j.compedu.2013.04.006

Tracey, M. W., Hutchinson, A., & Grzebyk, T. Q. (2014). Instructional designers as reflective practitioners: Developing professional identity through reflection. *Educational Technology Research and Development, 62*(3), 315–334. http://dx.doi.org/10.1007/s11423-014-9334-9

Twiner, A., Coffin, C., Littleton, K., & Whitelock, D. (2010). Multimodality, orchestration and participation in the context of classroom use of the interactive whiteboard: A discussion. *Technology, Pedagogy and Education, 19*(2), 211–223. http://dx.doi.org/10.1080/1475939X.2010.491232

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard

(2017). Learning analytics for natural user interfaces. *Journal of Learning Analytics*, *4*(1), 24–57. http://dx.doi.org/10.18608/jla.2017.41.4

applications. *American Behavioral Scientist, 57*(10), 1500–1509.

Wang, P., Tchounikine, P., & Quignard, M. (2015). A model to support monitoring for classroom orchestration in a tablet-based CSCL activity. In G. Conole, T. Klobučar, C. Rensing, J. Konert, & É. Lavoué (Eds.), *Design for teaching and learning in a networked world* (pp. 491–496). Springer. http://dx.doi.org/10.1007/978-3-319-24258-3_45

Wigdor, D., & Wixon, D. (2011). *Brave NUI world: Designing natural user interfaces for touch and gesture*. Elsevier.