# Studying collaborative learning space design with multimodal learning analytics

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*Milica Vujovic*
*(Милица Вујовић)*
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*To my parents*

*To my brother*

*To Drago*

# Abstract

Research has provided relevant advances regarding evidence-based design for productive learning. For example, in the field of collaborative learning, there is extensive evidence about some key learning design elements, such as about methods to structure the sequence of activities, about group formation techniques or about technology mediating collaboration. However, advances have been more limited in the line of evidence-based design of collaborative learning physical spaces. Contradictorily, research on learning spaces and their impact on teaching and learning have been a field of inquiry for decades. Existing studies have explored how learning spaces can have a role in inhibiting or encouraging students' participation in active learning tasks, such those applying collaborative learning methods. But the methods used in these studies have provided limited empirical evidence about the effects of specific design elements of collaborative learning spaces on students' behaviours. In this context, technology advances regarding data capture and analysis tools open new opportunities and challenges to overcome this lack of evidence. In particular, Multimodal Learning Analytics (MMLA) approaches are seen with increasing potential to advance learning space research.

This dissertation contributes to emerging MMLA research aiming at disentangling the effects of space design elements and their interaction with other learning design elements, to help advance the evidence-based design spectrum towards more fruitful learning. In particular, the thesis focuses on the interaction of *table shapes* in learning spaces with the *group size* learning design element. The dissertation also explores the relevant, but often neglected, *gender perspective*. An experimental design methodology is applied with the aim to answer research questions related to (1) the difference in students' behaviour when two table shapes and two group sizes are used, (2) indicators relevant for collaborative learning space research and (3) data collection, analytical and visualization techniques. Contributions include first empirical evidence about the influence of the table shape on student behavior, with effects arising from the interaction of table shape with group size and student gender. Moreover, the dissertation offers a new case that discusses MMLA indicators in this field and explores how motion capture, temporal analysis and aggregated visualization can contribute to collaborative learning space research.

## Resumen

Ha habido avances importantes en la investigación en el ámbito del diseño para el aprendizaje efectivo basado en evidencias. Por ejemplo, en el ámbito del aprendizaje colaborativo, se han conseguido evidencias sobre algunos elementos importantes de su diseño, como los métodos para estructurar las secuencias de actividades, las técnicas de formación de grupo o la tecnología que media la colaboración. Sin embargo, el avance ha sido más limitado en el área del diseño de los espacios físicos para el aprendizaje colaborativo. Contradictoriamente, la investigación sobre los espacios de aprendizaje y su impacto en la educación han sido objeto de investigación durante décadas. Estudios existentes han explorado cómo los espacios de aprendizaje juegan un papel en inhibir o favorecer la participación de los estudiantes en tareas de aprendizaje activo, como las que aplican métodos de aprendizaje colaborativo. Sin embargo, los métodos utilizados en estos estudios han generado muy pocas evidencias empíricas sobre los efectos que elementos específicos de esos espacios tienen en el comportamiento de los estudiantes. En este contexto, los avances en las tecnologías para la captura y el análisis de datos ofrecen nuevas oportunidades, y retos, para cubrir esta falta de evidencias. En particular, el potencial de la Analítica de Aprendizaje Multimodal (MMLA, de sus siglas en inglés) se está vislumbrando como especialmente prometedor para avanzar la investigación sobre los espacios de aprendizaje.

Esta tesis doctoral contribuye al campo emergente de MMLA con el objetivo de desgranar los efectos de los elementos de diseño en los espacios de aprendizaje y su interacción con otros elementos de diseño para el aprendizaje. El objetivo último es ampliar el espectro del diseño basado en evidencias para el aprendizaje efectivo. Para ello, la tesis se centra en estudiar la interacción de las formas de las mesas con el tamaño de grupo, como elementos de diseño sobre el espacio y sobre el método de aprendizaje. La tesis también explora la perspectiva de género, una perspectiva relevante pero no suficientemente considerada en el ámbito. La metodología empleada es de diseño experimental y se plantean preguntas de investigación relacionadas con: (1) las diferencias en el comportamiento de los estudiantes cuando se utilizan dos tipos de mesas y tamaños de grupo; (2) los indicadores de analítica de aprendizaje relevantes en la investigación de espacios de aprendizaje colaborativo; (3) las técnicas para la recogida, el análisis y la visualización de datos. Las contribuciones de la tesis

incluyen unas primeras evidencias científicas sobre la influencia de las formas de las mesas en el comportamiento de los estudiantes, considerando la interacción con el tamaño de grupo y el género. Además, la tesis también ofrece un nuevo caso de recogida de datos que permite revisar la validez de indicadores MMLA propuestos en el campo y explorar como aproximaciones de captura de movimiento, análisis temporal y visualización avanzada pueden contribuir a la investigación en espacios para el aprendizaje colaborativo.

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# Chapter 1 - Introduction

## 1.1 Introduction

Learning space is a still insufficiently researched area, especially in the field of collaborative learning (Byers et al., 2018; Beckers et al., 2015; Sutherland & Sutherland, 2010; Cukurova et al, 2020), that requires advanced research and analytical methods. One such approach, Multimodal Learning Analytics (MMLA), has recently shown promise as a tool for learning space research (Healion et al, 2017; Martinez-Maldonado et al, 2020), as it provides comprehensive insight into learning processes and behaviours (Ochoa & Worsley, 2016; Blikstein & Worsley, 2016) by using computational approaches to collect and analyse data of various modalities (Cukurova et al, 2020). This dissertation lies at the intersection between three research fields (learning space, collaborative learning, and MMLA), which determines the context within which research questions are framed and a research methodology is established.

The motivation for this dissertation stems from the personal interests that have emerged from years of multidisciplinary experience in the field of architecture and the sensing technologies applied for the improvement of interior spaces. Also, additional interest arose from years of practice in education that showed the lack of a common language between educational and architectural practice in creating spaces that are better adapted to specific learning designs. Furthermore, in witnessing the possibilities of technology, a challenge has emerged to combine different fields that will contribute to the exploration of learning space. Finally, as space is capable of shaping social interactions and practices (Lefebvre & Nicholson-Smith, 1991; Massey & Whitt, 1994), it is therefore worth exploring in the context of education.

Starting with architecture as a primary interest, it has been clear that architectural design has not generated enough scientific evidence when it comes to designing learning spaces (Gislason, 2010; Picus et al, 2005; Schneider, 2002). Architectural research is usually reduced to the study of pre-existing examples (Martin, 2002; Schneider, 2002), which is a legitimate approach. However, this means that research actually takes place after the construction of the space. These surveys, usually informal, are normally kept within the local bounds of a single architectural practice or, at best, inform those specific designers to advance future projects. However, conclusions rarely go beyond these local frameworks and so in most cases do not reach a wider audience or the research public.

Certain types of space have been explored to a greater extent than others. Hospitals (Fernandez Nieto, 2021; Joseph & Rashid, 2007; Donetto et al, 2017) and transport terminals (Shuchi et al, 2018; Gharehgozli et al, 2019) are often the subject of studies to improve their functioning. Lately, educational spaces have also been the focus of research (Gislason, 2010; Martinez-Maldonado et al, 2020), but the methodologies are as diverse as the contexts in which the research is conducted. The gap that exists in learning space research will be discussed in more detail and the groundwork that preceded the definition of the research questions will be described in the following sections.

In order to research learning space, certain tools and techniques are necessary. As in any field, technology has afforded a number of opportunities that provide new research perspectives. However, the variety of possibilities can also lead to limitations and the challenge is to select adequate technology. As the answer to this challenge is not immediately apparent, research is necessary to discover which methodology and technology have the ability to provide an insight into the impact of space on user behaviour. Through the interplay of findings in the literature (on collaborative learning spaces and multimodal learning analytics), and the motivation previously mentioned, the experimental design methodology was established. Thus, the research presented in this dissertation aims to explore collaborative learning spaces by applying an experimental design research methodology to answer the research questions.

This research addresses not only the field of education, or more specifically technology in education, but also other areas that rely on the study of learning space. These include architecture, furniture design, and the social sciences, among others. However, the dissertation adopts an approach from the perspective of Learning Analytics, which uses data about learners and the contexts that surround them in order to understand and optimise the learning process and learning environment (Siemens, 2012). Specifically, interest in collaborative learning spaces has become a narrow topic of interest, firstly because it represents an innovative approach that is increasingly present in practice. In this way, students encounter an environment similar to the one that awaits them after their education in the professional world. The collaborative skills they acquire become necessary for any discipline. Another influence on the specific interest in collaborative learning spaces is the complexity of collaborative learning (Kirschner et al, 2011) and the needs it has in terms of the space in which it takes place (Carvalho et al, 2020).

Two major data collection scenarios were performed through experiments and form the basis of the dissertation. The first chapter explains in detail how the research has been organised around data collection scenarios. They are a result of previously established research questions defined on the basis of the literature ('Theoretical framework' section) and described in detail ('Research question' section). After formulating the research questions, a methodology based on experimental design was developed, which is described in more detail in the 'Research methodology' section. This section also covers the detailed methods used during the research, results after the experiments, and the discussion that followed. Examined in detail are how the collected data were analysed by employing different techniques as well as how the results were presented and discussed in view of the research questions. The next chapter, 'Main contributions', examines the contributions, together with the publications and projects, related to the work in the dissertation. 'Limitations, Conclusion, and Future Work' are the last sections in the first chapter of the dissertation. The next five chapters (from Chapters 2 to 6) present papers that were published in journals or conferences, in addition to submitted papers that combine the research work conducted as part of the dissertation.

## 1.2 Theoretical Framework

There are multiple factors that can affect student behaviour in collaborative learning activities. Key factors can range from the learning scenario design to students' individual or common characteristics. In terms of learning scenario design, factors include the formulation of the epistemic task, the social (group design), and the set (place, tools, artefacts) arrangements (Goodyear & Carvalho, 2014). In terms of student characteristics, examples of factors are sociocultural background, prior knowledge, and gender (Prinsen et al., 2007). Research on collaborative learning has provided evidence about how the interplay between different factors affect the processes of collaboration (Janssen & Kirschner, 2020). The main body of evidence in this line has essentially focused on student, group, task, and technological characteristics. While there has been research considering the influence of factors related to the physical context, the existing findings are inconsistent and framed in limited scenarios for data collection (Cukurova et al., 2018).

With the aim of contributing to emerging MMLA research that seeks to disentangle the effects of collaborative learning space design elements and their interaction with other factors affecting student behaviour in collaborative learning activities, this dissertation focuses on the shape of shared tables as a specific element in the physical design of collaborative learning environments and analyses how it affects student behaviour in their interplay with group design and gender factors. The theoretical framework of this dissertation considers the three main knowledge areas outlined below.

Section 1.2.1 explains how research on learning spaces and their impact on teaching and learning have been a field of inquiry for decades. It surveys previous studies supporting the notion that space plays an important role in (collaborative) learning processes, but with limitations deriving from the methods used, as they provided limited empirical evidence about the effects of specific design elements of collaborative learning spaces on student behaviour.

Section 1.2.2 reviews other factors affecting collaborative learning processes. In particular, when considering key learning design elements related to the pedagogical methods, the dissertation focuses on group size as a relevant design factor. In relation to student characteristics, the focus is on the gender perspective.

Finally, section 1.2.3 concentrates on Multimodal Learning Analytics (MMLA) and its potential to advance learning space research. Specifically, it reviews previous studies in the field of learning spaces with a focus on collaborative learning and multimodal learning analytics in order to identify the challenges and gaps that exist. The intersection of the aforementioned fields reflects the specific context in which this dissertation is situated. Narrowing the topic through the identification of gaps will also be discussed to clarify the path that led to the formulation of the research questions.

### 1.2.1 Collaborative learning spaces and furniture

Research in the field of learning spaces has been carried out for many years. Barnard (1854) was among the first to systematically examine learning spaces by studying a series of classroom arrangements and mapping the position of teachers in relation to space, with the aim of establishing the connection with student attention. In a later study conducted by Rubin (1972), the relationship between seating arrangement and communication between teachers and students was analysed further. Although not conclusive, the findings suggested that there is a relationship between seating arrangements and pretested IQ scores (Rubin, 1972). By the end of the twentieth century, multiple studies were concerned with exploring the learning space. Gunter et al. (1995) published recommendations for the proxemics based on the detected movement strategies of teachers and their interaction with students. These included recommendations for the proximity of teachers to students, students to students, and to general teacher monitoring of their own movement patterns. Furthermore, Burda & Brooks (1996) reported how students sitting in the first rows, as opposed to those sitting in the back, had higher motivation scores at the beginning of the course and maintained them until the end. In more recent times, instructional proxemics has been used even more often as a term referring to the effects of the physical space of the learning environment on the student learning process (McArthur, 2015). The study cited indicates that learning space impacts student learning in terms of students' behaviour, affect, and cognitive learning and the use of the space is shaped mainly by the way a teacher is able to moderate his/her actions.

When considering more specific educational contexts, recently developed teaching practices and emerging technologies have created a need for new configurations of learning space. The new basis for learning models is team teaching and collaborative learning (Carvalho et al., 2020). However, research in the field of learning spaces reveals that there is insufficient examination of the transition between the traditional classroom and innovative learning spaces (Byers et al., 2018). A pedagogical change that introduced collaborative learning has shaped activities and behaviours in a new way. Byers et al. (2018) state that it is difficult to understand how teachers navigate through these changes between learning spaces. In their study, using real-time observation metrics, the authors report that changes in space affected elements of teachers' pedagogical practice and student activity. Blackmore (2011) offers an interesting perspective in his review by addressing connections between learning space, teacher practices, and student learning by defining four stages of research: the design phase, implementation and transition phase, consolidation phase, and re-evaluation phase. However, there is insufficient empirical evidence linking theses phases to student perception, effects, and use of space. Creating a conceptual framework connecting learning space and learning theories, Beckers et al. (2015) attempted to clarify the alignment of learning spaces to the changing educational context. Their conclusion was that **changes in education are much faster than what learning spaces can accommodate**. In further research (2016), the same authors address the learning space preferences of higher education students, in the belief that the physical learning space contributes to the outcome of their learning activities. In their study, the researchers examined both individual and collaborative learning. In both cases, quiet spaces are the preferred option and this preference is even more pronounced in the case of collaborative learning. The same study also concludes that the aesthetic component is not as relevant as comfort or a high level of autonomy in quiet environments. Finally, they raise the point that collaborative space is a specific learning environment that requires additional research.

Focusing on collaborative learning space, the authors of various studies have presented the difference between traditional classrooms and spaces for collaborative learning. In traditional classrooms, learning content is packed and delivered to students in the form of presentations (Brown & Long, 2006). Attention control is largely assigned to students, which often requires avoiding distracting thoughts and looking for suitable spaces that can facilitate this (Zumbrunn et al., 2011). This requires new spatial forms such as project rooms or small group work spaces that are, for example, configured adequately to support active learning models (Fisher, 2005). In other words, the goal of the new spaces is to include features that will encourage interaction between people as well as innovation in learning activities by encouraging shared reflection and inquiry, as well as developing various perspectives, among other practices. Sutherland & Sutherland (2010) examine these new learning spaces centred on new collaborative learning models and point out the **importance of understanding the participant behaviour in the space in which learning takes place**.

In addition, students at different developmental levels tend to behave differently when working in different physical spaces (Kumar et. al., 2008). For example, the differing physical characteristics of a space can have a disruptive effect by increasing the time of off-task actions during learning activities in the case of younger students (Godwin & Fisher, 2011). With older students, the impact of space on behaviour, progress in learning, and involvement has also been demonstrated in several studies (Midgley, 2006; Pai et al., 2014)

If we look deeper at specific aspects of physical learning spaces, seating arrangements and classroom layout have a strong connection with the deployment of educational resources (Yuan, et. al., 2017). For example, shared seating is one of the forms of social bonding, as it uses spatial structures to encourage interaction and thus promote collaboration (Croker, et. al., 2015). Conversely, other forms of spatial structures such as non-transparent partitions in combination with desks arranged in grids limit awareness between students in co-located learning contexts (Yee & Park, 2005). Furthermore, the different geometric shapes, colours, and lighting used in the interior design of a learning space have been shown to have an impact on student behaviour (Francis & Raftery, 2005; Blinne, 2013; Colbert, 1997). For instance, when applied in active learning spaces, round tables for multiple students encourage more on-task actions by students (Brooks, 2012). On the other hand, rectangular tables arranged in rows are more suited to lecture-type activities (Brooks, 2012). Lastly, studies have shown that the very perception of the space by students influences their behaviour, learning progress, and engagement during learning activities (Pai, et al., 2014; Midgley, 2006).

A review of the literature indicates the problems revealed by the research base on learning space. First of all, changes in the domain of education and new learning models, such as collaborative learning, emerge much faster than what learning spaces can accommodate. Furthermore, collaborative learning requires specific spatial characteristics and the relationship between learning design and learning space is still insufficiently explored. In order to understand the needs that arise in terms of learning space, understanding the behaviour of participants in the learning process for which space is provided is necessary. Accordingly, exploring collaborative learning space requires knowledge of the characteristics of collaborative learning.

### 1.2.2 Group Size and Gender in Collaborative Learning

Collaboration is a fundamental skill in modern society (de Lima & de Souza, 2017; Häkkinen et al., 2017). Moreover, in the field of education, collaborative learning has become a widely accepted pedagogical method (Roschelle, 2020). Orchestration of collaboration by teachers is influenced by the physical space because it involves coordinating the needs of learning tasks through different social levels (individual work, group work, whole class) with student actions, who often interact with physical artefacts (eg tables) in the classroom (Alavi & Dillenbourg, 2012). In other words, there are extrinsic constraints that arise from the educational context that have been neglected in studies of the orchestration of collaboration that takes place in the classroom (Dillenbourg & Tchounikine, 2007). Unlike intrinsic constraints associated with a pedagogical method, such as group formation or sequencing of tasks, extrinsic constraints involve a classroom layout that was once inconsistent with learning design (Goodyear & Carvalho, 2014; Pérez-Sanagustín, et. al., 2012).

Research on collaborative learning space cannot observe the intrinsic and extrinsic constraints of educational contexts separately. Among the different factors affecting these constraints, as explained above, the thesis focuses on one learning design factor and one personal characteristic: group size and gender. Numerous studies in the field of collaborative learning have focused on **group size** and interaction dynamics. Although a large number of studies claim that smaller groups are more efficient, the differences between dyads and triads and the superiority of one group size over another has split opinion. What is characteristic of both of these group sizes is the ability to develop expert/novice patterns, which is important for the collaborative process (Edstrom, 2015). However, studies indicate that differences do exist between dyads and triads. With dyads, studies have found that two group members tend to use equipment optimally when engaged in practical tasks, which leads to more efficiency (Shanks et al., 2013). However, these findings should be interpreted carefully, as according to Crook and Beier (2010), this efficiency could also be related to the task itself. On the other hand, Pieira-Diaz et al. (2019) argue that dyads are often considered as peer-learning, while triads can generate real collaboration. This is explained by triads' capacity to trigger coalitions, negotiations, majority/minority influence, and conflict, which can all be beneficial for learning. In addition, Wiley and Jensen (2006) examine the pros and cons of both dyads and triads in a mathematics course. They point out that triads can encourage new perspectives and improve problem-solving activities, while also allowing members to resolve conflicts more often than in dyads. In any case, the conclusion is that, in this particular context, triads outperformed dyads Like many studies, this dissertation does not attempt to provide a generic answer to questions about group size, but focuses on a very specific context and contributes to a better understanding of differences between different group sizes in terms of the influences of the space.

Various student characteristics can affect collaborative learning activity (Prinsen et al., 2007). The relationship with gender, as a student characteristic, has been shown to have an impact on collaboration (Janssen & Kirschner, 2020), though the interaction of this factor with the environment is still insufficiently explored. Accordingly, this dissertation examines the influence of the physical space on the behaviour of students of different genders who participate in collaborative learning activities. The research that does exist shows that group formation, in terms of gender composition, clearly influences learning outcomes. Cen et. al. (2016) report that heterogeneous groups of mixed genders and diverse skills benefit more from collaborative learning than homogenous groups. The literature also shows that female-only and balanced-gender groups tend to be better suited to collaborative learning activities (Zhan et al, 2015; Cen et al., 2014). If we look at students individually, research conducted by Stump et al., (2011) presents findings where female students used collaborative learning strategies more frequently compared to their male peers. Another interesting finding on female students is that they more frequently seek help from other students during collaborative activity (Seymour & Hewitt, 1995). In addition, there is evidence that female students tend to respond better to verbal stimuli when working in a mixed-gender group (Zeldin & Pajares, 2000). In direct comparison, another study investigated how students' individual learning performances and knowledge elaboration processes in Computer-Supported Collaborative Learning vary when dyads where composed differently in terms of gender (Ding et al., 2011). This study found that female-only dyad participants outperformed female peers in mixed-gender dyads, while this difference was not observed with male participants. Furthermore, Vogt et al. (2007) report how female students experienced disrespect from male students in engineering study programs.

### 1.2.3 Multimodal Learning Analytics in learning space research

The literature defines Multimodal Learning Analytics in different ways. One is as the study of a variety of learning-related constructs using multimodal data capture and signal processing in a complex learning environment (Ochoa & Worsley, 2016). Blikstein & Worsley (2016) describe MMLA as a combination of multiple data processing techniques that enables a more holistic insight into learning processes and behaviours. Cukurova et al. (2020) emphasise how MMLA uses computational approaches to collect and analyse data from various modalities from physical and digital environments. Additionally, multimodal data sets enable the simultaneous collection of data that crosses the boundaries between human body actions (subtle body language), mind actions (neurobiological processes), and interactions with the environment (physical actions) (Järvelä et al., 2019). The main feature of multimodal data is that it is derived from various subjective (self-reports) and objective (log data, physiological measures, etc) channels (Järvelä et al., 2019). Overall, multiple data sources and data types are used with advanced analytical techniques in order to make meaningful progress in learning analytics.

What is important for MMLA is that the literature points to one of the main goals of this field, which is the ability to study collaborative, realistic environments that are not computer mediated (Ochoa & Worsley, 2016). It is not just automation and a desire to examine the use of technology in a new context that determines the use of MMLA. Measurement of physiological parameters, for example, is one aspect that is impossible to perceive without the use of technology (Malmberg et al., 2019). Even in the detection of movement, it has been shown that it is possible to detect aspects with the help of technology that are not easy to identify during observations (Cukurova et al., 2018). So, in addition to automation and advanced computational techniques, MMLA actually offers unique insights into deeper layers of behaviour. Thanks to the availability and affordability of high-frequency data devices, data can be collected and analysed in order to obtain information about the learning process that has not been available so far, thereby contributing to the field of learning analytics and learning design. The studies presented in this section cover research on MMLA in collaborative learning contexts and on learning space. The specific contextualisation of applying MMLA in these areas helped to establish research methodologies for applying MMLA in understanding the collaborative learning space.

The aforementioned learning space studies, which show the development of this specific area, used different types of data to conduct the research. Multimodality was present at a certain level from the very beginning, although the application of technology was limited by the degree of its development at that time. However, the intersection of different types of data and analysis techniques have created the basis for the development of MMLA as it exists today. As we have seen, the first studies of learning spaces can also serve as examples of the development of MMLA in this domain. Barnard (1854) used observations, illustrations, and maps as the primary tools to investigate teachers' interactions with the classroom space. In the later study, conducted by Rubin (1972) the relation between seating arrangement and the communication between teachers and students was studied. Social and physical interactions were observed, the results of which were later triangulated with the answers from student questionnaires. At the end of the twentieth century, multiple studies were concerned with exploring the learning space. What followed was the addition of new modalities and expansion of the research process with new types of data. Gunter et al. (1995) used video recordings and observations in order to detect the movement strategies of teachers while circulating through the classroom and later analysed the interactions between teacher and students. Another study that examined the position and physical distances between teachers and students aimed to identify student motivation and used surveys (Burda & Brooks, 1996).

MMLA techniques are diverse and focus primarily on the actions performed by the participants in the learning process, such as facial expressions, verbal intonation, eye gaze, physiological measures, etc (Blikstein & Worsley, 2016). However, other contextual aspects have received less attention, such as those related to the physical space in which learning takes place (Martinez-Maldonado et al., 2018). MMLA, with the help of increasingly affordable ubiquitous devices and multimodal sensors, can increase the speed of analysing emerging large data sets (Martinez-Maldonado et al., 2018). By doing so, new opportunities open up in terms of studying learners' proximity, movements, and location, but also of the need for theoretical foundations to align new analytics with pedagogical goals. One study that addresses these complex relations between people, artefacts, space, and time (Martinez-Maldonado et al., 2018) developed a theoretical perspective for physical learning analytics based on Distributed Cognition Theory, concept of Internet of Things, and MMLA. With data as a crucial aspect of understanding the physical aspects of learning, example prototypes demonstrate how important contextualisation is in defining a multimodal system.

Therefore, MMLA can provide a new kind of insight into the processes that take place when students, both in the physical and digital environments, participate in creating new solutions to problems, gaining new knowledge, and communicating with their peers (Blikstein & Worsley, 2016). The automation possible in the data collection process and the level of detail allows researchers to closely examine the learning process and the phenomena that accompany it. Thanks to this, MMLA techniques allow for better support in terms of pre-pedagogical approaches and learning materials. However, the essence of MMLA is to combine different techniques for comprehensive analysis, especially when applied to complex contexts where student actions are often unpredictable (Blikstein & Worsley, 2016).

The set of different types of data collected by multimodal systems requires different approaches in analysis. MMLA entails automation that generates data best suited to quantitative analysis (Ochoa & Worsley, 2016). However, research in technology-enhanced learning (TEL) often requires qualitative analysis. Consequently, as MMLA is an important element of this dissertation, both quantitative and qualitative analysis are necessary (Blikstein & Worsley, 2016). In other words, the mixed-method approach has found an application in learning space analysis as it provides a more complete understanding of the problems examined than when only one of the methods is used (Fraenkel et. al., 1993). The power of bringing these two methods together lies in combining their strengths. A number of recent studies show how, for example, qualitative analysis contributes to physiological measurements such as electrodermal activity (EDA) (Malmberg et al., 2019; Sobocinski et. al., 2020). Similarly, in research on medical staff training, qualitative analysis that complements the set of measurements made with sensors (EDA, voice activity, movement, etc.) greatly contributes to the analysis of subject behaviour (Martinez-Maldonado, et. al., 2020).

Another challenge resulting from the application of MMLA is the way to quantify qualitative data so that they can be included in the analysis of data captured by automated techniques. Epistemic Network Analysis (ENA) is a statistical tool based on Quantitative Ethnography (QE) that models connections between elements of qualitatively coded datasets (Shaffer, 2018; Shaffer, et. al., 2016; Shum, et. al., 2019). In other words, when coding certain student actions (parts of conversations, physical actions, etc), ENA accumulates the co-occurrences of the codes within certain analysed segments of the activity (Shaffer, et. al., 2016) and generates dynamic network models made up of nodes and edges, where nodes are coded actions and edges are links between those actions. The thickness of the edge between two nodes indicates the strength of the connection between the actions. ENA been applied in MMLA, where it has been used to analyse data collected during nursing training (Shum et. al., 2019). ENA has also been employed in the analysis of differences between students with high learning gains and those with low learning gains (Csanadi et. al., 2018). In the analysis of dyads, ENA is applied to model networks of shared eye gaze and how it develops over time (Andrist et al, 2015).

## 1.3 Research questions

The theoretical framework has positioned the current research of collaborative learning space more precisely at the intersection of three areas: **learning space**, **collaborative learning**, and

**multimodal learning analytics**. A literature review indicated suggested lines of research so that collaborative learning spaces could be further developed. These findings on possible future directions, together with gaps identified, helped in formulating the research questions for this dissertation.

The goal of collaborative learning spaces is to identify features that will encourage people to interact in ways promoted by our constantly evolving collaborative practices, such as engaging in shared reflection and inquiries, developing various perspectives, etc (Wiley, 2006). Sutherland & Sutherland (2010) examine these new learning spaces centred on new collaborative learning models and point to the **importance of understanding participants' behaviour in the space in which learning takes place**. Collaboration as a new model of learning, informed by the needs of professional environments (de Lima & de Souza, 2017; Häkkinen et al., 2017), is different in its specifics compared to the classical model of teaching (Brown & Long, 2006; Zumbrunn et al., 2011) and therefore requires special attention when considering the space in which it takes place. Participant characteristics such as education level, group size, and gender are also described as relevant and sometimes even as crucial for the development of collaboration in the literature (Kumar et. al., 2008; Godwin & Fisher, 2011; Shanks et al., 2013; Crook & Beier, 2010; Pieira-Diaz et al., 2019). Furthermore, the need for a more detailed examination of the collaborative learning space is evident because elements such as tables and their shape play a role in student behaviour (Francis & Raftery, 2005; Blinne, 2013; Colbert, 1997; Brooks, 2012). As a promising tool used in complex contexts in educational research, MMLA can be employed to study the interactions between elements of the space and aspects of collaboration by combining multiple types of data (Malmberg et al., 2019; Cukurova et al., 2018; Martinez-Maldonado et al., 2018). Figure 1 shows the intersection of sub-aspects of the three researched areas mentioned that provides the specific research context of this dissertation.

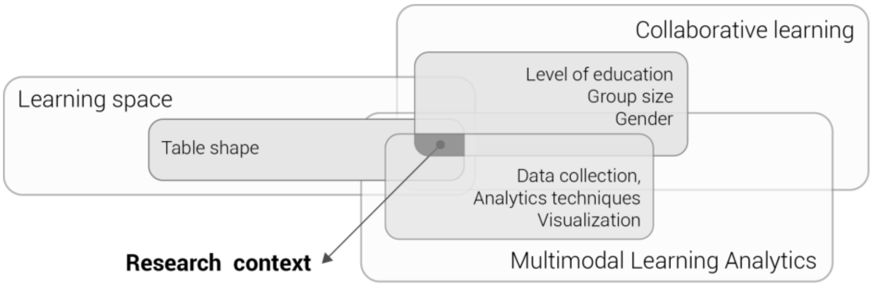

Figure 1. Specific research context

This defined context helped us to frame the examination of the collaborative learning space and its effects on students using MMLA. Thus, the **main research question** is: **How can MMLA support an understanding of the effects of learning space on student behaviour during collaborative activity?**

By recognizing the complexity of collaborative learning space research, the initial need was to segment the aspects that comprise the main research question and to define groups of research questions with more specific focuses. The research questions are interrelated and addressed transversally in several experimental studies. The sequential order of their presentation in the dissertation does not necessarily indicate the sequence in which they were answered.

### 1.3.1 RQ1 What is the difference in student behaviour between round and rectangular tables?

Narrowing the interest to the shapes of tables, the first group of research questions was formulated and focuses on the specific aspects of collaboration that this variable may affect. Various studies have reported on the influence that the learning space and the shapes present in it have on student behaviour (Yuan et al., 2017; Croker et al., 2015; Yee & Park, 2005; Francis et. al., 2013; Colbert, 1997). The education level, group size, and gender of students also influence the development of collaboration (Kumar et. al., 2008; Godwin & Fisher, 2011; Shanks et al., 2013; Crook & Beier, 2010; Pieira-Diaz et al., 2019; Wiley & Jensen, 2006). However, the interaction of these parameters has not yet been sufficiently examined. Questions arise over – if multiple aspects can affect collaboration – the extent to which the impact of those aspects intersects. These aspects of collaboration are addressed in the first group of research questions:

*RQ 1.1 Does table shape have the same effect on university and elementary school students?*

*RQ 1.2 How does table shape affect groups of different sizes?*

*RQ 1.3 How does table shape affect students of different genders?*

### 1.3.2 RQ2 What indicators are relevant for collaborative learning space research?

The second group of research questions refers to the analysis of indicators that can be meaningful in the study of the influence of table shape on student behaviour. These indicators have been determined based on the literature and rely primarily on pioneering, though still preliminary, studies that examine space through the influence of table shape on collaboration through a multimodal approach (Spikol et al., 2018; Cukurova et al, 2018). Given the parallels in the multimodal approach adopted by both, this dissertation takes these existing studies as guides to the analysis of physical learning space and, accordingly, the indicators of *distance between students*, *range of head movement*, and *level of participation* have been selected.

Through the two data collection scenarios in which data sets were obtained, including university students and elementary school students, the relevance of these indicators to the research of collaborative learning space in new scenarios was examined. Later in the research process, after the first set of was analysed, ENA was introduced with the idea of examining the *temporal correlations* of university student actions as indicators useful for collaborative learning space research. Based on studies that indicate the relevance of the temporal component (Malmberg, et. al., 2017; Reimann, 2009) as well as the application of ENA for this purpose (Shaffer, et. al., 2016), it is clear that this indicator is significant when studying learning spaces. Therefore, the three indicators mentioned above were expected to be relevant when examining the impact of space on the process of collaborative learning and each indicator is considered in the research questions in this group:

*RQ 2.1: How relevant is 'distance between students' as an indicator when researching collaborative learning space?*

*RQ 2.2: How relevant is 'range of head movement' as an indicator when researching collaborative learning space?*

*RQ 2.3: How relevant is 'level of participation' as an indicator when researching collaborative learning space?*

*RQ 2.4: How relevant is the temporal correlation of student actions as an indicator useful for researching collaborative learning space?*

### 1.3.3 RQ3: Which data collection, analytical, and visualisation techniques can be used for collaborative learning space research?

Technological advances in data capture and analysis tools have afforded new opportunities to address the lack of evidence in collaborative learning space research. In particular, MMLA approaches are increasingly seen to have the potential to advance learning space research. This dissertation studies some of these approaches. Given the focus on the physical aspects of student behaviour, a motion capture system was used to determine its effectiveness in detecting and analysing student movements during collaboration. Along with video recordings generated by video cameras, the physical aspects of student behaviour were analysed. The aim of studying the potential of a motion capture system is to establish adequate techniques to measure and analyse efficiently the indicators of the impact of the learning space on collaboration. Therefore, this technique was assessed in both data collection scenarios.

The first steps focused on collecting quantitative data from the motion capture system and conducting statistical analysis. Video recording was used as a second modality for data collection. Its analysis was done qualitatively, through coding of students' on-task actions. Therefore, the dissertation examines the extent to which qualitative analysis is important in this context, as a common method in educational research, while highlighting the need to combine quantitative and qualitative analysis (Malmberg, et al., 2019;

Sobocinski, et. al., 2020; Martinez-Maldonado, et. al., 2020). Also, through the lens of computational data analysis techniques, new approaches such as Epistemic Network Analysis (ENA) have found a place in research, in which ENA has been used as a demonstrably effective tool for studying the temporal aspects of the collaborative process (Andrist, et al, 2015). The main feature of ENA – the modelling of co-occurrences of actions – proves to be useful in various contexts (Shum et. al., 2019; Csanadi et. al., 2018; Andrist et. al., 2015), which is why this tool was considered for this research as well. Furthermore, the visualisation of data for inspection by researchers is also one of the relevant facets of data analysis (Martinez-Maldonado et al., 2020). Researchers need visualisation techniques that allow them to explore the data obtained from different modalities to support sense making. One essential factor to bear in mind is the variability in knowledge required to interpret different types of data. Due to the collection of different types of data, this dissertation began by examining the role of visualisation intended for researchers of different profiles to be used in the analysis process. Thus, the third group of research questions addresses analytical techniques and their usefulness in exploring collaborative learning space.

*RQ 3.1: How efficient are motion capture systems when used in collaborative learning space research?*

*RQ 3.2: How can qualitative analysis in an MMLA approach support collaborative learning space research?*

*RQ 3.3: How can a temporal analysis perspective using Epistemic Network Analysis support collaborative learning space research?*

*RQ 3.4: Is it possible to visually present parameters detected by MMLA approaches?*

All three groups of research questions arose from the main research question, which was previously formulated within the research context. Figure 2 shows groups of research questions with sub-questions. The work presented in this dissertation focused on answering the research questions and contributing to the field of collaborative learning space research. The following sections explain the methodology used to obtain answers to the research questions posed.

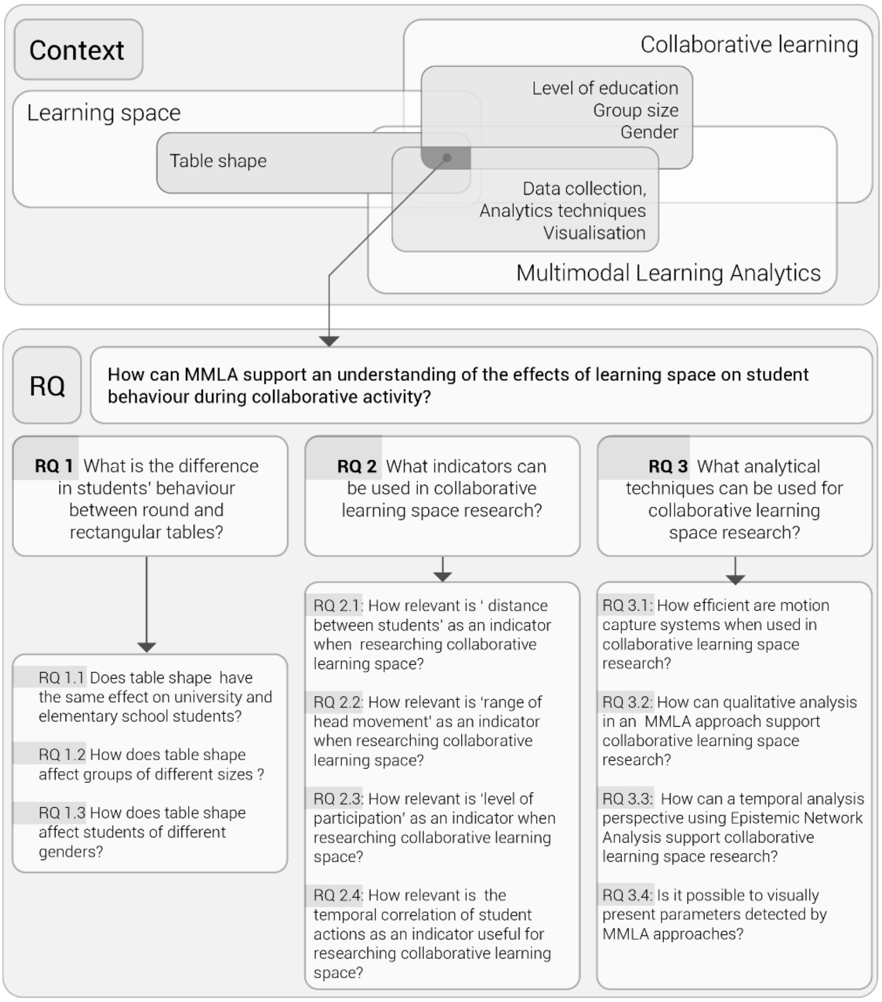

Figure 2. Research questions

## 1.4 Research Methodology

### 1.4.1 Experimental design methodology

Previous sections introduced the research questions for this dissertation and in order to answer them it is necessary to establish the relationships between the variables – learning space and collaboration – using MMLA. According to the literature (Fraenkel et. al., 1993; Easterling, 2007; Kirk, 2012), the research methodology that is most effective in achieving this goal is **experimental design methodology**. The possibilities that this methodology offers to answer the research questions posed are those of directly influencing certain variables and measuring their effects. This manipulation of variables is one of the basic features that distinguishes experimental design from other research methodologies. In this way, there is an opportunity to explain the relationship between learning space and collaboration in more detail and provide at least a partial determination of what causes those relationships. Another basic feature of experimental design is the possibility of comparing treatments or conditions (Fraenkel, et. al., 1993, Kirk, 2012), which is an additional value this methodology possesses for understanding the relationships between variables. Thus, as has been previously mentioned, the essence of experimental design is to explore the relationship between variables, and comparison helps to determine the different effects that may occur by manipulating those variables. Besides these two basic features of experimental design, there are other important characteristics for the research to be considered experimental. The research presented in this dissertation is exploratory and based on identifying the changes that occur in dependent variables when independent variables are manipulated. Given the complexity of the context, there was a need to use a laboratory setting in order to control additional unplanned influences. Even so, the learning scenario was authentic.

As stated previously, experimental design has certain characteristics that must be maintained, which will be discussed further in the following sections. In addition, research conducted according to this methodology employs certain methods that need to be explained. The research methods applied will be presented after a detailed explanation of the research methodology. In this dissertation, the research on learning space was operationalised by examining the influence of table shape on participant behaviour involved in collaborative learning. As a tool used for testing, a multimodal system was deployed in multiple data collection scenarios that provided the data set as input for further analysis. Thus, as well as understanding the impact of space, the goal is to consider the possibilities of MMLA and its capacity to generate new data and analysis. First, however, in order to clarify the methodology applied, its characteristics and the way in which they are realised in this particular context will be discussed. The components of experimental design methodology will be further elaborated within the context of this dissertation and the development of research will be explained in detail.

## Characteristics of experimental design

As previously mentioned, some of the characteristics of experimental design are common to the implementation of experimental methodology in all contexts. Regardless of the various descriptions of methodologies, due to their adaptation for research purposes the following characteristics should be present in every experimental design in order for it to be considered credible (Figure 3). Firstly, every experiment should have a *comparison of groups*, which requires a previous *group design*. In addition, a key feature for experimental design is the *manipulation of the independent variable* by a researcher. Furthermore, two types of controls should also be included in all experimental design methodologies: 1) *control of extraneous variables*; and 2) *control of threats to internal validity*. An explanation of these main characteristics follows, as well as their contextualisation in the present research.

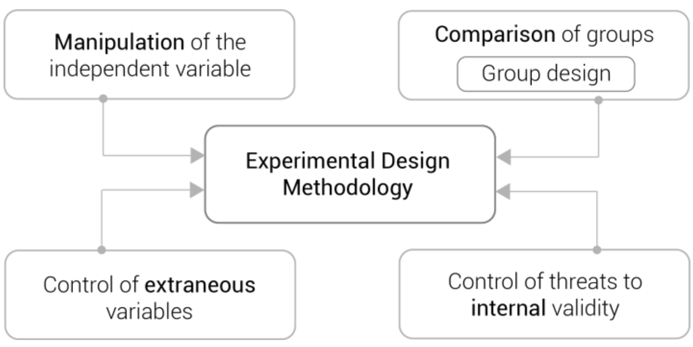


*Figure 3. Main characteristics of experimental design methodology*

*Comparison of groups and group design*

An experiment usually involves two groups of subjects, one of which is considered experimental and the other the control. In the field of education, a control group with no treatment is rare and there are, instead, comparison groups (Fraenkel, 1993). In this case, two groups receive treatment, but the treatment is different. Bearing in mind the aim of the dissertation, where the influence of table shapes on the collaboration process is examined, the two comparison groups were assigned to use two different table shapes (round and rectangular). Furthermore, two data collection scenarios were designed and they involved: (1) university students; and (2) elementary school students (Figure 4).

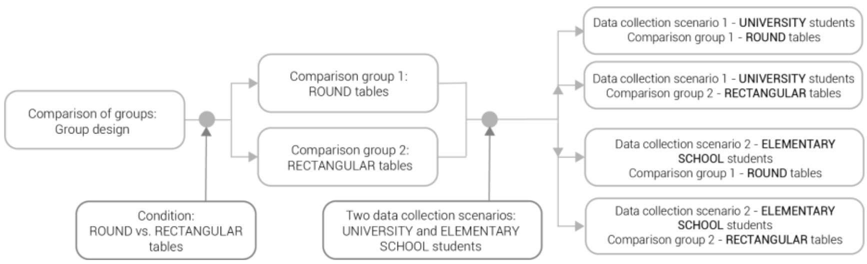


*Figure 4. Formation of comparison groups*

Two experiments for two data collection scenarios were designed and conducted in a laboratory context. For both experiments, two approaches to group design were considered appropriate in the next step. One was: 1) *Random assignment with matching*; and the other, 2) *Factorial design* (Figure 5). Random assignment with matching involves pre-matching of subjects according to a certain criterion based on prior research, theory, and/or the experience of the researcher, after which randomisation is performed. Factorial design increases the number of independent variables and thus increases the number of relationships between variables. The added value is that it is possible to study the interaction between variables. Factorial design was chosen here as the basis of the research because of its advantages, but before its application, random assignment with matching was also applied.

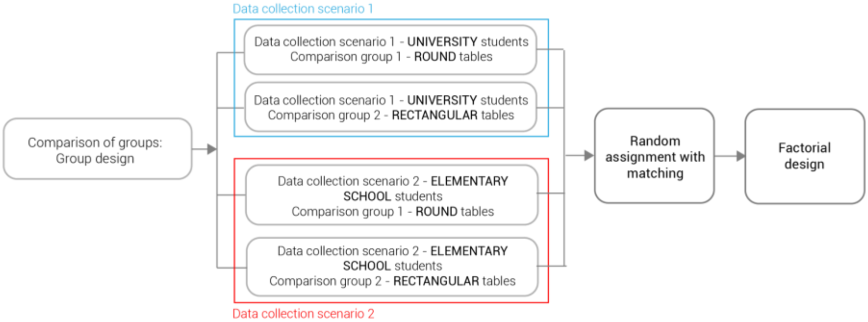


*Figure 5. Group design approaches*

The first data collection scenario in a laboratory setting focused on university students, who engaged in an engineering design activity. Students were first matched according to the study programme to which they belonged, as well as according to gender. This was done so that there would be students in each group from as many different study programmes and of different genders as possible. Due to the applied learning design, which alternated between triads and dyads, there were two members of the same gender in each group, though there was always at least one person of the opposite gender. When it comes to the study programmes , each group is assigned three students from different study programmes. After matching, students were randomly assigned to one of two comparison groups and later to smaller groups that conducted the activity. Factorial design was reflected in the fact that there were two group sizes (dyads and triads), two genders, and two table shapes. In this way, it was possible to examine the interactions between these variables.

The second case focused on elementary school students, in which matching was done only according to gender. In addition, the same factorial design was applied as with university students, where the aim was to examine the interactions between table shape, group size, and gender. Group design is a step that serves as a basis for further successful control of external and internal influences that can disrupt experimental design. It is important to note that, in group design, it is not always possible to control everything in educational research and that limitations are something common in this context.

*Control of extraneous variables*

Different methods can be used to control *extraneous variables*. The goal is to eliminate or minimise the possible effects of potential threats. All compared groups are thereby as equivalent as possible for all dependent variables. In the description of the group design process, *randomisation* and *matching* have already been mentioned. Explained in more detail here is how these methods, together with *building the variable into design*, were used in this research to control the extraneous variables.

*Randomisation*, in terms of the control of extraneous variables, means eliminating biases that may arise from the characteristics of the subjects. In its basic form, randomisation involves the completely random assignment of subjects to different groups after their recruitment. In general, randomisation is a key element of experimental design, but it is sometimes necessary to make further adjustments if there are known differences that can be eliminated before randomisation. Depending on the context of the research, the researcher can prepare the ground for more efficient randomisation using *matching*, which is the classification of subjects according to a particular criterion. As described in the 'Group design' section, in two experiments used in this dissertation, matching was used to classify students according to their gender and their degree programmes. After that, randomisation was done by combining categories in each group. Another method employed in this study to control extraneous variables was *building the variable into design*. In this case, as one of the criteria by which matching was done, gender was built into the experimental design as an independent variable. Consequently, the previous categorisation was used, but its influence on the collaboration process was also considered. Figure 6 presents the process of matching and randomisation with the aim of controlling extraneous variables.

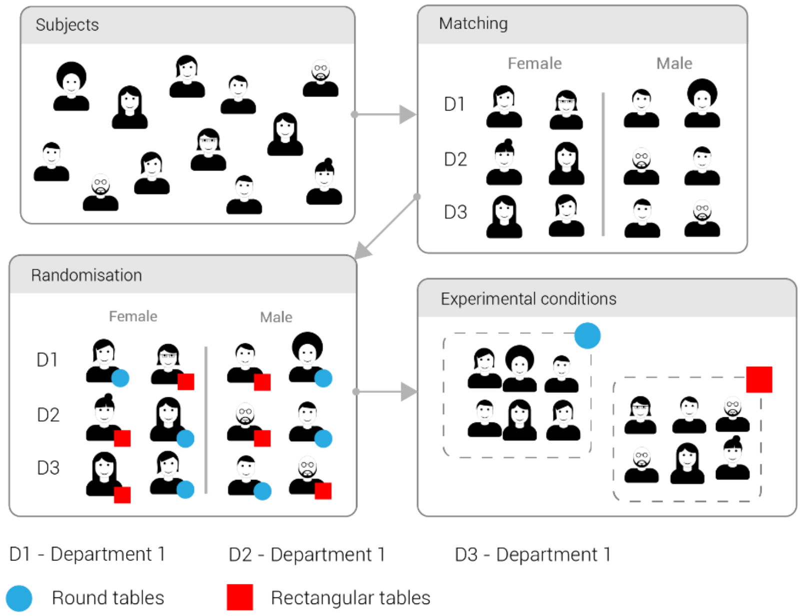

*Figure 6. Matching and randomisation of subjects*

*Manipulation of the independent variable*

Another crucial criterion for proper experimental design is manipulation of independent variables. When manipulating independent variables, it is important to clearly define the forms that a variable has and which form is assigned to which group. In the experimental design, manipulation of an independent variable can be classified into three categories: 1) one form vs the other form; 2) the existence or non-existence of a particular form; and 3) variations within a single form. In the experiments conducted for this research, the first category of manipulation (one form vs. the other form) was used.

Firstly, the table shape variable was manipulated by defining two table shapes as two different conditions. This manipulation is the primary topic of research on how space influences the collaborative process. Although manipulation is a strong term, it is clear that in this case it refers to the assignment of two different forms to the variable. Therefore, we used round and rectangular tables as two conditions and assigned students to two major comparison groups. Within these two comparison groups, further manipulation was done with two additional variables: group size and gender.

Manipulation of group size was achieved through a learning design where the Jigsaw Collaborative Learning Flow pattern (Aronson et al., 1978; Hernández-Leo et al., 2006) allowed for alternation between dyads and triads. A Jigsaw pattern involves changing groups during a collaborative activity to help students gain expertise in an area and help their home group reach a solution by applying that expertise. In this study, the collaborative activity consisted of three phases in which students first, in triads, developed a role-sharing strategy, i.e. opted for individual expertise. After that, each member of the two triads formed a new group with one member of the other triad. In this way, from two triads, three dyads were formed in which each worked on the formation of a different expertise. After the second phase, the students returned to their home groups. In terms of gender, matching provided control of this variable so that each group had members of different genders (Figure 7). Through the manipulation previously mentioned, control of variables was carried out and clear analysis was subsequently enabled, in the knowledge of what all the possible influences were.

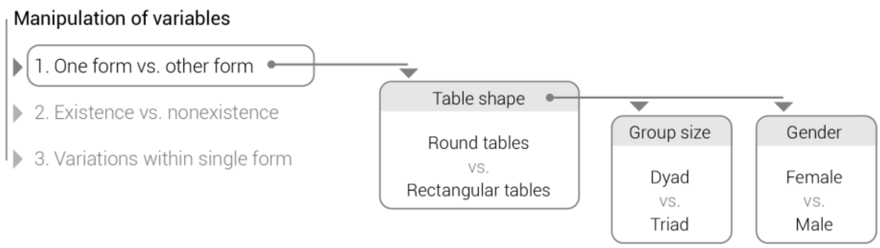


*Figure 7. Manipulation of the independent variables*

*Control of threats to internal validity*

Internal validity threat control involves detecting parameters that may affect the interpretation of data and thus jeopardize the research. In other words, it ensures that only independent variables act on dependent variables and that there is no influence of other unplanned variables. Fraenkel et al. (1993) explain that, in qualitative research, good internal validity can be achieved if unplanned factors are systematically excluded. Identifying and addressing threats to internal validity is often overlooked in research (Fraenkel et. al., 1993), but the importance of conducting analysis at the very beginning of an experiment design is essential to minimising threats.

Internal validity is closely related to external validity and the social sciences entail a trade-off between the two (Jimenez-Buedo & Miller, 2010). Trade-offs need to be assessed very carefully, which is why a systematic analysis of the impact of possible threats to internal validity must be conducted thoroughly. The literature provides support in assessing risks to internal validity by categorising possible threats. However, because of the differences between each experiment, researchers should be trained to recognise threats that are beyond even the established categories. Some of these considered important for the research context of this dissertation are: *subject characteristics*, *mortality*, *location*, *instrumentation*, *testing*, *history*, *maturation*, *subject attitude*, and *implementation*. The threats were considered during the creation of the experimental design and the response to them will be explained in detail in the following paragraphs.

In terms of *subject characteristics*, 'selection bias' can present a threat to internal validity. In addressing this threat, certain aspects such as age, gender, ability, socio-economic background, religious beliefs, political beliefs, etc, must be considered. The choice of variables that could influence the results of the experiment depends on the context of the research as well as on the experience of the researchers conducting it. By recognising age and gender as potential influences on internal validity, and as relevant factors in the research, these factors were adopted as dependent variables in the experiment. Ability as a selection criterion was also considered in terms of prior knowledge and was applied as a filtering factor in the selection process. Namely, during the recruitment of students, one of the conditions was that students did not have prior knowledge in the field that would be covered during the collaborative task. Consequently, students with prior knowledge were not included in the experiments. Factors such as socioeconomic status, religion, etc, were not considered influential in our research context.

*Loss of subjects* or *mortality* is a common threat in experiments as the studies take place over a certain period of time and unpredicted factors can affect subjects 'presence. In educational research, the most common subjects are students and they may be absent from experiments due to relocation activities, illness, etc. In addition, an experiment usually passes through multiple phases, and if one subject does not complete all of them, that sample is considered invalid. If the study involves comparing groups and there is a loss of subjects, the consequence is an unequal number of subjects for the different conditions. So, the critical importance of minimising these threats to internal validity as much as possible is clear. In this dissertation, from the beginning of the creation of the experimental protocol, loss of subjects as a risk to internal validity has been taken into account. First, besides the selected subjects, a group of students was created as replacements in case those selected for the experiments did not show up. Of the 36 students recruited, three students did not show up on the day of the experiment, which is why the replacements took their places. In addition, a certain number of subjects were lost because some of the data were not complete due to equipment failure or occlusion. As a result of the uneven loss of subjects in both groups, the number of subjects analysed had to be equalised eventually. Therefore, from the group that had more complete data, not all subjects were included in the final analysis. In other words, of the 36 subjects who participated in the experiment, data from 24 subjects were analysed (12 subjects from each group).

When we consider *location* as a threat to internal validity, this refers to the physical aspects of the environment where the experiment takes place. The best way to control this parameter is to keep the location constant for all participants. In order to control this factor in our case, the same laboratory setting was maintained for all experimental sessions. Moreover, the lighting, room temperature, ventilation, and surrounding furniture, as well as the researchers present, were the same for all groups. Therefore, the risks posed by the experiment's location were kept to a minimum.

*Instrumentation* can also pose a threat to the internal validity of an experiment. One of the problems that can arise is Instrument Decay. This happens when the instrument allows for a different interpretation of the results, which is often the case with observations and coding of student actions. If the researcher needs to code a large amount of data, fatigue can occur, which leads to different results at different stages of coding. The solution to this problem is scheduling the data analysis to certain periods of day or limiting the time assigned to coding. In this dissertation, coding of student actions and data analysis took place during pre-defined time slots on a daily basis (6 hours each day per researcher). Data collector characteristics also represent a potential risk when it comes to instrumentation. In the experiments presented in this dissertation, a large amount of data was obtained by automatic methods, which precludes the problem of different data collector characteristics. The coding of student actions that depended on the researchers who worked on it was regulated by inter-coder reliability tests. In this way, the impact of data collector characteristics as a threat to internal validity was minimized. Data collection bias is another factor that can compromise internal validity if data can be manipulated during its collection. To avoid such bias, it is desirable to hire a data collector who is not familiar with the hypothesis being tested in the experiment. In our experiments, data collection was an automatic process which prevented any kind of external manipulation.

*Testing effect* is a phenomenon that occurs when questions in surveys (both pre-test and post-test) reveal the intentions or details of the experiment more than they should. For example, if a test that students take determines whether they will be selected or not and they become aware of this, it is possible for them to give incorrect answers to avoid being excluded from the experiment. In other words, tests should be carefully designed so as not to compromise the internal validity of the experiment and to ensure unbiased behaviour in students. During recruitment for our experiments, students had to fill out a test that assessed their prior knowledge of the topic of the collaborative assignment to be conducted during the experiment, but the instructions did not state whether any of this information was an excluding factor, only that the data served to group students appropriately for the experiments. This is how the control of testing as a risk factor was approached.

*History*, as a threat to internal validity, refers to any previous event that may affect the behaviour of subjects and the results of the experiment. This factor represents a real risk to the internal validity of the experiment, but is also very difficult to control. Since it was not possible to control the occurrence or impact of such events in our experiments (subjects came to the laboratory for two hours at a specific time), the measure we were able to take was to have a 20-minute briefing period to act as a buffer and to relieve any previous tension in the subjects, if possible.

*Subject attitude* threats may appear when there are control and experimental groups and the control group feels demotivated as a result of receiving no treatment. By having two comparison groups in our experiments, we avoided the possibility of attitude threats as a possible disturbance to internal validity. Another threat to internal validity we considered is the risk that can occur in the *implementation* phase of the experiment when multiple people are in charge of different parts of the experiment. In our experiments, this was addressed by assigning the same researcher and research assistant to be in charge of all measurements, thereby reducing the risk of threats during implementation.

Overall, the minimisation of threats to internal validity can be achieved with good planning, obtaining more information about the subjects participating in the experiment, and employing standardised methods. Applying these techniques should ensure appropriate experimental design and valid results. In the experiments covered by this dissertation, identifying and addressing the risks discussed minimised threats to the internal validity of the research (Figure 8).

| Control of threats to internal validity | |
|---|---|
| Subject characteristics | **Age** and **gender** were adopted as dependent variables in the experiment.<br>**Ability** (prior knowledge) was implemented as a filtering factor in the selection process. |
| Loss of subjects | Group of students was formed as **replacements** in case participants did not show up.<br>Uneven loss of subjects in groups solved by **equalizing number of subjects analysed**. |
| Location | The **laboratory setting was kept the same** during all sessions of the experiments.<br>The lighting, room temperature, furniture, researchers etc were the **same for all groups**. |
| Instrumentation | Defined time slots for coding were **scheduled** on a daily basis<br>**Automatic data collection** and **inter-coder reliability** tests were conducted |
| Testing effect | Pretest **not suggesting** the criteria for the selection of subjects and **not revealing** the details of the experiment |
| History | **Briefing period** of 20 minutes that could have a buffer effect and relieved any previous tension in the subjects if possible |
| Subject attitude | Having **two comparison groups**, we avoided the possibility of having the attitude threat as a possible disturbance to internal validity |
| Implementation | Assigning the same researcher and research assistant to be in charge of **all the measurements** |

*Figure 8. Control of threats to internal validity*

Figure 9 shows the basic characteristics of the experimental design methodology, as well as the way in which they were considered in the context of the dissertation.

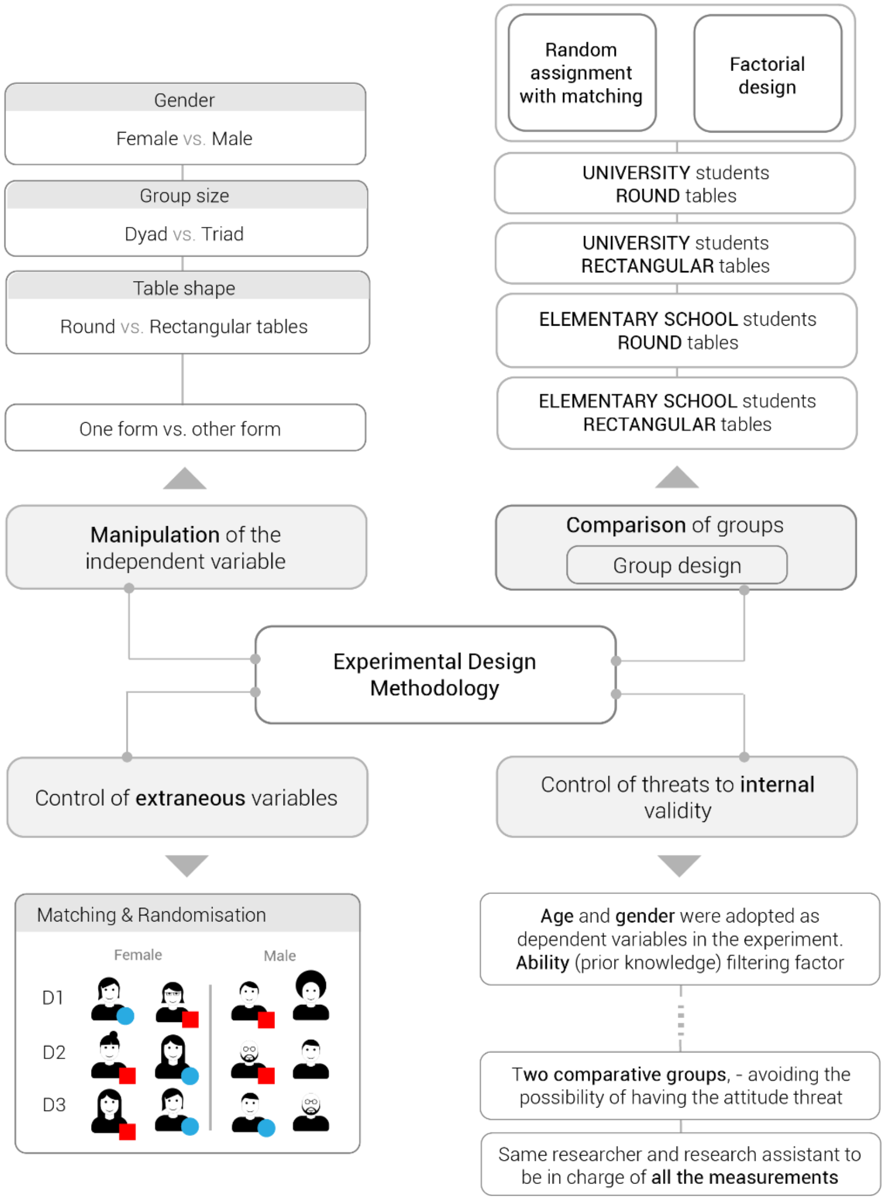


Figure 9. Experimental design methodology - overview

### 1.4.2 Methods

Two data collection scenarios were designed and carried out in experiments for this dissertation. The main difference between them was the age group of the participants (university and elementary school students). Instrumentation and procedure were kept as similar as possible. Unavoidable practical differences will be explained in detail. More complete data was obtained for university students, which directly affected data analysis and provided the possibility of more approaches with this age group. The following sections present the methods applied and an overview of essential information is presented in Table 1. It is worth mentioning that the published and submitted papers included within this dissertation explain the methods applied in experiments in greater detail. In this first chapter, the methods are introduced without going into detail.

Table 1. Information about two data collection scenarios

| **Aspect** | **Data collection scenario 1** | **Data collection scenario 2** |
|---|---|---|
| *Participants* | N = 24; University students | N = 24; Elementary school students |
| *Location* | Laboratory at Pompeu Fabra University | Laboratory at Pompeu Fabra University |
| *Activity* | Design, program and build an interactive toy with an Arduino electronic platform | Designing cartoon-like artefacts using interactive computer game |
| *Duration* | 90 minutes | 90 minutes |
| *Measurement tools* | Motion capture system, video camera, observations | Motion capture system, video camera, observations |
| *Variables* | Distance between students, range of head movement, level of participation, coded on-task actions | Distance between students, range of head movement, level of participation |

*Participants*

The experiments were divided into two data collection scenarios, in which participants belonged to different age groups and were recruited in different ways. As previously described in the 'Comparison of groups and group design' section, student were assigned to different conditions randomly, with matching, in both scenarios.

The first data collection scenario involved an extracurricular training activity that included a physical computing design task in which university students were invited to participate. The recruiting process resulted in 150 registered student volunteers interested in participating in the experiment. Based on random assignment with matching, 36 students from different engineering degree programmes and in different years of study who had no prior knowledge of the topic were selected. Also, an equal number of male and female participants was achieved. The 36 selected students, aged 18 to 24, formed 12 (Jigsaw) groups. After subject selection criteria, which included good camera coverage in order to obtain valid data, gender balance as much as possible, and balance of table shapes, the data for eight groups, i.e. 24 students, were analysed. As previously explained in the section on 'Group design', 12 subjects were assigned to the first condition and used round tables, while the other 12 subjects were assigned to the second condition and used rectangular tables. The final cohort of 24 subjects comprised 11 female students and 13 male students. All groups were mixed gender and due to the odd number of participants in home groups (triads), there were two group structures. One structure consisted of two female and one male member, while the other consisted of two male members and one female.

The second data collection scenario involved elementary school students, who were recruited as part of a technology-focused summer school activity. 24 students, aged six to eight, agreed to participate in the experiment with parental consent. The students formed eight (Jigsaw) groups. Throughout the experiment, a teacher from their school was present in the laboratory, though they were not involved in the activity. According to the 'Group design' strategy, four groups of students were assigned to the first condition and carried out the activity using round tables. The other four groups used rectangular tables. Gender balance was not possible with these elementary school students, which is why this scenario was excluded from analyses of how table shape influences the behaviour of students of different genders. The second paper, presented in Chapter 2, with the featured papers in Chapters 4 and 5, provide more details about the participants in both data collection scenarios.

*Instrumentation*

In both data collection scenarios, students participated in a collaborative activity. For each level of education (i.e. elementary and university), appropriate activities were designed and, while the two activities were similar in nature, they were also adapted to the respective level of the students. In both cases, the task was to design an artefact. A Jigsaw pattern flow structure was applied, which first organised students into triad home groups. After the initial phase, the students regrouped into groups of two, by which each dyad was assigned one member from the home triad (Figure 10). In this way, students gained a particular expertise that they later applied in their home group. The task lasted 90 minutes and was open-ended, which meant that each group could come up with a different design as a solution. Prior knowledge was not required and during recruitment students who had no prior knowledge were selected.

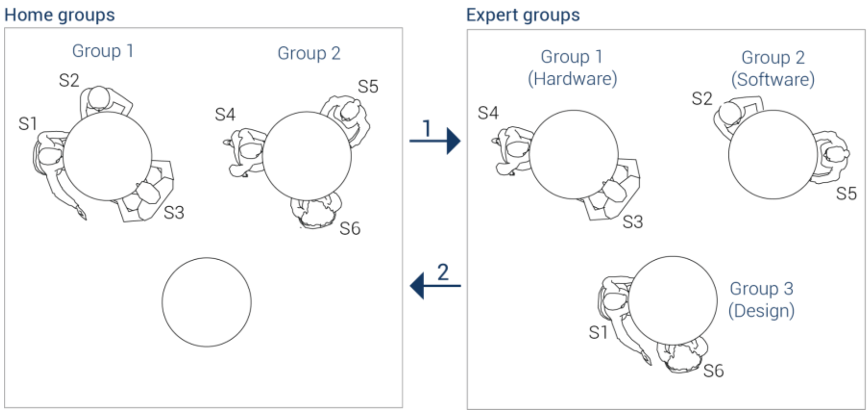


*Figure 10. Alternations between triads and dyads according to Jigsaw collaborative pattern*

In the first data collection scenario, university students were tasked with designing, programming, and creating an interactive toy using the Arduino electronic platform. The level of difficulty was low and all necessary instructions were provided. In the second data collection scenario, the collaborative activity with elementary school students involved the use of a video game to carry out the cartoon-like artefact design task. Students had to use both the game and artefacts collaboratively, following the clues presented to them, to produce their solution. Both the participants and instruments are discussed in more detail in the second paper, which is presented in Chapter 3, as well as in the papers in Chapters 4 and 5.

*Procedures*

The data collection procedure was established prior to the implementation of the data collection scenarios. The following paragraphs will provide an overview of the procedures used in this dissertation, but more detailed descriptions of the procedures are given in the papers that are an integral part of this dissertation.

For data collection in a laboratory environment, various equipment was used to collect motion capture data and video recordings. Ambient parameters such as room temperature, lighting, sounds, and the presence of researchers were constant throughout the experiment. In the first data collection scenario, the motion capture system was deployed with an appropriate protocol for setting reflective markers. Prior to the experiment, a motion capture system was tested and a specific protocol for reflective markers was established. This system was used to acquire two variables: the distance between students and the range of head movement. In addition, the cameras were placed at a height of two meters and positioned to cover the activity from two different angles. The goal was to avoid occlusion of student actions as much as possible. The level of participation was obtained by analysing the videos and encoding the physical aspects of the interaction using the NISPI framework (Cukurova et. al, 2018). The two observers harmonised their scoring by encoding the same video segments and aligning the scores. For the second data collection scenario, video recording was made with the same cameras and the same setup. Data was coded according to the pre-established coding scheme and inter-rater reliability was established prior to the final coding of the on-task actions. Chapters 2 and 3 explain the procedures discussed in this section in more detail.

*Data Analysis*

The two data collection scenarios generated a vast amount of data. The first data analysis included both data collection scenarios and consisted of three multifactorial analyses of variance (ANOVAs), which examined the influence of independent variables on dependent variables. There were three independent variables (table shape, educational level, and group size) and three dependent variables (participation level, distance between students, and range of movement) collected by the motion capture system. In addition to quantitative analysis, a qualitative analysis was conducted that included visual transcription and open coding to determine on-task and off-task actions. After the qualitative analysis, triangulation of the quantitative analysis results followed, in order to explain them in more detail. The second paper, discussed in Chapter 3 provides more detailed insight into the data analysis described here.

The second data analysis was conducted on the data collected from the first data collection scenario, meaning that only university students were involved. As previously mentioned, two video cameras were used to record student activities during the experiment. The analysis is based on coding student actions by using a predetermined coding system of on-task actions. The coding system was formed by crossing information from the literature and findings on student behaviour obtained through observations. The coding includes *explanation*, *discussion*, and *nonverbal interaction* as social on-task actions, and *interaction with physical artefacts* as physical on-task action. More details on the coding of student actions is presented in the paper in Chapter 4. Epistemic Network Analysis (ENA) was applied to model the links between the coded on-task actions, and dynamic network models were generated. This analytical approach was used in order to examine to what extent the temporal component of collaborative development can be helpful in understanding the effects of the learning space. The paper in Chapter 5 reports on the application of the ENA with the data collected in data collection scenario 1.

*Ethics*

Prior to implementation, the process of data collection and analysis had been approved by the ethics committee appointed by the LaCaixa InPhinit Fellowships Programme Department. All participants in the experiments were informed about the process of data collection and their analysis. University students were provided with the consent form and verbal explanation of the details of the experiment, and signed consent forms were collected from them prior to the experiments. In the case of elementary school students, both students and parents were informed about the details of the experiment and were provided with the consent form, which parents were to sign and were collected by the teacher that was in charge of bringing students to the laboratory. The forms were handed over to the researcher prior to the experiments.

The ethics perspective in MMLA is indeed a delicate topic, as recognised by the research community and the research group within which this dissertation has been conducted. This concern has led to the publication in Appendix A, which focuses on the exploration of ethical principles and procedures used when MMLA technologies and techniques are applied. There is an increasing concern that the ethical procedures and principles are not strictly followed as collected data grow in complexity and invasiveness. Therefore, there is a growing need to examine the ethical aspects of MMLA research closely. As a modest contribution to the ethical perspective, the publication in Appendix A introduces an informed consent comprehension test for educational technology research, with the aim of assessing the effects of enhancing MMLA consent forms on understanding of informed consent and on rates of enrolment.

## 1.5 Main contributions

### 1.5.1 Main contributions

The main contributions presented in this dissertation concern the empirical evidence collected in case studies, examination of indicators, and analytical techniques for studying collaborative learning spaces. An overall empirical approach based more on evidence and experience rather than on pure theory defined the experimental design methodology, which guided the analysis of two data collection scenarios that yielded the results from which the contributions emerged. In addition, the topic of visualisation was initially examined and presents a particular form of contribution, on the basis of which the grounding for future work was defined.

The focus of the first group of contributions is on adding initial evidence of the relevance of physical learning space in the process of learning design, by demonstrating how one table shape triggers more participation in collaborative activity in the case of elementary students. The findings also suggest that the evidence is not as strong in the case of university students. Furthermore, analysis of on-task actions through coding and statistical analysis provided the first empirical evidence of the impact of table shape on different group sizes and genders. Also, further extension of the research to the use of Epistemic Network Analysis confirmed that there is a difference in behaviour among university students when different group sizes and genders are considered.

In determining indicators of the influence of table shape, already established indicators from the literature were used and tested in the case studies. Of the three indicators – distance between learners, range of head movement, and participation level – in this context only participation level proved to be a relevant indicator for understanding the effects of table shape on collaboration. However, an additional indicator, the temporal perspective on the occurrence of actions during collaboration, was analysed and shown to be meaningful in examining collaborative learning space effects.

Finally, the data collection and analytical techniques applicable to learning space research were examined. Specifically, the main contributions relate to an assessment of the use of motion capture systems, the application of MMLA, the application of epistemic network analysis, and visualisation as a data analysis technique.

**Empirical evidence**

The first group of contributions refers to the work presented in this dissertation that contributes the first evidence of the need to consider the characteristics of the physical learning space as a relevant aspect of comprehensive learning design processes. The data collection scenarios in which the influence of table shape was examined provide findings on the different effects of table shape with two different educational levels. Initially, the results were obtained using statistical analysis and further confirmed by qualitative analysis. Although the sample size was small, the literature supports its utility (Hackshaw, 2008) by indicating the acceptability of significance tests in the case of small sample sizes as long as they are not presented in a confirmatory manner with generalisable results, but rather as exploratory studies, which is the case in this dissertation. The aim of highlighting the significant results obtained in an exploratory study is to highlight aspects relevant to further research. This dissertation adds the first evidence, with implications for future research and practice, of the importance of considering physical space, and more specifically table shape, in the collaborative learning design process. These contributions are discussed in more detail in Chapter 2.

When considering participation level in collaborative activity as an indicator, the influence of table shape is more obvious in the case of elementary school students than in that of university students, where further research is needed. Previous studies have reported on the effect of developmental level and learning environment on learner behaviour (Godwin & Fisher, 2011; Kumar et al., 2008; Midgley, 2006; Pai et al., 2014). The results of those experiments confirm these findings and indicate that round tables increase the level of on-task participation and thus have a positive effect on elementary school students' behaviour during collaborative activity. However, for university students, the differences between participation levels at round and rectangular tables were not significant. The established experimental methodology therefore proved to be useful in providing the first evidence relating to younger students, while further examination of older students is needed . It can be concluded that the shape of the table, as an aspect of the learning space, seems to support the learning process depending on student age. Therefore, the dissertation contributes with:

- *First evidence indicating that round tables have positive effects on elementary school students' behaviour when participating in collaborative learning activities by increasing levels of on-task participation.*

- *First evidence of the potentially greater influence of table shape on the behaviour of elementary school students than that of university students, as reflected in their participation levels in collaborative activity.*

The dissertation is contributes with the first evidence of the impact of group size on university students' on-task actions and presents several different approaches in the analysis of the influence of group size on the development of on-task actions. Inferential statistical analysis provides the first evidence of the greater use of physical artefacts in dyads as opposed to triads, even though the experiment took learning design into account by ensuring that the need to use physical artefacts was the same for both group sizes. More details on these contributions is presented in Chapter 4. The findings are consistent with reports from the literature reporting that equipment use in practical tasks is higher in dyads (Shanks, et al., 2013). In addition to interacting with physical artefacts, the study of statistical analysis showed that there is a clear tendency – although it is not statistically significant – for dyads to engage in discussion much more than for triads, regardless of table shape. This confirms the findings from the literature, which conclude that the exchange of ideas and strategies is dependent on small size groups (only two members) (Granados & Wulf, 2007).

Further work on analytical methods included Epistemic Network analysis as a tool and examined same on-task actions, but from a temporal co-occurrence perspective. More detailed information on this contribution is provided in Chapter 5. Taking as a starting point the findings in the literature that note a propensity for more complex behaviour in terms of coalition formation, negotiation, and conflict in triads, ENA showed how these behaviours differ when different forms of tables are used. Discussion and interaction with physical artefacts, which in certain ways suit the reported characteristics of triads, are more pronounced when they use round tables. However, when it comes to dyads, the literature points to actions such as the exchange of ideas and strategies for mutual improvement, which can also be related to frequent discussion, together with interaction with physical artefacts. As in triads, the frequency of co-occurrences between discussion and interaction with physical artefacts is not the same with both table shapes. Rectangular tables seem to trigger more of these actions with dyads. Therefore, the presented case studies suggest that, for triads, round tables trigger more co-occurrences between discussion and interaction with physical artefacts, while for dyads, the same actions are triggered more often when rectangular tables are used. These findings led to the following contributions based on empirical evidence:

- *First evidence that students interact more with physical artefacts when working in dyads.*

- *First evidence indicating that round tables trigger more frequent co-occurrences between discussion and interaction with physical artefacts in the case of triads.*

- *First evidence indicating that rectangular tables trigger more frequent co-occurrences between discussion and interaction with physical artefacts in the case of dyads.*

In addition, the work presented in the dissertation contributes the first evidence indicating that gender, in interaction with table shape, influences university student behaviour when they are working with physical artefacts. From an experiment involving university students, the first promising signs for the field of collaborative learning concerning the effects of table shape on on-task actions are emerging and showing different tendencies between genders. Although this is preliminary evidence and more research is needed to make it conclusive, the difference between genders can be seen in the influence of the space. Building on the known findings from the literature on the role of gender in collaboration that have drawn certain conclusions and indicate uncertainty in the behaviour of female students when it comes to engineering tasks (Vogt, et al., 2007), these experiments aimed to deepen research and see if certain changes in the environment can explain differences in behaviour more clearly. It has been shown that female and male students behave differently depending on the environment.

Male students engaged in more discussion when they used round tables. Logically, in contrast, nonverbal interaction was more frequent when they used rectangular tables. On the other hand, the first evidence indicates that female students tend to discuss more when they use rectangular tables, as opposed to male students. Furthermore, the low frequency of action changes in female students is pronounced and may be one confirmation of the uncertainty previously noted in the literature, which is a consequence of female students' expectation that male students possess greater knowledge (Vogt, et al., 2007). More details on the findings presented are available in the paper discussed in Chapter 4. Furthermore, in Chapter 5, a paper on the application of Epistemic Network Analysis confirmed previous findings on the differences between two table shapes when two genders are considered. Therefore, the two main contributions are:

- *First evidence indicating more discussion among male university students when using round tables*.

- *First evidence indicating more discussion among female university students when using rectangular tables.*

- *First evidence indicating more frequent co-occurrences of interaction with physical artefacts and nonverbal interaction when round tables are used in the case of female students.*

- *First evidence indicating more frequent co-occurrences of interaction with physical artefacts and discussion when round tables are used in the case of male students.*

Figure 11 features contributions related to the first group of research questions.

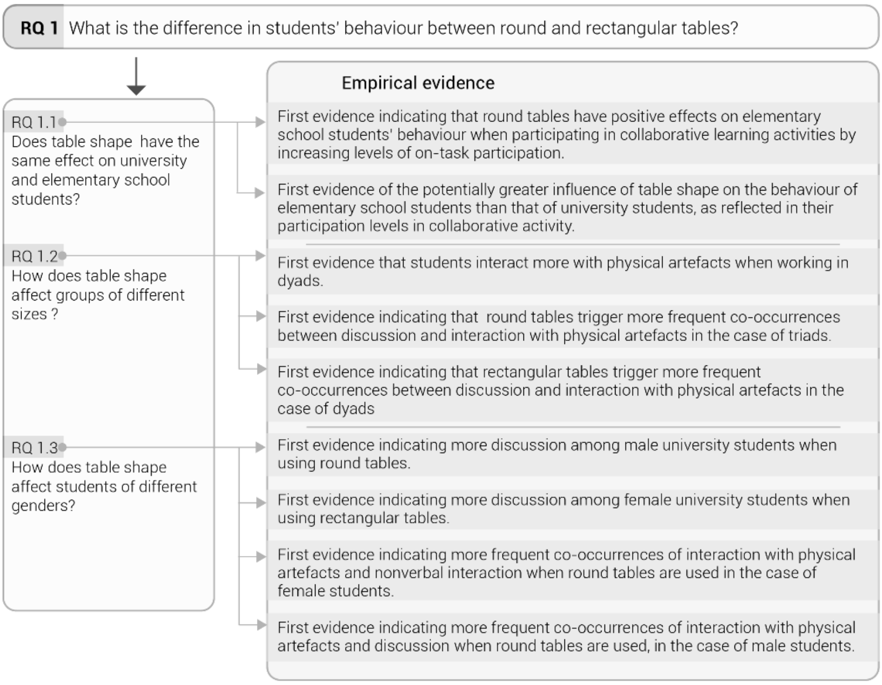


*Figure 11. Contributions related to the first group of research questions*

## Indicators

The second group of contributions relate to the data collection scenarios and the relevance of indicators in providing insight into the effects of table shape. Based on previous studies in the field of multimodal learning analytics, the distance between learners and the range of head movement were adopted as indicators and measured using a motion capture system (Schneider & Blikstein, 2015; Spikol et. al., 2017). However, statistical analysis did not show significant differences in these indicators between the two table shapes. In the context of this dissertation, these two indicators, used independently of other methods, did not prove to be key indicators of differences in collaborative behaviour. On the other hand, the distance between learners can be more informative as an indicator of table shape effect if examined in relation to on-task versus off-task actions, which will be further explained in the following paragraphs.

In contrast to the distance between learners and the range of head movement, the participation level has been shown to be a relevant indicator in assessing the effects of table shape in collaboration. Student engagement in collaborative activity was assessed using this indicator based on the NISPI framework (Cukurova, et al, 2018). There is a statistically significant difference between the two table shapes and it indicates that elementary school students participate more in collaborative activity when they use round tables. Therefore, the contributions related to indicators are (Figure 12):

- *'Distance between learners' and 'Range of head movement' are not necessarily key indicators of collaboration when observed independently of on- and off-task actions.*
- *'Level of participation' and 'temporal co-occurrence of on-task actions' were relevant indicators in providing first evidence of the effects of table shape.*

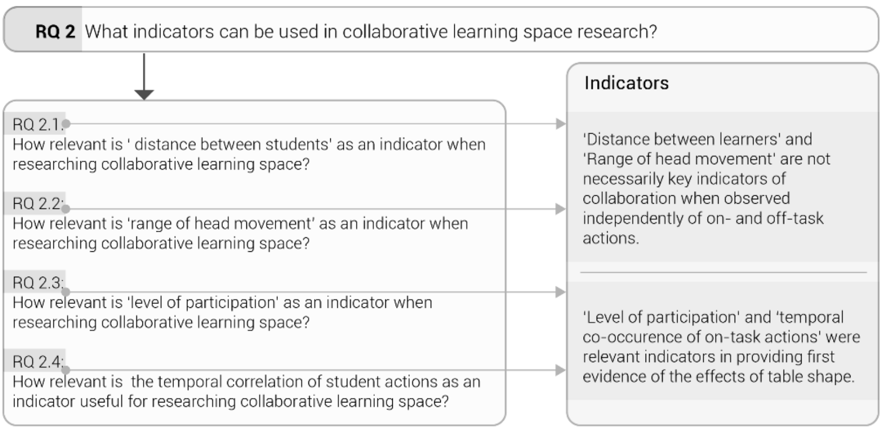


*Figure 12. Contributions related to the second group of research questions*

### Data collection, analytical techniques and visualisation

The primary contributions in terms of data collection, analytical techniques, and visualisation are related to the assessment of motion capture as a technique to consider in MMLA that can facilitate more efficient study of physical learning spaces and their effects. On the application of MMLA in the study of learning space, physical parameters such as movement and distance have already been reported in the literature (Healion et al., 2017; Martinez-Maldonado, 2017; Martinez-Maldonado et al., 2020). Given that automation of measurement and analysis of these parameters is essential for efficient research, different automation techniques have been used. Video and sound analysis, together with time-lapse and still photographs, all triangulated with qualitative analysis, have been shown to be useful in the automation of the learning space analysis process (Healion et al., 2017). Furthermore, the analysis of classroom proxemics involved an indoor positioning system for automatic analysis of the connection between teacher, students, and learning space (Martinez-Maldonado, 2017; Martinez-Maldonado et al., 2020). In line with the idea of improving the effectiveness of detection and analysis of multimodal data, and guided by studies that point to the importance of researching the physical parameters of participant interaction in the learning space, the motion capture system was deployed and examined as part of MMLA.

In order to examine the efficiency of the motion capture system, the first experiment focused on analysing the simultaneous measurement of three indicators (distance between learners, movement speed, and gaze direction) and on speeding up the analysis process compared to methods previously applied in the literature. The experiment showed that the motion capture system can effectively track multiple participants in an experiment, which is an advance compared to other studies using a camera or deep learning algorithms for depth perception. It is worth noting, though, that motion capture could face problems in tracking larger numbers of participants. Effectiveness of motion capture system as part of the MMLA system was demonstrated by detecting distance between learners and movement speed efficiently.

The introduction of the motion capture system to test the learning space and measure the mentioned parameters required the integration of the system infrastructure into a collaborative experimental setup. The most critical part of the adjustment was the marker protocol, which involved mounting reflective markers on the participants' heads. Iterations have led to a protocol that involves only one marker on the head, which greatly simplifies the procedure. In this way, a larger number of participants in the experimental space does not negatively affect the measurement process. Markers are visible and the motion capture system gives clear results without interference. Therefore, two indicators are measured efficiently, while with the third indicator, gaze direction, there are certain limitations in detection, and this requires additional resources in order to provide valid data. So, a case study showed the ability of the motion capture system, together with a one-marker protocol to quickly and efficiently detect movements, which was applied in the next case study. The papers presented in Chapter 3 explain the examination of a motion capture system in more detail. In the area of motion capture systems, this dissertation contributes:

- *Data collection scenario and data set enabling the assessment of a motion capture system as part of a multimodal learning analytics system to detect distance between learners and movement speed in a case study of university students.*

- *Data collection scenario and data set showing the establishing of rapid detection of known indicators (distance between learners and movement speed) by introducing a new one-marker protocol and accelerated data analysis.*

Furthermore, the dissertation contributes to knowledge of data collection scenarios by showing the relevance of triangulation results from qualitative analysis with results obtained from the quantitative analysis of data obtained through the application of MMLA. Although new techniques involving automation in detection and analysis are increasingly common, the literature (Malmberg, et al., 2019; Sobocinski, et. al., 2020; Martinez-Maldonado, et. al., 2020) emphasises the need to use qualitative analysis to verify or confirm the findings of quantitative analyses.

In the data collection scenarios involving university and elementary school students, qualitative analysis provided a more detailed understanding of the statistical analysis when focusing on the statistically significant difference between the effects of round and rectangular tables on participation levels. Qualitative analysis linked the results of the statistical analysis to the difference between on-task and off-task actions. More precisely, the first empirical evidence on greater participation by elementary school students when they use round tables for collaborative activity was actually obtained from the triangulation of quantitative and qualitative data. More details are presented in the second paper in Chapter 3. The main contributions related to the application of MMLA in collaborative learning space research are:

- *Qualitative video analysis suggests that closeness (small distance between students) is an indicator of participation for both elementary school and university students when observed in on- and off-task actions.*

- *Indication of relevance of MMLA analysis in explaining and confirming findings related to the higher participation levels of elementary school students when round tables are used.*

In terms of analytical techniques, the dissertation contributes with the data collection scenario showing how ENA analysed the temporal correlations between students' on-task actions and how this can offer deeper insights into collaborative differences. The analysis identified the different effects of table shape on the course of student actions during collaboration. More details on the analysis of the temporal aspect of collaboration using ENA are presented in Chapter 5. Specifically, the contributions involved applying epistemic network analysis and examining co-occurrences of actions in order to identify differences in student behaviour in two different learning environments. The analysis was conducted to examine group size and gender and the first evidence suggests that round tables trigger more discussion and interaction with physical artefacts in the case of triads. On the other hand, rectangular tables tend to prompt the same actions more frequently with dyads. It has been shown that the analysis of the temporal perspective allows us to see how the shape of the table affects different group sizes. Furthermore, temporal perspective analysis has provided insight into the differences in students' behaviour when two different genders are observed. Accordingly, findings in the literature on the importance of the temporal aspect in collaborative learning research (Teasley et al, 2008; Malmberg et al, 2017; Reimann, 2009) and suitability of ENA for studying this aspect (Andrist, et al, 2015) have been confirmed. The contributions of this dissertation on temporal perspective analysis are reflected in:

- *Showing the usefulness of temporal analysis perspective in collaborative learning space research through the application of ENA.*

In addition to these contributions, the previously discussed topic of MMLA data visualisation was focused on displaying all the parameters detected by the MMLA system simultaneously in order to determine the relationship between them. The integrated visualisation of all data is currently in its preliminary phases and further steps are planned as future work. More details about initial research on visualisations is presented in Chapter 6. Figure 13 shows the contributions related to the third group of research questions.

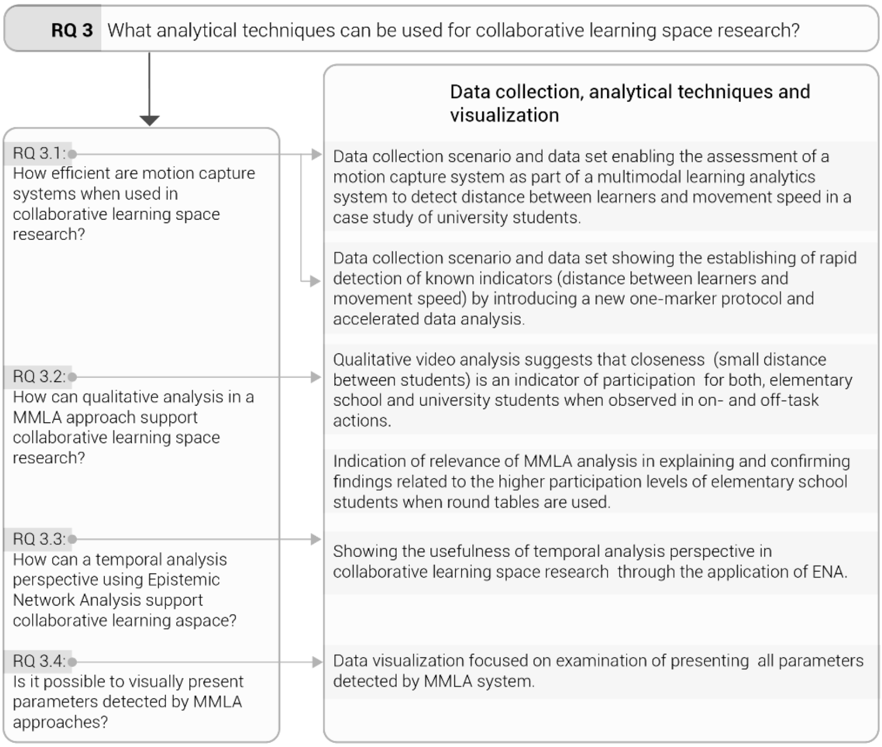


*Figure 13. Contributions related to the third group of research questions*

### 1.5.2 Publications

This dissertation is a compendium of the research papers listed in Table 2, which were published or in the process of publication at the time of submission of the dissertation.

Table 2. List of publication included in the dissertation

| Publication type | Paper | *Publication(s)* * |
|---|---|---|
| Book chapter | Vujovic, M., & Hernández-Leo, D., Martinez-Maldonado, R., Cukurova, M., Spikol, D., (TBD). ‘Multimodal Learning Analytics and the Design of Learning Spaces’. (book chapter submitted) | *BC1* |
| *Manuscript ready to be submitted* | Vujovic, M., Hernández-Leo, D. (TBD). ‘How do table shape, group size, and gender affect on-task actions in collaborative learning activities?’ (to be submitted) | *S1* |
| Journal paper | Vujovic, M., Hernández-Leo, D., Tassani, S., & Spikol, D. (2020). ‘Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study’. *British Journal of Educational Technology*, *51*(5), 1597-1614. | *J1* |
| Journal paper | Vujovic, M., Amarasinghe I., Hernández-Leo, D. (TBD). ‘Studying collaboration dynamics in physical learning spaces using Epistemic Network Analysis’, *Sensors.* (accepted with minor revisions) | *J2* |
| Journal paper | Beardsley, M., Martínez Moreno, J., Vujovic, M., Santos, P., & Hernández-Leo, D. (2020). ‘Enhancing consent forms to support participant decision making in multimodal learning data research’. *British Journal of Educational Technology*, *51*(5), 1631-1652. | *J3* |
| Conference paper | Beardsley, M., Vujovic, M., Theophilou, E., Hernández-Leo, D., & Tresserra, M. P. (July 2020). ‘The challenge of gathering self-reported moods: Cases using a classroom orchestration tool’. In *2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT)* (pp. 355-359). IEEE. | *C1* |
| Workshop paper | Amarasinghe, I., Vujovic, M., & Hernández-Leo, D. (2020). ‘Towards teacher orchestration load-aware teacher-facing dashboards’. In Giannakos, M., Spikol, D.., Molenaar, I., Di Mitri, D., Sharma, K., Ochoa, X., Hammad, R., editors. *Proceedings of CrossMMLA in practice: Collecting, annotating and analyzing multimodal data across spaces co-located with 10th International Learning and Analytics Conference (LAK 2020)*; 2020 Mar 24. Aachen: CEUR; 2020. p. 7-10. CEUR Workshop Proceedings. | *W1* |

| | | |
|---|---|---|
| | Related to the journal paper:<br>Amarasinghe, I., Hernández-Leo, D., Michos, K., Vujovic, M. (early access) An Actionable Orchestration Dashboard to Enhance Collaboration in the Classroom, IEEE Transactions on Learning Technologies. DOI: 10.1109/TLT.2020.3028597 | |
| Conference poster | Vujovic, M., Hernández-Leo, D. (2019). 'Shall we learn together in loud spaces? Towards understanding the effects of sound in collaborative learning environments', *International Conference on Computer Supported Collaborative Learning*, Lyon, France, pp. 891-892. | C2 |
| Conference poster | Vujovic, M., Tassani, S., & Hernández-Leo, D. (September 2019). 'Motion capture as an instrument in multimodal collaborative learning analytics'. In *European Conference on Technology Enhanced Learning* (pp. 604-608). Springer, Cham. | C3 |
| Conference demo paper | Beardsley, M., Vujovic, M., Portero-Tresserra, M., & Hernández-Leo, D. (September 2019). 'ClassMood app: a classroom orchestration tool for identifying and influencing student moods'. In *European Conference on Technology Enhanced Learning* (pp. 723-726). Springer, Cham. | C4 |

**J: journal article; C: Conference paper; W: Workshop paper; BC - Book Chapter, S-submitted (or about to be submitted) manuscript*

### 1.5.3 Contribution to research projects

This dissertation was funded by the European Union's Horizon 2020 research and innovation programme under Marie Skłodowska-Curie grant agreement No. 713673. Doctoral candidate Milica Vujovic has received financial support through the La Caixa INPhINIT Fellowship Grant for Doctoral Studies at Spanish Research Centres of Excellence awarded by La Caixa Banking Foundation in Barcelona, Spain.

Partial funding supporting the dissertation work was provided by the SMARTLET project. The dissertation contributes to SMARLET objectives by applying MMLA in research on how space affects on collaborative learning processes, and an Internet of Things-enriched experimental environment was created and used in the research process. Table 3 presents details about the SMARTLET project:

Table 3. Details about the SMARTLET project

| | |
|---|---|
| Name of the Project: | **SMARTLET** (**Learning analytics to enhance the design and orchestration in scalable, IoT-enriched, and ubiquitous Smart Learning Environments**) |
| Duration: | 2018 – 2020 |
| Funding entity: | European Regional Development Fund as well as the National Research Agency of the Spanish Ministry of Science, Innovations, and Universities (TIN2017- 85179-C3-3-R) |
| Participating entities: | University Carlos III de Madrid, Madrid, Spain<br>Universidad de Valladolid, Valladolid, Spain<br>Universitat Pompeu Fabra, Barcelona, Spain |
| Principal Investigator (UPF): | Davinia Hernández-Leo |
| Website: | https://smartlet.gsic.uva.es/ |

Participation in the Spotlighters project involved partial collaboration on the design of a classroom orchestration tool (ClassMood App - with a component for collecting self-gathered data), as an output of this project. Table 4 presents details about the Spotlighers project:

Table 4. Details about the Spotlighters project

| | |
|---|---|
| Name of the Project: | **Spotlighters – Student Paths to Resilience with the Science of Stress** |
| Duration: | 2018 – 2021 |
| Funding entity: | European Regional Development Fund as well as by the National Research Agency of the Spanish Ministry of Science, Innovations and Universities (TIN2017- 85179-C3-3-R)<br>Erasmus+ Programme, European Commission (2018-1-ES01-KA201-050646) |
| Participating entities: | University of Helsinki<br>Autonomous University of Barcelona<br>University of Western Macedonia<br>Metropolia University of Applied Sciences<br>LOOP.bz<br>Advancis<br>BOON |
| Principal Investigator (UPF): | Davinia Hernández-Leo |
| Website: | http://www.spotlighters.eu/ |

## 1.6 Limitations

The dissertation presents the use of experimental design methodology in studying the influence of space, specifically table shape, on collaborative learning. The research questions were defined and – through experiments intended to create data collection scenarios in laboratory conditions – data were collected and analysed to obtain the results. To answer the research questions, the contributions of the dissertation are presented and described in detail. However, due to the application of the experimental design methodology to a sample size set by practical constraints, certain limitations emerged. These limitations will serve to define directions for future research.

### 1.6.1 Laboratory setting

The experimental design methodology determines the control of variables so that they can be manipulated and the impact on other variables may be observed. For adequate control of variables, the experiment was conducted in a laboratory environment. Conducting research in laboratory conditions could be considered a limitation due to the fact that certain parameters cannot be controlled to such an extent when it comes to real learning environments. Therefore, replicating the experiment in a real setting would require certain adjustments. Additionally, the sense that students may have of being in an unconventional learning space is inevitable. However, in order to understand the effects that result from the influence of different physical environments, it is necessary to remove as many uncontrolled variables as possible, which is why this research was conducted in the laboratory. Furthermore, the equipment needed to detect motion consists of eight cameras mounted on the ceiling and a workstation, which all together require the experiments to be conducted in a laboratory.

### 1.6.2 Different age groups

Another limitation stems from testing different ages of students. For the validity of measurement, student tasks for different age groups should be as similar as possible. The goal was to create a task that would be similar and generate a similar level of collaboration. However, as this was a design task for both university and primary school students, it is clear that the task could not be exactly the same, but had to be adapted to their respective levels. Although the task was designed to require student collaboration, creative thinking, and decision making, as well as the use of laptops and other tangibles, the differences that exist can be considered another limitation of these experiments.

### 1.6.3 Gender balance

Due to the complexity of collaborative activities and the overall experimental setup, there were certain limitations on gender balance. During the recruitment process, students identified as one of two genders: male or female. Although the selection process yielded the same number of female and male students, the forming of groups of three members meant that having an equal number of members of the same gender in each of the groups was not possible. Therefore, a strategy was adopted so that each group had at least one member from each genders. Also, analyses of student gender were not done at group level, but individually. Namely, when analysing the interaction of variables such as table shape or group size with gender, individual data for each of the students were used, grouped by gender, and then compared with each other. This dissertation was limited to examining two group size determinations and consciously accepted gender restrictions. This limitation prevented an even more detailed analysis of the impact of desk shapes on students of different genders, but provided the way forward for future work, which could use an established methodology to study gender when in terms of other group sizes wherein full gender balance can be achieved.

### 1.6.4 Sample size and data collection limitations

Sample size limitations are common to related studies. In the field of educational technology – due to a number of parameters such as learning design, participant characteristics, and equipment – it is difficult to recruit a large number of participants. Especially when it comes to collaborative activities, which require a complex experimental setup, some limitations on recruitment are inevitable. Additionally, ethical issues also impose limitations to some extent, especially with younger students. The process of obtaining consent can often be lengthy due to the required consent of the parents of younger students or cause the withdrawal of participants. Another difficulty encountered during the research for this dissertation was the COVID-19 pandemic, which caused the cancellation of already prepared experiments that were supposed to expand the data set.

Furthermore, the limitations of data collection in a complex multimodal system are also reflected in the results. Coverage of student actions required a carefully designed equipment setup protocol. However, the loss of a piece of data is often inevitable due to the inability to cover every corner of the collaborative space when six subjects are positioned inside of it. Moreover, in a certain percentage of the experiments, parts of the equipment failed, which was often not evident until after the end of the session. To further complicate matters, failure of one part of the system was usually insufficient grounds for abandoning the entire session as stopping other equipment would have been even more damaging.

### 1.6.5 Collaborative learning design

The learning design applied in the experiments was based on the Jigsaw collaborative learning flow pattern, which carries a limitation in terms of the generalisability of results to other collaborative learning designs. However, the activity is designed to be open-ended, which is characteristic of many collaborative activities. On the other hand, the Jigsaw collaborative pattern does allow for the forming of dyads and triads within a single activity in a structured way. Further, it enables a balanced workload for each student as much as possible in the given conditions, which ensures the equality of subjects in the analysis process. Notwithstanding the above, limitations exist and additional measures such as student questionnaires regarding workload are required. Additional data obtained from the questionnaire would also be relevant for this study. Particularly when researching the impact of the environment on students of different genders, additional knowledge of their previous experiences would potentially help to further clarify the findings.

## 1.7 Conclusion

As explained in Section 1.3, the aim of the dissertation is to examine how MMLA can support an understanding of the effects of learning space on student behaviour during collaborative activity. Through a series of research questions, the aim was to determine the influence of table shape on student behaviour, given different group sizes and student genders. An experimental design methodology was established and the experiments carried out provided results that generated certain contributions. The conclusions are diverse and will be presented in the order of the research questions posed.

### 1.7.1 On RQ1: What is the difference in student behaviour between round and rectangular tables?

> *RQ 1.1 Does table shape have the same effect on university and elementary school students?*
>
> *RQ 1.2 How does table shape affect groups of different sizes?*
>
> *RQ 1.3 How does table shape affect students of different genders?*

On the first group of research questions, the findings indicate that table shape does influence the process of collaboration. They provide the first empirical evidence of a difference in the behaviour of elementary school students when using different desk shapes during collaborative activities. Round tables triggered more participation in collaborative activity among elementary school students independently of group size and gender. These findings have implications for the practice and consideration of space as inseparable from learning design. Further steps that applied ENA led to additional conclusions highlighting the impact and interaction of table shape with group size and gender. These findings involve co-occurrences of student actions and show how the actions common to dyads when working at round tables are the same as those common to triads at rectangular tables. The results indicate a difference due to the use of different desk shapes that should also inform practice, as is the case with the effect identified on elementary school students.

When we consider the first empirical findings on the effects of table shape on students of different genders, it suggests that table shapes play a relevant role in the collaborative learning process and should therefore undoubtedly be considered as an essential consideration in the learning design process. Most importantly, the interaction of elements such as table shape and group size with gender demonstrates the need to contextualise and examine this issue in more detail. Besides gender, the differences highlighted in the findings also provide an insight for teachers and educational researchers into the physical environmental factors that must be accounted for when creating a learning design.

### 1.7.2 On RQ2: What indicators are relevant for collaborative learning space research?

*RQ 2.1 How relevant is 'distance between students' as an indicator when researching collaborative learning space?*

*RQ 2.2 How relevant is 'range of head movement' as an indicator when researching collaborative learning space?*

*RQ 2.3 How relevant is 'participation level' as an indicator when researching collaborative learning space?*

*RQ 2.4 How relevant is the temporal correlation of student actions as an indicator when researching collaborative learning space?*

The second group of research questions focused on the relevance of the indicators used in researching collaborative learning space. From the literature, it can be gathered that certain indicators in this area are not informative enough, while others are. The 'range of head movement' indicator proved to be the least relevant for studying the influence of table shape in the dissertation experiments. This does not mean that this indicator is not relevant to others context in which the impact of the environment is examined, but the findings presented in this dissertation indicate that this physical parameter is not informative enough when studying differences in student behaviour in different environments. The 'distance between learners' indicator also proved to be less relevant in this study after statistical analysis was conducted. However, by introducing qualitative analysis to clarify the results of statistical analysis, it has been shown that this indicator can be informative when complemented by the results of targeted observations. The contributions previously mentioned of the first empirical evidence of increased participation by elementary school students when using round tables arose precisely from the triangulation of the results from qualitative and quantitative analysis of the distance between students and related this indicator to more participation. Accordingly, the importance of MMLA in collaborative learning spaces research is emphasised. Therefore, based on the results obtained in this dissertation, it can be concluded that 'distance between learners' is a relevant indicator, with the condition that it is analysed as described above.

It can also be concluded that the 'participation level' indicator has proven to be significant in showing the differences between table shapes when considering elementary school students. Statistically significant differences demonstrate the importance of using this indicator in the context of this study and of its further application in future experiments in both this and other contexts in the study of collaborative learning space. We may further conclude that, in addition to statistical analysis, qualitative analysis also confirms the findings and once again shows that MMLA plays an important role in the use of these indicators in the analysis of learning space.

In the case of university students, the three indicators examined did not show significant differences between table shapes, and therefore the first conclusion is that they are not key indicators for this age group in this experimental context. However, with the introduction of ENA and the temporal component as indicators, findings have been obtained that in the interaction of table shape, group size, and gender, there are significant differences in on-task behaviour of university students. The same table shape in dyads and triads causes completely different co-occurrences of on-task actions. Similar results were obtained with the two genders. Co-occurrences of actions show the development of actions over time and it can be concluded that the temporal component is a relevant indicator in the study of collaborative learning space. An obvious additional value is that by introducing a temporal component in the analysis of student behaviour, we can come to conclusions that are not easily achievable by the usual methods employed in educational research (statistical analysis, coding and counting, etc).

Thus, the indicators above, which have their basis in the literature, are not equally relevant for the study of collaborative learning space in this context. 'Participation level' and the temporal component of on-task behaviour proved to be more relevant indicators, while 'distance between learners' and 'range of head movement' were less relevant. It is worth highlighting that these conclusions are limited to the research context presented in this dissertation. By examining these particular indicators, the goal was to determine not only their individual relevance, but also their interrelationships and how best to approach their analysis. One further conclusion is that the relevance of indicators is closely related to the context, as well as to the way in which they are analysed. The use of MMLA has proven to be extremely relevant in this context. In addition, ENA has shown its usefulness in examining the temporal component of the collaboration process.

### 1.7.3 On RQ3: Which data collection, analytical, and visualisation techniques can be used for collaborative learning space research?

> *RQ 3.1: How efficient are motion capture systems when used in collaborative learning space research?*
>
> *RQ 3.2: How can qualitative analysis in an MMLA approach support collaborative learning space research?*
>
> *RQ 3.3: How can a temporal analysis perspective using Epistemic Network Analysis support collaborative learning space research?*
>
> *RQ 3.4: Is it possible to visually present parameters detected by MMLA approaches?*

The search for answers to the third group of research questions led to certain conclusions about the analytical methods used in the study of collaborative learning space. First of all, motion capture systems were examined as a technique for collecting and analysing data on the physical parameters of collaboration (distance between students and range of head movement). The results led to the conclusion that these indicators can be measured efficiently with this system. The only caveat that is important to note is that it is necessary to adapt the application of the motion capture system to each of the contexts. Namely, in the context considered in this dissertation, it was necessary to establish a specific marker protocol that provided recordings with as little occlusion as possible. Integrating a motion capture system into an experimental setup requires adaptation to the context, but it can be concluded that this system has the potential to further explore the physical aspects of collaboration and, accordingly, to study the space.

Furthermore, the results of the experiments also led to the conclusion that MMLA is very important in the process of analysing the collaborative learning space. As mentioned earlier, the triangulation of quantitative and qualitative data led to conclusions about the influence of the table on the participation levels of elementary school students. The results of the qualitative analysis clarified and supported some of the findings obtained by the quantitative analysis.

Further analysis included introducing ENA as a tool used to extend the study of university student behaviour. In the first phase, in which statistical analysis was used in combination with qualitative analysis, no significant differences were found in the influence of two table shapes on university students. However, by introducing an analysis of the temporal component using ENA, a more detailed examination of the collaboration process over time was introduced and significant differences in the co-occurrences of actions have been discovered. Therefore, it can be concluded that ENA is also a method that supports research of collaborative learning space.

The initial steps taken in the process of data visualisation as a technique to aid data analysis showed that this technique shows some potential. However, within this dissertation, the visualisation examination focused on the first steps in design and interviewing a small number of participants. As the initial findings were not extensive, however, this method certainly requires more detailed research.

## 1.8 Future work

Future work should address the aforementioned limitations as well as further development of the research directions initiated in this study. These directions are discussed in the following paragraphs.

### 1.8.1 Larger sample size

One of the main goals of future work is to increase the number of subjects in order to confirm the findings obtained and examine in more detail the trends that previous analyses have revealed. In addition to confirming the findings, a larger number of subjects would enable better gender balances, which would generate additional analyses such as more detailed analyses within each group. First of all, increasing the number of subjects would allow for the repetition of the same experimental design in which university and elementary school students in a laboratory environment would engage in collaborative activity according to the experimental design methodology presented in this dissertation. This would be enable researchers to confirm the findings in the same context and serve as a transition to the next step. This step would be an increase in the number of subjects achieved by organising experiments in a real environment.

### 1.8.2 Real learning environment

Conducting experiments in a real environment would require adjustments to the experimental setup, though it would also provide new insights into the effects of the environment on behaviour. In addition, the influence of the laboratory environment on students, which certainly has some effect, would thus be eliminated. Furthermore, the real environment would enhance consideration of the learning design. While the application of the Jigsaw collaborative learning flow pattern does affect the generalisability of the results, it also allows for alternation between two groups and is an essential part of the methodology employed in the dissertation. Therefore, this aspect would be retained in a real environment, but some future steps would by necessity involve other types of learning design. With new designs, the range of variables would be expanded, but the influence of the environment on collaboration would take a crucial step towards generalising the findings.

### 1.8.3 Additional data sources

Future work would also include the collection of additional data through questionnaires in order to gain more detailed insight into the workload experienced during the experiment and previous experience of gender-related aspects. The introduction of new modalities will also be considered in future iterations of the experiments. Measuring physiological parameters such as electrodermal activity and heart rate, as very common indicators of collaboration in the literature (Malmberg, 2019; Sobocinski, 2020), shows the potential to further explain the effects of the environment on student behaviour. Also, data on physiological parameters, together with data collected through questionnaires, can provide additional insight into the state of the student prior to the experiment, which would expand the scope of the research. Self-reported data collection and electrodermal data collection were explored in related research in which I participated and is presented in Chapter 6 and in Appendix B.

### 1.8.4 Table shapes

Another important aspect that should be addressed in future work is using more table shapes that could be applied in collaborative work and whose impact would be examined. It is clear that there are many options and that increasing the number of variables risks even lower generalisability of the findings. However, the introduction of new table shapes would be introduced as a separate experiment, without changing other parameters, so that other variables would remain the same while only this parameter would change. In addition, the total number of different shapes, two, would remain the same in preliminary studies. It would thereby be possible to compare the results with previous findings.

## 1.9 Structure of the dissertation

The dissertation is a compilation of papers published or submitted for review during the deposition of the dissertation. The articles are arranged in chapters according to the topic they cover. Each chapter begins with an introduction explaining the article and its place in the context of the dissertation, and covers one or several research questions as well as presenting the contributions previously explained.

*Table 4: Publications presented through dissertation chapters*

| *Chapter* | *Title* | *Publication(s)** |
|---|---|---|
| *Chapter 2* | ‘Multimodal learning analytics and the design of learning spaces’ - book chapter | *BC1* |

| | | |
|---|---|---|
| *Chapter 3* | 'Motion capture for measuring physical aspects of collaboration' | *C3, J1* |
| *Chapter 4* | 'On-task actions in collaborative learning spaces' | *S1* |
| *Chapter 5* | 'Temporal relations between on-task actions in collaborative learning spaces' | *J2* |
| *Chapter 6* | 'Extending modalities with electrodermal activity and visual analytical approaches' | *W1, C2* |
| *Appendix A* | About ethics in MMLA | *J3* |
| *Appendix B* | About self-reported data | *C1, C4* |

**J: journal article; C: Conference paper; W: Workshop paper; BC - Book Chapter, S- submitted (or about to be submitted) manuscript*

# Chapter 2 - Multimodal learning analytics and the design of learning spaces

This chapter extends the presentation of the theoretical framework of the dissertation and compares the overall contributions of this PhD work with related work. The publication presented in this chapter is:

- ‘Multimodal learning analytics and the design of learning spaces’ - with the main study of the dissertation presented in connection with two key studies from related work. The publication is a submitted book chapter showing the use of MMLA from different perspectives and addressing different aspects of the collaborative learning space.

## 2.1 Multimodal learning analytics and the design of learning spaces

The following manuscript was submitted as the book chapter in the book, *Multimodal learning analytics*, to be published by Springer.

| |
|---|
| Vujovic, M., & Hernández-Leo, D., Martinez-Maldonado, R., Cukurova, M., Spikol, D., (2021). ‘Multimodal learning analytics and the design of learning spaces, *Multimodal learning analytics*’. (submitted book chapter) |

# Multimodal Learning Analytics and the Design of Learning Spaces

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**Abstract.** Research on learning spaces and their impact on teaching and learning have been a field of inquiry for decades. Yet, technology advances regarding data capture and analysis tools have led to a significant evolution in the field, opening new opportunities and challenges. This chapter features the role of multimodal learning analytics in learning space research. In particular, the chapter presents an overview of the evolution of analytical studies about learning spaces with a focus on the development of Multimodal Learning Analysis (MMLA) over time. The chapter also offers three detailed examples from current research that illustrate how different MMLA methods enable spatial analysis to study learners and teachers actions in collaborative learning settings. The examples bring out interesting results informing the design of learning spaces while showing at the same time the complexity of its effects on learning processes. By bringing together an overview of the evolution in this research line and current studies with their findings, the chapter highlights the increasing potential of MMLA to advance learning space research.

**Keywords:** Multimodal Learning Analytics, Learning Spaces, Learning Design

## 1. Introduction

The role of physical space in the entire learning process has proven critical (Ching, 2014; Carvalho & Goodyear, 2014). The classroom, as an integral element of the learning process, has been the subject of numerous studies (e.g. Weinstein, 1981; Barrett, et al., 2015; Rands & Gansemer-Topf, 2017). However, the very notion of the classroom has become much broader than it was a few decades ago. Novel architectural classroom designs, such as open-plan and flexible classrooms (Reh et al., 2011; Neill, & Etheridge, 2008), and the intensive use of emerging digital classroom technologies are becoming more present. Therefore, the spaces for learning and the complexity of the learning process unfolding in them are rapidly co-evolving, in part, thanks to the emergence of novel tools and associated practices in technology-enhanced education. Furthermore, the classroom as a physical environment is inseparable from the actions and interactions that occur in it. This means that there is a strong relationship between architectural and learning designs (Goodyear, 2020). Innovations in the field of education, in terms of learning methods, have initiated changes in the field of architecture of educational buildings, adapting the space to new needs (Park & Choi, 2014; Huang, et al., 2019). Conversely, like in every built environment, physical features of the space affect the processes that take place within it, creating different atmospheres, and encouraging or preventing specific actions, feelings and impressions from emerging.

The importance of learning spaces is also acknowledged in the field of architecture, where a large number of architects specialize in this sub-area (Attai et al., 2020a; Attai, et al., 2020b; Scott-Webber, et. al., 2017). It is thus critical to identify design principles to create learning spaces that consider the complexity of the learning processes unfolding in the built environment and effectively support the particular needs of teachers, learners and relevant stakeholders. Nevertheless, in order to understand the impact of designed learning spaces and how design principles can impact learning activities, more research is needed.

Some design principles for creating physical spaces that positively influence the learning process have been considered and researched in practice, at least implicitly. Teachers have always considered how to physically organize students during their classes in accordance with the learning design. The intuitive actions that the teachers commonly undertake in relation to the configuration of the physical learning space have been experimentally investigated since the 19th century (e.g. Barnard 1854; Rubin, 1972). However, the affordances offered by technology have made it much more possible for these, usually manual, data collection and classroom observations to become a testing ground for the automated data collection and new analytical methods. The emergence of sensors and Multimodal Learning Analytics (MMLA) techniques can offer new ways for studying learning spaces and the learning activity that occurs in them.

Recent MMLA studies have shown great progress in exploiting the possibilities offered by new sensing technologies (e.g. indoor positioning trackers, cameras, proximity beacons, and depth sensors) to capture data from physical learning spaces automatically. Automation is bringing new possibilities for capturing traces about multiple modalities of learners' interaction. The contribution of this chapter is a discussion of the evolution of MMLA systems that can be used to investigate various aspects of learning spaces. Focusing on three case studies that use different methods of spatial analysis, the complexity of the physical learning spaces impact on the learning process is illustrated. Furthermore, the chapter brings together current studies and their findings in one place with the aim to point at the importance of learning space research.

## 2. Research on learning spaces: from traditional to computer-based analysis

Early studies on learning spaces focused on observations and information gathered from the participants mostly manually, with occasional video recordings. Even before the existence of advanced technology that enabled the automation of data collection and analysis, it was clear that different data modalities were needed to understand the classroom environment better. One of the first explorations of the impact of learning spaces on learning was conducted by Barnard (1854). He pioneered the research on the learning space from the angle of optimizing the position of teachers to enhance the attention of students by systematically examining a series of classroom arrangements. The study was based on observations, illustrations and maps created to compare various conditions. More recently, the position of teachers in relation to furniture has also become the subject of research. For example, Rubin (1972) analyzed the relationship between seating arrangements and the extent to which teachers and students communicate. Two data modalities were used in this case: observations of social and physical interaction, and students' questionnaires. Furthermore, in the late twentieth century, several studies started to examine the learning space by incorporating additional data modalities. For example, teachers movement strategies (positioning throughout the classroom) to balance interaction with students were analysed using observations and video recordings as data sources (Gunter et al., 1995). The impact of physical proximity between teachers and students (with a disability) on the student's sense of agency was analyzed by measuring interpersonal distances measurement and conducting interviews with students (Giangreco, et al., 1997). A study analyzing student motivation also examined the position of students in relation to the constantly changing position of teachers (Burda & Brooks, 1996) by using a survey. An important milestone in research on learning spaces was the period marked by the introduction of new learning models that required the use of computers when analysis of teacher-student interactions in physical spaces began (Sills-Briegel, 1996). At that point, the use of technology was limited and the development of learning design proceeded faster than the integration of technology into the research of the learning space.

In sum, a large number of studies have dealt with the interaction of students and teachers in different environments on qualitative data collected by observations. However, manual data collection methods had their limitations and the need for more modalities. For example, observations on movement, distances, the position of people, and interactions with each other took time, required trained observers, and were prone to errors (Barnard, 1854; Rubin, 1972; Gunter et al., 1995).

| Spatial aspect | Research interest | Modalities | Example |
| --- | --- | --- | --- |
| 1854 Classroom seating arangement | Maximize techers' surveillance of students and students' attention directed to the teacher | Observations<br>Illustrations | The importance of the classroom seating arrangement was discussed by Bernard (1854), who did an exessive study on the details of the learning space organization. An overview of schools indicates the beginning of research into the relationship between teachers, students, and space. The focus was on the teacher as the main focal point in the classroom and the main object of students' attention. The review of spatial details opened the possibility for the development of numerous studies. |
| 1972 The location of the teacher in relation to the classroom furniture | Effect of the communication processes occuring between the techers and students | Observations<br>Students' questionnaires | Rubin (1972) researched a real setting, where 84 students were split into four groups and every week assigned with random seats in a classical classroom. Both students and teachers completed semantic differential scales. Students evaluated the seating arrangements and feelings about the environment while teachers evaluated students' performance and complaints about the environment. Results implied that the seating arrangements |
| 1995 Teacher movement strategies (through the classroom) | Balancing the interaction with students | Observations<br>Video recordings | Gunter et al. (1995) reviewed several studies that examined the proximities in the classroom and showed that results indicate the importance of teacher's closeness to the student. The authors developed a set of recommendations which refer to the optimal distances between teacher and students that facilitates attention maintenance. Furthermore, the recommendations propose setups that neither cause disruptions nor hinder shared advice from the teacher. |
| 1996 Position of students in relation to the changing position of teachers | Student motivation | Invetnory measuring achievement motivation | Burda & Brooks, 1996 conducted a study about the seating arrangement, students' traits, and students' success in learning. Finding revealed that students with high achievement motivation more often decided to sit in front rows. However, learning outcomes did not differ greatly between students sitting in different rows. |
| 1996 Interaction between teachers and students | Interaction between teachers and students in environments with and without computer | Observations | Sills-Briegel (1996) examined the difference between classroom and computer lab, with the hypothesis that, in terms of proxemics, teacher's behaviour will be the same. The hypothesis was rejected with the findings related to the behaviour of teachers. In the computer lab, as opposed to the classroom, they were either too close to the students or too far from them. |
| 1997 Physical proximity of teachers and students | Student's sense of being disturbed | Observations (distances)<br>Inteviews with students | Giangreco et al. (1997) examined student-teacher proxemics in the context of students with disabilities. They depended on two instructors - general teacher and instructional assistant. The closeness of the instructional assistant was essential for the learning process. However, in some parts of the class, assistants kept close distance while students didn't consider it necessary. Therefore, the findings imply that the distances should be further examined carefully and adjusted throughout learning activity. |

**Fig. 1.** Timeline presenting selected research on learning environments and different modalities collected in a manual way

However, the introduction of digital technology into learning analytics brought new levels of understanding of the physical learning environment context. In particular, multimodal learning analytics introduces a new way of thinking through multiple sources of data as a strategy to record features that cannot be easily observed and the ability to scale up data collection across multiple learning spaces. This way, the potential influence of the learning space in the learning process can be examined more closely. Sensing technology has made it possible by combining data traces from multiple modalities of interaction and capturing numerous types of data from one learning context. Figure 2 presents example studies that have deployed new technologies in MMLA to study physical aspects in various learning environments.

Recent studies have examined classroom arrangements through various types of collected data such as cultural features (Haghighi & Jusan, 2012) and the nature of the task (Wannarka & Ruhl, 2008). Furthermore, more detailed analysis of learning space arrangements relates to proxemics - a theory which investigates non-verbal communication between people in order to understand how they understand and use space around them to obtain communication goals (Hall, et. al., 1968). Instructional proxemics has been coined as a term to refer to the effects of the physical space of the learning environment on the student learning process (McArthur, 2015). McArthur (2015) conducted a study which indicates that learning space impacts student learning in terms of students' behavioral, affective, and cognitive learning and the use of the space is shaped mainly by the way a teacher is able to moderate his/her actions.

A step forward in this direction was made by introducing sensing technology into the exploration of instructional proxemics. Martinez-Maldonado et al. (2020) use the term classroom proxemics where the emphasis is placed on indoor positioning tracking systems that measure the movement of a teacher through the classroom and the impact of their position on the learning process of students. Although a large number of teaching guides prescribe how teachers should position themselves in relation to students in the classroom (e.g. Arends, 2014; Jones, et al., 2007; Scrivener, 2005), there is an evident lack of empirical evidence that can indicate the superiority of one approach over another. Another study dealing with the physicality of the learning space was conducted in the context of medical education (Echeverria, et. al., 2019). Students were performing a training session where a variety of multimodal data was acquired with the objective to understand how they moved and used artefacts in the physical space.

Additional modalities such as head and hand movement extracted from video recordings and an MMLA system have also been used to address the challenge of understanding intra-group interactions across digital and physical learning spaces (Cukurova, et al., 2018). Moreover, interactions between students and teachers, as well as their relation to space and objects around them, were observed to provide insights into the physical nature of collaborative work (Healion, et al., 2017).

| Spatial aspect | Research interest | Modalities | Example |
|---|---|---|---|
| 2015<br>Measuring aspects of body-laguage based on head tracking | Information about students' attention | Video recordings<br>Computer vision techniques | McArthur (2015) conducted a study with 234 college students participating in public speaking classes. The study revealed that the instructional environment had infulence on learning outcomes. Furthermore, the results suggest the relevance of the instructional proxemics in providing learning success. |
| 2017<br>Analysing students and teacher movement around furniture | Better insight into physical nature of collaborative work | Observations<br>Video recordings | Healion, et al. (2017) conducted the analysis of physical movement in collaborative setting in order to better understand the learning process. Findings demonstrate how multimodal learning analytics can be relevant in tracking the physical aspects of collaboration and supporting the research of small groups. |
| 2018<br>Extracting the face movement of the leacturer and students | Interactions between the acitions of teacher and students | Video recordings<br>Image processing techniques | Watanabe, et. al. (2018) used image processing to extract the face movements from teacher and students in order to track the interactions between teacher and students in lectures delivered using blackboard. Findings reveal that more research should be conducted in the context of the effects of learning environment on the behaviour of students. |
| 2018<br>Head and hand movement in space | Understanding both digital and physical environment | Video recordings<br>Computer vision techniques | Cukurova et. al. (2018) conducted a study where non-verbal behavioural data was collected. Head and hand movement was recorded during colaborative problem sovling activity. Furthermore, Nonverbal Indexes of Students' Physical Inter-activity (NISPI) framework was applied. Finding indicate that NISPI framework is a useful tool for research of physical aspects of collaboration. |
| 2020<br>Motion capture measuring student movement | Understanding how table shape, group size and level of education affect collaboration | Video recodings<br>Motion capture system | Vujovic et. al. (2020) report that the table shape has potential effect on the level of participation when different age groups are conducting collaborative activity in dyads and triads. In this study, motion capture sytem and video recordings were used. Triangulation between qualitative and quantitative data was applied. |
| 2020<br>Tracking movement of the professor through the classroom | Impact of techer's position on the learnin gporcess | Indoor localization<br>Interviews<br>Validation sessions | Martinez-Maldonado et. al (2020) used indoor positioning data to analyze and visualize movement of four teachers. Setting for this experiment was physics classroom and and three distinct learning designs were applied. Finings imply the usefulnes of the visualizations for teachers insight into their practice. |

**Fig. 2.** Timeline presenting selected research on learning environments and different modalities collected in a manual and automatic way

Studying learning space and its impact on various educational and learning outcomes is not an easy task. Complexity in researching the learning environment is reflected in the large number of interactions that occur between objects and people in the learning space. Therefore, creation and meaningful usage of multimodal datasets require new data processing techniques. A review on methods for the data collection on learning contexts that combine digital and physical spaces points to various directions of research needed to be taken in order to obtain more deployable and sustainable data collection setups (Chua, et. al., 2019). Those directions involve a deeper investigation into feedback and visualization systems, deployment of multimodal systems in ecological studies and extended application of mobile devices and sensors. Computer vision techniques can be used to mimic large-scale gaze tracking in order to measure aspects of body-language based on head tracking that provide information on student's attention (Raca, et al., 2015). The use of image processing techniques has found its application in the analysis of the interaction between teachers and students in a traditional environment where blackboard is used. In addition to extracting the face movements of the lecturer and students from images, key actions, such as explanations by the lecturer and note-taking and listening behaviours by students, have been modeled using multilayered neural networks (Watanabe, et al., 2018). Similarly, other complex computer vision techniques have been developed to infer students' engagement with collaborative problem-solving in real-world, dynamic learning environments (Kasparova, et al., 2020).

Overall, this discussion on the evolution of analytical studies about learning spaces shows this has been a field of inquiry for decades. The perceived relevance of the learning space became more and more manifest, and the researchers sought means to better understand its impact on the learning process. However, the pace of learning design evolution, learning space evolution and development of technology was not the same. Given the interconnectedness of these elements, it is clear that certain misalignments are due to exist and the gaps in research require much attention. New studies dealing with the research of furniture in the learning space and its role as part of learning design can provide new insights, but also motivate a growing number of new questions. Furthermore, new findings can provide new implications for the field of learning design and learning space design in terms of the importance of spatial elements in dimensions of learning, such as social, epistemic and affective. Selected examples of different MMLA systems applied in learning space research will be presented in the next section.

## 3. Examples of MMLA studies focused on effects of learning spaces

In this section, we present three cases that illustrate the use of various automated spatial analysis techniques to examine the complexity of the physical space and potential impacts on teaching and learning. Two examples present studies on the use of different furniture in collaborative learning scenarios and how the characteristic of the physical space can lead to different students' behaviours. The third example presents a classroom proxemics study that examines the interaction of teachers and students with the furniture as well as their position in relation to it.

### 3.1 The PELARS project: Standing for better collaboration

One aspect of the PELARS (Practice-based Experiential Learning Analytics Research and Support) project focused on the physical design of the workspace to encourage collaboration for the group and the individuals (Healion, et al., 2017). The researchers analysed how students and teachers move and interact with each other and the objects at hand. These investigations aimed to understand how to design a learning space that can reinforce the equity in the engagement and participation of the learners in collaborative problem-solving tasks. These initial investigations drove a design process that resulted in an MMLA system that was integrated into the furniture that was able to generate insights into the physical aspects of collaboration. The feedback between the physical interactions and the MMLA system were further used to suggest improvements in the design of educational environments.

The PELARS project team used the principles of Universal Design (Story, 1998; Mace, 1998) to guide the design of the learning space. The Universal Design (UD) principles promote equity and were interpreted as follows: i) physical profile and ability of learners (design to allow usage by a broad range of abilities), ii) ergonomics (ensuring height, reach, sight-lines etc. are suitable for the learner groups or are adjustable, iii) skill level of learners (the learning space and objects in it should be intuitive to use, iv) maturity (learning space design should account for intentional misuse, safety considerations etc., v) teacher and learner interaction (the design should enable equitable interactions in terms of dynamics and time.

As part of the project and using the UD principles, the study iteratively investigated and designed a learning space for collaborative problem-solving. Two of the design iterations are described that illustrate how the project investigated the needs and iterations of the learning space design with the MMLA system. (Healion and Russell, 2015). The first trial focused on learners and the teachers' inter-group interactions, whereas the second trial focused on intra-group interactions. The initial hypothesis of the two studies was that the participants in design focussed project- based learning (PBL) activities would move more using standing round tables and generate more interaction with their peers within their group compared to seated rectangular tables. The analysis methodology included qualitative and quantitative data acquired using multimodal data sources consisting of video recordings, sound recordings, still and time-lapse photographs, interviews, student feedback and data obtained by the MMLA system.

The first design intervention faced difficulties with an incomplete dataset due to the unexpected movement out of the perimeter of the recordings. Before the second intervention, the MMLA system was adjusted and the analysis scope was extended beyond the specially designed learning spaces. However, the results of the trial one suggested that standing tables encouraged more significant physical movement of the students during the collaborative problem-solving activity. The greater ease of movement of the standing students pointed to the encouragement of students to have initiated more frequent interactions with their peers in other groups. Additionally, groups at the standing tables were much more likely to change the group configuration during the activity and to reform it according to their needs and changing roles. The standing versus the seated features of the tables, the shape of the standing tables also seemed to have influenced configuration changes of learners. For the groups at the standing tables, the round table seemed to encourage the most configuration changes, followed by the hexagonal table, and the square table. From observations, it was noted that the facets or sides on the hexagonal and square table seem to act as locators for students to denote positions that they were more likely to return to. The more defined the facet, as in the square table, the greater the likelihood that the students return to their previous position (Healion et al., 2017).

In the second trial, the intra-group interactions were investigated. Results showed that the standing tables seemed to encourage students to work closer together physically. On a more frequent basis, the standing students stood shoulder to shoulder as close as personal space would allow viewing a laptop, to discuss the task and during the component building in the angles between. In contrast, students at the low tables sat at right angles or faced each other. The number of initiated interactions between students at the standing tables also increased compared to the seated tables (Healion et al., 2017) (Figure 3).

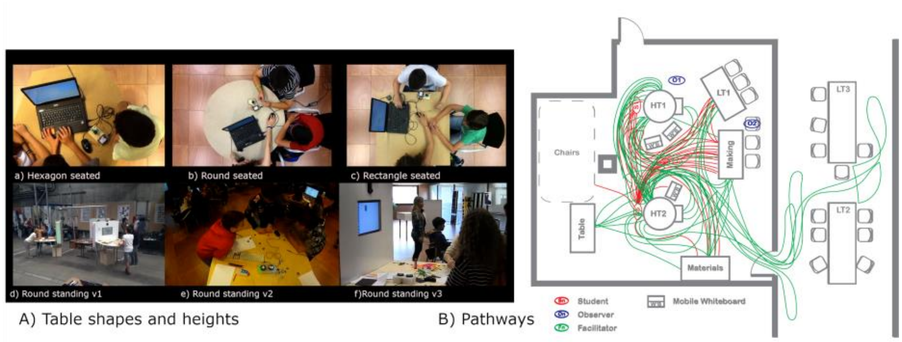


**Fig. 3**. Image A) illustrates the different table designs and the PELARS MMLA system. Image B) Hodological map of student and teacher pathways in the learning space

The results from these two design iterations have shown that different furniture designs, the learning space does indeed influence the inter-group and intra-group interactions of learners in collaborative problem-solving tasks. Although preliminary, the findings indicate that round standing tables can encourage more physical movement during collaborative activities. The results show that students are more likely to change group configuration according to their needs and changing roles. Two interventions also suggest that the facets of rectangular tables make students return to their previous position more frequently and the height of the table (standing) encourages students to work closer to each other. The design of learning spaces and the use of objects in it can lead individuals monopolising delivery of specific tasks, whether programming based or relating to the physical assembly of the learning activity. The combined shape of the table and the positioning of the monitor in the learning space can support shared task completion and more collaborative interactions within and between groups. The design and placement of the furniture elements within the learning environment have shown from these examples to influence the number of movements and interactions between the student groups. Additionally, the hodological pathways of the teachers and the students were captured and analyzed giving insight to the activities outside of the furniture (Figure 3). These designs of the learning space can be optimised through the ergonomic and anthropometric considerations of the learners and teachers to better support the learning outcomes of the activity. In these interventions, increasing the mobility and interactions were key to enable effective collaboration among and within groups in dynamic, collaborative problem-solving environments. However, depending on the needs and expected learning outcomes of the activity, different variations can be considered and designed.

### 3.2 The SmartLET project: studying the interplay of table design and educational level

The study on learning spaces and their effects on the behaviour of students during collaborative learning was also motivated by a gap in the literature regarding the relationship between the learning design, the learning space and students' behaviour, also considering different student profiles (e.g. educational levels). As an important skill in modern society, collaborative problem solving (CPS) (de Lima & de Souza, 2017) has been a widely applied pedagogical method (Alavi & Dillenbourg, 2012). Previous research has shown how places and furniture can facilitate, or constrain, beneficial conditions for certain teaching and learning strategies (Godwin & Fisher, 2011; Blinne, 2013; Colbert, 1997; Francis & Raftery, 2005). Moreover, previous studies have shown that behavior of students of different ages varies depending on physical characteristics of the learning contexts. For example, there is evidence showing how different visual features of space tend to distract young students (Godwin & Fisher, 2011). Furthermore, physical learning environment perception of older students impacts their behaviour in learning, as well as their progress and involvement (Midgley, 2006; Pai, et al., 2014). Therefore, research of all aspects, including spatial, requires the attention of the research community.

A study carried out in the context of the SmartLET project highlighted the potential of multimodal learning analytics to explore the interplay between the collaborative table design, the group size (as a relevant element in the learning design) and the educational level (Vujovic, et. al., 2020). Furniture was examined as the primary focus, and by using new data sets, the study aimed to critically examine patterns of participation and indicators related to the physical and the social interactions. Focusing on authentic CPS activity, two cases were observed where each case included two levels for each independent variable (Figure 4). Two table shapes (round and rectangular) were studied in interaction with two levels of education (elementary school students and university students) and two group sizes (two and three participants). The students were engaged in design tasks that were conducted in small groups and orchestrated using the broadly accepted Jigsaw pattern (Aronson, 1978; Hernández-Leo et al., 2006). This pattern introduces a collaborative learning flow where, by forming small changing groups, complex tasks are being solved in a way that enables positive interdependence and individual accountability while achieving fruitful learning.

**Fig. 4.** Experimental setup with different table shape and participants at different educational levels (reproduced from Vujovic, et. al. (2020))

The first case included 24 university students, all aged 18-24, who participated in an extracurricular training focused on design tasks in physical computing, following a Jigsaw collaborative pattern. Out of the eight groups of three students that participated in the data analysis, four of them were assigned to rectangular tables, and the other four were assigned to round tables. In the second case, 24 elementary school students, all aged 6-9, divided in eight groups conducted the activity as part of an educational summer school focused on technology. Also following a Jigsaw collaborative pattern, four groups were assigned to round tables, and four groups were assigned to rectangular tables.

In both cases, students participated in the open-ended task. University students worked on the open-source electronic prototyping platform with the task of designing and making a prototype of the interactive toy. The task required a combination of design, hardware, and software skills, and each member of the three- member team focused on one of these skills. Students received instructions and no prior knowledge in the mentioned areas was required. Elementary school students had the task to use a computer game to design a digital object - carriage. As with older students, each team member in younger students was assigned to become familiar with the specific skill. To adapt the open-ended task to a younger age, skills were presented through game characters such as blacksmith, carpenter and artist. Students were not required to have prior knowledge and instructions were provided prior to the beginning of the activity.

As mentioned, the analysis included three independent variables - *table shape*, *level of education* and *group size*. Their influence on three dependent variables was examined - *level of participation*, *distance between learners*, *range of head movement* of learners. Frequency of interaction with other students and with physical artifacts was measured as a *level of participation* for each student. *Distance between students* represented the distances between heads of students in the same group, throughout the whole activity. *Range of head movement* was calculated as a standard deviation of the distance between learners. Moreover, qualitative data from the observations was collected to provide understanding of the nature of participants 'actions (on-task / off-task) during the collaboration.

Due to the complexity of the activity conducted in terms of multiple people conducting multiple actions at the same time, data acquisition was conducted via a multimodal system consisting of a motion capture system and video cameras. The multimodal system was established with the aim to record different physical aspects of students behaviour. The motion capture system provided automated acquisition of data on the distances between students and the range of head movement based on wearable markers that were mounted on students via headbands. The video recordings provided data for the level of partition and observations for qualitative analysis.

Promising results regarding the effects of the learning environment on the collaborative process were obtained from the analysis of the interactions between these variables. The findings indicate that round tables contribute to increased levels of on-task actions with elementary school students. Qualitative analysis explains this by linking table shape with students 'movement needs which implies that certain physical forms facilitate preferred movements and thus enable more convenient participation in collaborative activity. Furthermore, results imply that physical interaction between learners alone is not sufficient to provide a comprehensive understanding of collaboration without the context of on-task and off-task actions. These findings are important for informing the future application of MMLA systems. Overall, the presented study adds evidence about the importance of learning space as the relevant aspect in the process of collaborative learning design while MMLA with its variety in methods shows great potential for further research.

### 3.3 Moodoo: characterising teachers' positioning in the classroom

Based on foundations of proxemics, the term *analytics for classroom proxemics* was proposed to refer to the use of indoor positioning systems to automatically analyse the relationship between teachers, students and objects in the physical learning space and the impact of that relationship on the learning processes (Martinez-Maldonado, 2017; Martinez□Maldonado et al., 2020a). In this second study, researchers particularly focused on modelling spatial teaching dynamics and how these can be shaped by the characteristics of the learning design and the individual teaching strategies of educators. The research included an indoor positioning system that was tracking the movement of teachers, based on which a composable library of algorithms for studying instructional behaviours of teachers in different scenarios was proposed: the Moodoo library[1] (Martinez□Maldonado et al., 2020b). Moodoo (indoor positioning metrics) consists of metrics for different aspects such as teachers' stops, teachers transitions, teacher-student interactions, proximity to classroom resources of interest, co-teaching and metrics related to focus of positional presence. Metrics presented in this work are showing promising results in providing information for teachers that can be used for informed decision-making as a contribution to the expansion of teacher's classroom actions.

This library was put to the test in the context of a first-year undergraduate unit in the area of physical modelling. A teacher and a teaching assistant co-taught each class in pairs in the same (16.8 x 10 metres) laboratory classroom. They had to supervise and provide feedback to 30-40 students working in 10-13 small teams of 2- 3 students each. This study was particularly interesting from a space design point of view, since the learning space remained the same while different teachers enacted three distinct learning designs. The first learning design (LD1) was a prescribed group task in which all students had to conduct the same experiment following a step-by- step guide. In contrast, the second learning design (LD2) followed a project-based learning approach, in which students were asked to formulate their own project. LD1 and LD2 were similar in the sense that each team had to find a space in the classroom and work on their own experiment. A third learning design (LD3) was a theory-testing

[1] https://gitlab.erc.monash.edu.au/rmat0024/moodoo

lab. In this case, the expected spatial dynamics were completely different since 4 experiments were set up by the teachers in different parts of the classroom and students had to move around one experiment at a time.

In this study, teachers were asked to look at their own data and reflect on their positioning strategies and those of other teachers. Qualitative analysis of these reflections showed that the meaning of space changes throughout the duration of the class and across classes. One of such reflections was about how teachers divide the classroom space during their co-teaching. For example, Figure 5 presents heatmaps of three classes in which the same pair of teachers taught different classes corresponding to the learning designs LD1-3 (left, middle and right respectively).

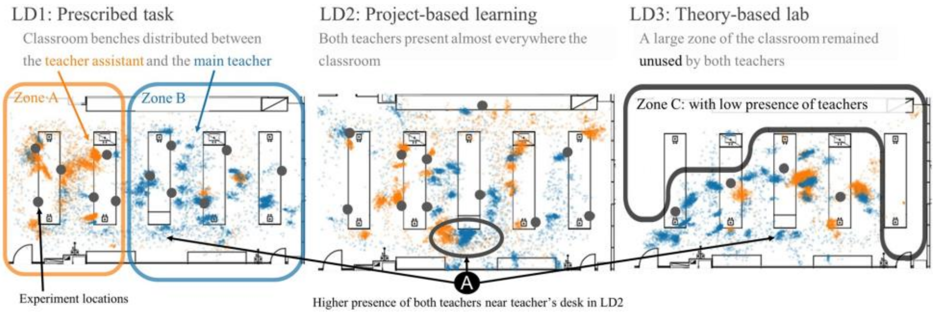


**Fig. 5.** Three example heatmaps of three classes (taught by the same teachers) in which both teachers behaved differently according to the three distinct learning designs (LD1, LD2 and LD3). The main teacher's data points are shown in blue and the teaching assistant's in orange. Gray dots indicate the positions where experiments are located (reproduced from Martinez-Maldonado et al., 2020b).

Figure 5 (left) shows one example of a class corresponding to LD1 in which the teaching assistant focused on the two first benches where students worked (see Zone A) and the main teacher on the other three benches (see Zone B). This clear division of the classroom "territory" did not emerge in most of the other classes (LD2 and LD3, examples in Figure 5, middle and right). Another key difference in terms of territoriality was in classes in which LD3 was enacted where large classroom zones were not used (see very low or no presence of both teachers in Zone C in Figure 5, right). Finally, classes in which LD2 was enacted presented a high presence of one or both teachers near the teacher's desk for long periods of time (see Figure 3, Point A) since the students commonly need less help since each team of students creates their own project and students come closer to the teacher only when needed.

This and other teaching behaviours have been studied in relation to the learning design and personal teaching preferences. This work can potentially serve as a foundation to create upgraded methods in data collection and visualization that, in combination with previously mentioned studies on indoor positioning, can enable evaluation of learning spaces and the activity unfolding in them. Yet, an important takeaway message from this work has also been the importance of considering teachers' and students' voices in the design of learning analytics innovations that rely on sensor data. Especially because the risks of pervasive surveillance using positioning tracking are evident. There can be a risk in using these data with the intention of monitoring teaching staff performance. However, teachers who have faced their own positioning data have emphasised the need for horizontal practices to design for data-intensive innovation in intelligent physical spaces that should be intended to support professional development or improvement of current teaching and learning practices.

# 5. Discussion

### 5.1 MMLA potential for informing the design of learning spaces in future research

The potential contribution of MMLA to advance learning spaces research is evident. Various data measurement and analysis techniques could speed up the research cycles by providing more accurate metrics about behaviours that unfold in the physical learning space. The combination of different modalities can provide insight into the layers of activities that have not been visible so far during observational studies. Another potential contribution is the complementarity of quantitative and qualitative methods. Observations have remained as one of the most common methods used as part of a multimodal system. However, in the foreseeable future we could also witness that systematic observations could get augmented by the automated generation of indicators to provide more precise information for evaluating how a learning space is being used or how a learning design is being enacted in the space. In sum, if we look at the development of learning spaces research and the application of multimodal analysis, through time (Figure 7), we see an upgrade in the existing analysis methods and the augmentation of manual analytical methods with automatic ones.

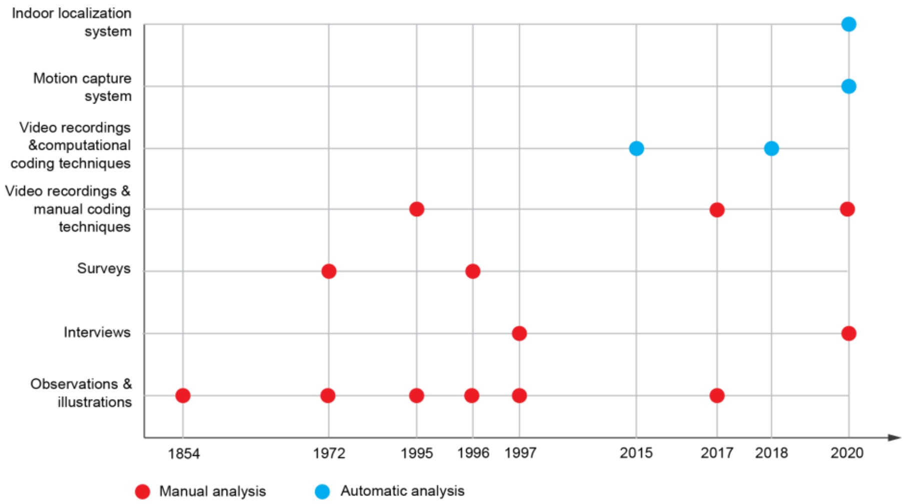


**Fig. 7.** Timeline presenting selected research on learning environments and different data sources modalities collected in a manually and automatically.

### 5.2 MMLA limitations to inform the design of learning spaces

Studies performed so far have been limited to specific learning contexts, which puts certain limitations to the generalizability of the findings. In learning contexts, collecting big datasets is difficult to achieve due to the diversity of learning designs. Real settings hardly ever involve repeating the same learning activity with the same teacher, the same students and the same learning environment. Capturing multimodal data with the variability that arises as a natural consequence of the learning process, and is not always predictable, is one of the key challenges set before the use of MMLA systems. Therefore the validity of a study is often threatened due to the inability to collect a sufficient amount of homogeneous data which presents a common limitation of MMLA studies. Moreover, in a real setting, controlled data collection is challenging due to the variables caused by environmental factors (air temperature, light etc.) that are difficult to control. MMLA systems can also be invasive. Wearable devices such as electrodermal activity sensors, eye-tracking devices etc. can become uncomfortable, while devices that surround students such as video cameras, motion capture systems, etc. may distract them and cause discomfort. Unnoticeable measuring devices and observers are difficult to achieve in terms of affordability and physical constraints that currently exist. Moreover, the use of MMLA systems in the study of learning spaces can cause significant concerns over the privacy of learners and teachers. The risks associated with pervasive surveillance should be identified and mitigated before any real-world implementation of MMLA systems. Although limitations exist, it is evident that the findings provided by MMLA about the effects of learning spaces are shown to be insightful and informative for learning design.

### 5.3 Beyond LA for learning space design

The design of learning spaces is also tied to architecture, ergonomics, anthropometrics domains and to the fields of product design and human-computer interaction. Nehme and colleagues (2020) extend the traditional user-experience of the interaction of products and systems into the built environment, the largest product that we interact with and this applies to learning spaces. However, much of the research on physical settings rely on the development of models and the use of observations and qualitative methods to investigate what happens in the learning space. The field of anthropometry has used technologies to measure, to understand and to recognize the challenges in how people fit between different products, spaces or environments. The focus has been on the physical aspects and the limitations of the body from a performance aspect (Dianat et al., 2020). In the last several years, researchers and practitioners in architecture have begun to explore the use of data as a source for the design. The design of these new spaces arises from the aggregation of open data (infrastructure, jobs, census, and other sources) and data captured by sensors to understand the flow of people to develop large scale urban interventions for development (Delso Gutiérrez and Sánchez-Vaquerizo, 2018). However, the focus of MMLA has been more on the learners rather than the learning space. Our intention with this chapter is to broaden the use of MMLA systems to help recognize the need to design the learning spaces better.

## 6. Concluding remarks

This chapter discusses the evolution of traditional research practices and recent MMLA systems used in studying various aspects of learning spaces. Three case studies have been used as examples to illustrate how MMLA approaches enable the study of the impact of space on educational scenarios. The first example covered the use of MMLA in studying the impact of various learning space features on inter- and intra- group interactions of learners during their engagement with a CPS activity. The second example shows the use of a motion capture system and qualitative data in examining how furniture plays an important role with students' level of participation in a collaborative learning activity. At last, the third example employs classroom proxemics with indoor positioning metrics and qualitative analysis to show how teaching strategies can be shaped by elements of learning design and affect spatial teaching dynamics. These examples build on existing MMLA applications developed over a long period of time explain how the evolution of technology has brought evident progress but also new challenges, with the findings indicating a promising potential for further development of this research direction.

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# Chapter 3 - Motion capture for measuring physical aspects of collaboration

This chapter discusses the application of the motion capture system as part of a multimodal system designed to explore the learning space. It contributes to an understanding of evaluations of the techniques applicable to MMLA systems, as well as examining the effects of table shape on student behaviour. The papers presented in this chapter are the following:

- ‘Motion capture as an instrument in multimodal collaborative learning analytics’ - discusses the examination of the efficiency of motion capture systems in measuring collaboration indicators and their usefulness in researching collaborative learning space.

- ‘Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study’ - presents an experiment that examined the influence of the table shape on student behaviour through two data collection scenarios using a motion capture system.

### 3.1 Motion capture as an instrument in multimodal collaborative learning analytics

The paper in this section was accepted and presented as a poster paper at the European Conference on Technology Enhanced Learning (ECTEL). Figure 14 shows the relationship between the paper presented in this chapter and the contributions of the dissertation.

Vujovic, M., Tassani, S., & Hernández-Leo, D. (2019, September). Motion capture as an instrument in multimodal collaborative learning analytics. In *European Conference on Technology Enhanced Learning* (pp. 604-608). Springer, Cham.

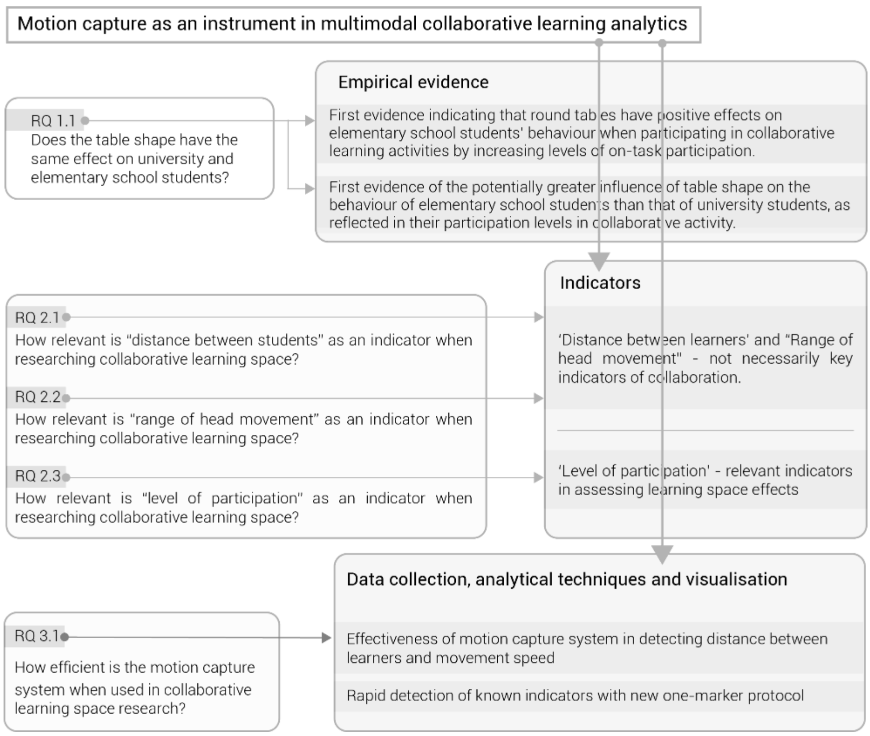


Figure 14. Relationship between the 'Motion capture as an instrument in multimodal collaborative learning analytics' paper and dissertation contributions.

# Motion capture as an instrument in multimodal collaborative learning analytics

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**Abstract.** In this paper, we describe an exploratory study where we investigate the possibilities of motion capture system as an instrument to consider in multimodal analyses of face-to-face collaborative learning scenarios. The goal is to understand to what extent motion capture can facilitate certain measurements leading to collaborative learning indicators that are currently time-consuming to achieve with other instruments. We focus on the simultaneous measurement of known physical collaboration indicators such as gaze direction, the distance between learners and the speed of movement/reactions. The study considers a lab setting simulating a classroom scenario based on the Jigsaw collaborative learning flow pattern, which proposes a sequence of activities with changes in group size and formation. Preliminary results indicate a high degree of applicability of the system in measuring these indicators, with certain limitations for gaze direction measurements. With appropriate marker position on the participants, the system is able to automatically provide desired measurements with satisfactory precision. Additionally, with a small number of additional markers, we were able to determine the way students used working surfaces (shared desks).

**Keywords:** Motion Capture System, Multimodal Learning Analytics, CSCL.

## 1 Introduction

Despite there is accumulated evidence about the benefits of collaborative learning, there are still many research questions about what happens in the collaboration process and what makes it more effective. In face-to-face settings, there is emerging research that uses multimodal learning analytics (MMLA) to identify indicators of fruitful collabo-ration. Some indicators have been already identified, such as collaborative will [1], equality and mutuality [2], symmetry [3], synchrony of groups' actions and gaze [4], the reaction time of participants to the actions of members of the group [5] or the dis-tance between learners (DBL) [6] etc. Multimodal measures leading to these indicators are diverse (video, audio, physiological data, …) and generate large amount of data, which require significant time-consuming analysis. In this paper, we select concrete physical collaboration indicators such as gaze direction (GD), the distance between learners (DBL) and the movement speed/reaction (MS), and propose and evaluate the application of a motion capture system (MCS) with the objective to simultaneously measure these indicators and accelerate the analysis process (Fig. 1).

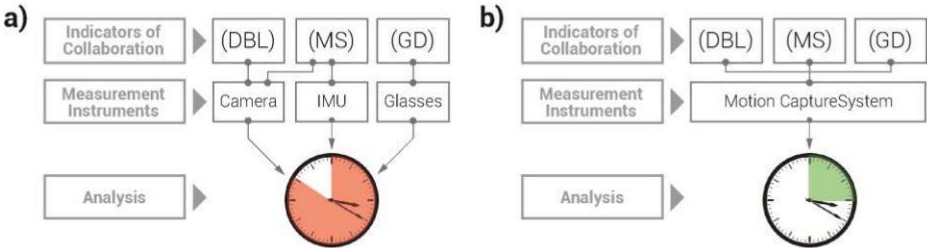


**Fig. 1.** Substituting various instruments with Motion Capture to accelerate the analysis.

## 2 Motion Capture in Collaborative Learning Analytics

To illustrate and evaluate the possibilities of MCS for collaborative learning analytics, we use a scenario based on the Jigsaw pattern [7] where students are grouped into small independent groups and where each student is assigned with a specific role. Students are then regrouped on the basis of their roles in order to gain expertise and share that expertise with other members of the group. Such a context is a complex environment where there are constant interactions of participants and group size and formation transformations. The monitoring of participant behaviour and factors that influence the collaboration process is a demanding task. As aforementioned, by selecting three indicators (DBL, MS, GD) we propose to substitute different sensors, like cameras, Inertial Measurement Units, eye-tracking glasses etc. with MCS. In comparison to other technologies that address the issue of movement detection (such as possibility of detecting pose using web camera, or deep learning algorithms for depth perception), we found that they face problems such as tracking bigger group of people or having nor so high accuracy rate. Regarding ethical issues, we have informed participants on details of the experiment and collected a consent form.

Application of motion capture systems is wide and cross-disciplinary [8]. The system applied in this study uses reflective markers and infrared cameras, where markers are placed on objects whose movement we want to detect. Because of the reflective surface, the cameras recognize them as points in space, based on which we get the desired physical parameters. The main advantage of the system is that it is possible to develop a marker protocol fully adapted to the needs of the research.

## 3 Evaluation of the Motion Capture System

We studied to what extend MCS represents a useful MMLA tool in the analysis of collaborative learning indicators in a Motion Caption Laboratory (left-down, Fig. 2), where we run an experimental protocol for a pair of three member groups that participated in one Jigsaw session. Movement analysis was performed using eight cameras

BTS Smart-DX 700, 1.5 MP 125 fps (BTS S.p.A., Milan, Italy). A custom marker pro-tocol was developed to follow the movement of the subjects analyzed using headbands with 5 non-aligned markers for each of the participants. Two lateral markers were placed at the level of the ears, the other two were at the back of the head at different levels and one marker on the top of the head (Head Motion Marker Protocol). Middle points between the rear and lateral markers were identified, together with the vector passing through these points. A calibration process was performed to identify the GD.

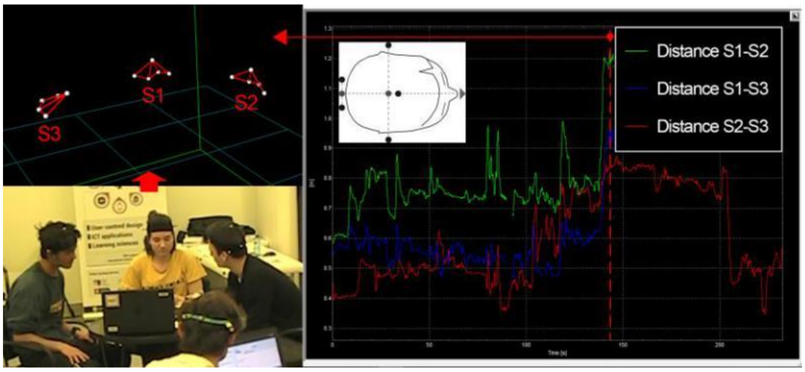


**Fig. 2.** Reconstruction of markers and presentation of the DBL in specific point in time

Nine measurements of five minutes each were performed to cover the three phases of the collaborative Jigsaw activity. The analysis tool enabled us to calculate the DBL and the MS within a few minutes based on the marker positioned at the top of the head and by selecting two operators (distance and derivatives). The GD calculation required additional operators, which took more time.

The Figure 2 shows the reconstruction of the markers (left-top, Fig. 2), capture from a video recording (left-down, Fig. 2), position of markers (middle, Fig. 2), and a graph that displays the DBL (left-down, Fig. 2) during one recording (300 seconds). One of the moments during the activity was randomly selected (red dashed line) to show that the tool can display the values at any given moment and various indicators at the same time.

The scope of this study is efficiency and comprehensiveness, which we analyzed through the speed of analysis and obtaining the desired indicators. The most time con-suming phase is the reconstruction of markers. Calculation of results in the case of two indicators (DBL and MS) takes several minutes, while the calculation of the GD takes 20-30 minutes. Video recordings are included and used to control the obtained results.

## 4 Discussion and Conclusion

The use of MCS as an instrument for multimodal analysis of collaborative learning has proved to be effective in the context of this study. The results of the study indicate the advantage of ease of detection of DBL and MS, due to the use of only one marker and the rapid analysis of data. With these indicators, the number of participants in the study does not affect the quality of the recording and analysis. Identifying the GD is done based on the position of the head and ignoring the movement of the eyes, which repre-sents a limitation that is difficult to overcome without the use of additional resources. With all indicators, a comprehensive display of data is possible and clearly visible, which is an additional quality of the system. The constraints that occur, in addition to the precise detection of GD, are the connection of the system to the physical environ-ment, which possible to overcome with different interventions, such as displacing sys-tem outside the laboratory or using mobile motion capture systems. All these interven-tions have disadvantages in terms of time or price, but they can be justified by beneficial contributions in the field of multimodal analysis. Future work should focus on addi-tional features useful to analyze collaboration processes (sitting arrangement, use of the desk surface) and that can be easily labeled, recorded and analyzed.

## Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and in-novation programme under the Marie Skłodowska-Curie grant agreement No. 713673. Milica Vujovic has received financial support through the "la Caixa" INPhINIT Fellowship Grant for Doctoral studies at Spanish Research Centres of Excellence, "la Caixa" Banking Foundation, Barcelona, Spain. This work has been partially supported by the National Research Agency of the Spanish Ministry of Science, Innovations and Universities MDM-2015-0502, TIN2014-53199-C3-3-R, TIN2017-85179-C3-3-R.

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## 3.2 Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study

The paper in this section was published in the British Journal of Educational Technology (BJET). *BJET* is a journal indexed in the Journal Citation Report (Q1). Figure 15 shows the relationship between the paper presented in this chapter and the contributions of the dissertation.

Vujovic, M., Hernández-Leo, D., Tassani, S., & Spikol, D. (2020). Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study. *British Journal of Educational Technology*, 51(5), 1597-1614.

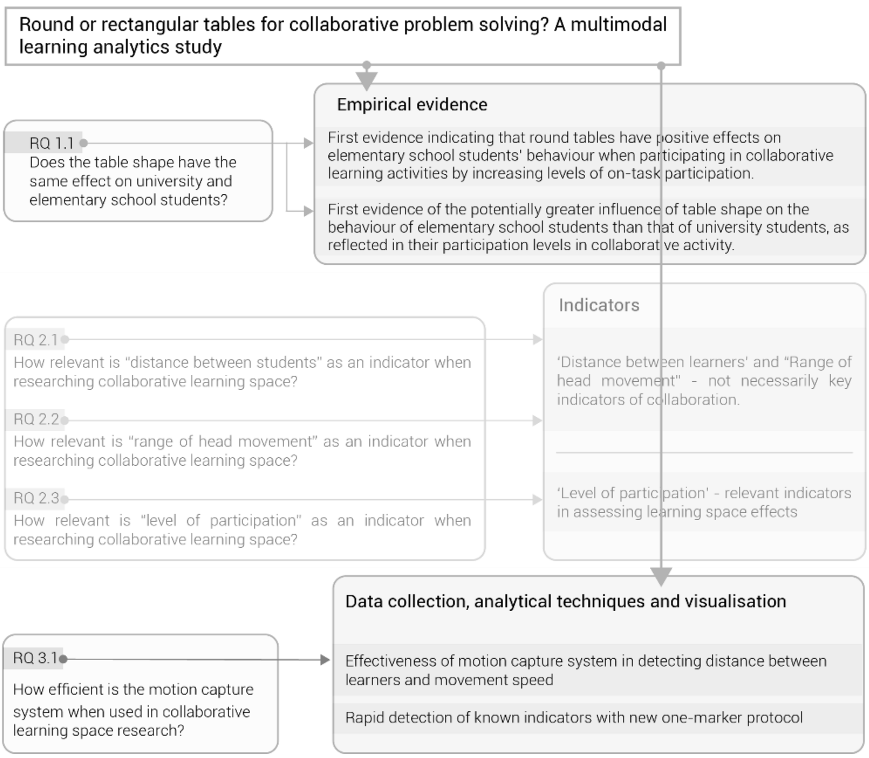


Figure 15. Relationship between the 'Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study' paper and dissertation contributions.

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# *Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study*

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**Abstract**

The current knowledge of the effects of the physical environment on learners' behaviour in collaborative problem-solving tasks is underexplored. This paper aims to critically examine the potential of multimodal learning analytics, using new data sets, in studying how the shapes of shared tables affect the learners' behaviour when collaborating in terms of patterns of participation and indicators related to physical social interactions. The research presented in this paper investigates this question considering the potential interplay with contextual aspects (level of education) and learning design decisions (group size). Three dependent variables (distance between students, range of movement and level of participation) are tested using quantitative and qualitative analyses of data collected using a motion capture system and video recordings. Results show that the use of round tables (vs rectangular tables) leads to higher levels of on-task participation in the case of elementary school students. For university students, different table shapes seem to have a limited impact on their levels of participation in collaborative problem solving. The analysis shows significant differences regarding the relationship between group size and the distance between students, but there is no substantial evidence that group size affects the level of participation. The findings support previous research highlighting the importance of studying the role of the physical environment as an element of learning design and the potential of multimodal learning analytics in approaching these studies.

## Introduction

Designing a space is not just about creating physical frames that define spatial divisions but also about facilitating an activity and reinforcing it with the characteristics of that space (Ching, 2014). In the context of educational space design (Felix & Brown, 2011), the space-activity

**Practitioner Notes**

What is already known about this topic

- There is a gap in the knowledge about how people collaborate in face-to-face environments.
- MMLA can be useful in studying face-to-face collaborative learning processes.
- Dependencies between the learning design, the learning space and students' behav-iour are underexplored.

What this paper adds

- An MMLA approach based on motion capture and video analysis.
- Case studies that employ a combination of methods for the analysis of MMLA data and qualitative analysis.
- Evidence about the impact of space design on face-to-face collaborative learning processes.

Implications for practice and/or policy

- The shape of classroom tables has effects on elementary school students' behaviour when collaborating.
- Learning design should be a comprehensive process that includes elements associated with the space.
- Learning space research requires comprehensive multimodal system analysis tools.

synergy must be emphasised as relevant where the field of architecture targets sensitive user groups and sensitive objectives (Malinin, 2017). Learning is a complex process and the subject of study in a number of multidisciplinary research areas. Previous research has already explored the physical facilitators of learning activities; however, the empirical evidence is limited (Keppell, Souter, & Riddle, 2011; Yeoman & Ashmore, 2018), especially when considering different ac-tive learning methods (Bennett, 2011; Lippman, 2015). This paper investigates the potential of multimodal learning analytics (MMLA) and uses new analytical methods and new data sets to study the impact of these contextual factors in the domain of collaborative learning and in terms of particular characteristics regarding its learning design (table shape and group sizes) and the educational levels involved.

*The design of physical spaces for learning*

Places and furniture can facilitate, or constrain, possible arrangements for certain teaching and learning strategies. One clear example is the case of collaborative problem solving (CPS), a fundamental skill in modern society (de Lima & de Souza, 2017; Häkkinen *et al*., 2017) and a widely accepted pedagogical method (Alavi & Dillenbourg, 2012). Teachers' orchestration of collaborative learning in the classroom is influenced by the physical context (Joyce-Gibbons, 2017). It involves the coordination of learners' desired actions, including the use of shared physical artefacts (eg, tables) in the classroom, in alignment with the needs of learning tasks at different social levels (individuals, groups, the whole class). Dillenbourg and Tchounikine (2007) point out that the extrinsic constraints derived from the educational context are sometimes neglected in classroom orchestration studies. Extrinsic constraints go beyond the constraints that are intrinsic to the ped-agogical methods (eg, group formation, the sequence of tasks) and include the classroom layout, which might not conform with the methodological requirements of learning design (Goodyear & Carvalho, 2014; Pérez-Sanagustín, Santos, Hernández-Leo, & Blat, 2012). Also, research on co-located learning stresses the relevance of shared educational and social spaces (eg, shared seating and the encouragement of social bonding), for example, in scenarios that gather het-erogeneous students (Croker, Fisher, & Smith, 2015). In these scenarios, spaces structured to encourage interaction were reported to be beneficial for improving collaboration and interprofes-sional rapport. Yee and Park (2005) further identified the problem of reduced awareness between participants in a co-located learning context due to the features of the physical space surround-ing them, such as non-transparent partitions and grid-organised desks.

Moreover, previous research shows that various aspects of the physical learning environment influence students' behaviour, pointing out certain differences in shapes, colours and lighting used in spatial design, (Blinne, 2013; Colbert, 1997; Francis & Raftery, 2005). Also, different developmental levels of students seem to express different types of behaviour when exposed to different physical settings in learning contexts (Kumar, O'Malley, & Johnston, 2008). Cognitive psychology research shows that attention, perception and thinking can be influenced by the physical environment. Young children tend to get distracted by different visual features that surround them (Godwin & Fisher, 2011), which can increase the off-task time during the learning activity. For older students, their perception of the physical learning environment has shown to impact behaviour, progress in learning and their involvement (Midgley, 2006; Pai, Menezes, Srikanth, & Shenoy, 2014).

*Further empirical evidence needed and the potential of MMLA*

There is a body of evidence on how the characteristics of the physical environment affect stu-dents' behaviour in CPS tasks. However, this body of evidence does not possess sufficient comprehensiveness in terms of connecting research and practice. Nardi (1996) points out that, when studying the learning context, the durable structures that are used across different situations are very important contributors to learning and not only a simple aspect of particular situations. These permanent physical structures should be addressed in research in order to reach a point where generalisable results can be obtained. Other research argues that the spatial element in educational practice is relatively underdeveloped due to the domination of social aspects, which change faster and require more attention (Gulson & Symes, 2007). Cukurova, Luckin and Baines (2018) also point out certain drawbacks in the literature where factors related to the learning environment do not get proper attention or are presented in a less comprehensible way. The au-thors explain how the learning context refers to the interaction between learners and multiple people, artefacts and environments, and they draw attention to the importance of comprehensive studies on contextual factors in bridging the gap between research and practice. The emerging use of MMLA, which considers different sensors and computer systems for data collection during learning activities (Pijeira-Diaz, Drachsler, Järvelä, & Kirschner, 2019), offers a methodological approach that can provide further insights into collaborative face-to-face spaces (Ricca, Bowers, & Jordan, 2019). The diversity of data (Spikol, Ruffaldi, Landolfi, & Cukurova, 2017), fusion and analysis methods (Shankar, Prieto, Rodríguez-Triana, & Ruiz-Calleja, 2018) and advanced developments in sensor technology (Schneider, Di Mitri, Limbu, & Drachsler, 2018) bring vast possibilities in terms of studying the effects of learning spaces. Furthermore, a study examining the movement of students and teachers around furniture, using MMLA, provided a better under-standing of collaborative learning processes (Healion, Russell, Cukurova, & Spikol, 2017).

Therefore, previous research shows that the learning space is a relevant element of learning designs that aim at offering the best possible methodological and supportive arrangements for students to learn. Moreover, research suggests that the effects of learning space characteristics can vary depending on the educational level. However, more research is needed to provide further evidence about how specific elements of the space affect learners when engaging in active learn-ing methods, such as CPS.

*Conceptual framing and research focus*

Multimodal analytics can help provide the necessary evidence; however, a literature review by Mangaroska and Giannakos (2018) shows that existing studies present a misalignment between learning analytics and learning design, which is potentially caused by the gap between easily col-lectible data and data that are meaningful in a pedagogical sense. The analytics layers for learn-ing design (AL4LD) framework (Hernández-Leo, Martinez-Maldonado, Pardo, Muñoz-Cristóbal, • Rodríguez-Triana, 2019) offers guidance to solve this misalignment by compiling meaningful variables into analytics layers that connect analytics with design. AL4LD builds on previously proposed frameworks focused on learning design and/or learning analytics (eg, Goodyear & Carvalho, 2014; Lockyer, Heathcote, & Dawson, 2013). This study uses AL4LD as the conceptual framing to establish links between measurable aspects of learners' behaviour and features of the learning design (Figure 1).

In this paper, we study the effects of table shape on human behaviour that relates to learners' interactions and participation in collaborative problem-solving tasks. Shared tables are one prominent physical element present in most collaborative places. The *places and set* of artefacts that support the realisation of a task are one of the data classes in the design layer in the AL4LD framework. The design layer also suggests the consideration of pedagogical constraints intrinsic to the pedagogical method (*tasks and social planes*) and their interplay with data classes in the learning analytics layer, such as those related to *learners' profiles* and the learning *process* (pres-ence and usage behaviour). The design of social planes is particularly relevant in collaborative learning scenarios, where group size is one of the design elements that has been seen to have an impact in facilitating fruitful collaborative learning (Avouris, Margaritis, & Komis, 2004; Pedaste & Leijen, 2019).

Therefore, to define the independent variables, we focus on the main aim of this study, which is in line with the primary focus of the investigation concerning how the shapes of the tables have different effects on learners' behaviours in terms of patterns of participation and indicators related to physical social interactions. The secondary focus is on two additional variables related to learn-ers' profiles (level of education) and the pedagogical method (group size)—examined in relation to the shape of the tables. In defining dependent variables, this study refers to notions already present in the literature and that belong to the learning analytics layer, such as *the level of partici-pation* (Cukurova, Luckin, Millán, & Mavrikis, 2018), *the distance between students* (Spikol, Ruffaldi, Dabisias, & Cukurova, 2018) and *the range of movement* (Vujovic, Tassani, & Hernández-Leo, 2019).

Therefore, the research question of this study was defined: Do different table shapes have differ-ent effects on learner behaviour (measured in terms of the level of participation, the distance

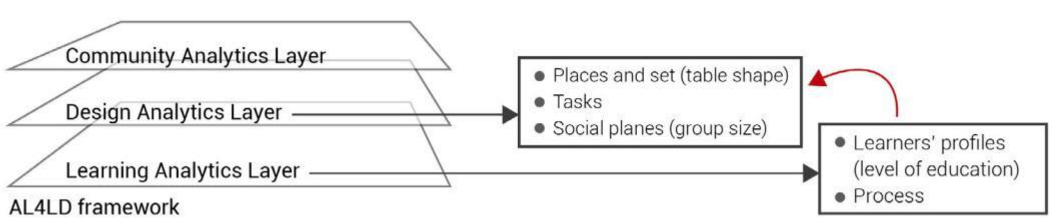


*Figure 1: Conceptual framing for the analytics of behavioural aspects in alignment with learning design decisions [Colour figure can be viewed at wileyonlinelibrary.com]*

between learners and the range of movement) for different group sizes (2 and 3 participants) and for different educational levels (school and higher education)?

## Methods

Two cases, focusing on authentic CPS activities, were studied, with each case involving two levels of independent variables, round and rectangular tables, and their interaction with two levels of education (elementary school students and university students) and two group sizes (two and three participants). The students were engaged in design tasks that were conducted in small groups and orchestrated using the broadly accepted Jigsaw pattern (Aronson *et al*., 1978; Hernández-Leo *et al*., 2006). This pattern proposes a collaborative learning flow where, by splitting students into small groups that change, they solve complex tasks in a way that enables positive interdepen-dence and individual accountability to be promoted so as to achieve fruitful learning.

### *Participants*

University students were invited to extracurricular training focused on design tasks in physical computing. During the recruitment process, out of more than 150 volunteers interested in the training, we selected 36 students with no prior knowledge of the topic, from different engineering degrees and in different years of study and with an equal number of male and female partici-pants. The 36 selected students, all aged 18–24, formed 12 (Jigsaw) groups and we analysed the data from eight of these groups. Out of the eight groups that participated in the data analysis, four of them were assigned to rectangular tables and the other four were assigned to round tables (Figure 2).

In the case of elementary school students, the activity was part of an educational summer school focused on technology. A total of 24 students chose to participate in agreement with and with the consent of their parents. The students, aged 6–9, came in eight organised groups led by a teacher from the same school, who stayed in the laboratory without interfering in the activity. Four groups were assigned to round tables and four groups were assigned to rectangular tables (Figure 3).

### *Materials and task description*

Both the university students and elementary school students participated in collaborative prob-lem-solving activities. There were two different activities, one for each level of education, similar in nature but adjusted to the age of the students. Both activities represented design tasks where specific artefacts were to be produced. Following a Jigsaw pattern flow structure, each session

*Figure 2: Two sitting arrangements that present different levels of independent variables in the study—university students*
*[Colour figure can be viewed at wileyonlinelibrary.com]*

*Figure 3: Two sitting arrangements that present different levels of independent variables in the study—elementary school students*
*[Colour figure can be viewed at wileyonlinelibrary.com]*

started with two groups of three members. After an initial phase of instructions regarding a di-visible task, they were organised into three different expert groups of two members (each coming from different initial groups) for a second phase of the activity where each group specialised in a sub-task. After finishing the sub-task, students returned to their initial Jigsaw groups and con-tinued work on the overall task. The task was open-ended, which meant that each group could have a different design in the end. At the end of the activity, each group presented their work. The duration of the activity was one and a half hours and no prior knowledge was required.

University students had to design, programme and build an interactive toy with an Arduino electronic platform. The interactive toy was to be designed using electronics connected to an Arduino board and additional elements such as cardboard and paper. The difficulty level was low and students were provided with the necessary instructions for each step of the process. Students were informed about the data collection and analysis that would follow this experiment and that had been approved by the ethical committee responsible, and consent from students was collected before the experiment.

The elementary school students conducted a collaborative design activity that started with the use of a computer game to motivate a follow-up task on designing cartoon-like artefacts. The objective of the game was to design a carriage for an imaginary king and queen, based on require-ments and suggestions from certain characters in the game. Throughout the phases, the partic-ipants had to look for cues in terms of which elements to use in the design and make decisions together as a group. The students and parents were informed on the details of the experiment and consent forms were obtained from the parents.

### *Measurements*

As previously discussed, we identified three independent variables, one of which was viewed as being primary (*table shape*) and the other two as secondary (*level of education and group size*). For each of these controlled inputs, we defined two levels of independent variables and tested their effect on the dependent variables. Two different table shapes—round and rectangular were used and within these two levels of independent variable, we defined two additional levels for each of the secondary independent variables. For the level of education, we had university students and elementary school students. The third independent variable—group size—was introduced as a relevant pedagogical requirement of the Jigsaw-based collaborative learning design and consid-ers group transformation during the activity. Part of the activity was conducted in groups of two and part of it in groups of three. Therefore, there were two levels for the group size independent variable. The effects of changes in the independent variables were measured on three dependent variables—*the level of participation, the distance between students* and *the range of movement*. In this way, we could measure how changes affect student behaviour and the ways in which different changes are connected.

For the level of participation, we measured how active students are in their interaction with other students and the artefacts used during the activity. The distance between students measures the distance between group members throughout the whole activity in order to compare various levels of the independent variables. The range of movement is based on the distances between students, measuring their extremes and reflects how far students moved from their original sit-ting positions.

Therefore, quantitative data were acquired to test the influence of the aforementioned factors on student behaviour during collaborative learning. Moreover, to offer an understanding of the phenomena behind the measured behaviours, qualitative data were also collected to observe the nature of participants' actions (on-task/off-task) during the collaboration.

*Procedure*

To measure the dependent variables in a laboratory setting, we used different equipment to ac-quire video and motion capture recordings. Ambient factors such as light, room temperature, wall colour, surrounding furniture, researchers present and environmental noise were exactly the same for all the conditions. The acquisition system was adjusted for this study to create a data collection process that was as automatic as possible. Motion features were detected and recorded by a motion capture system (Figure 4), a technology that allows us to measure physical parame-ters based on a pre-established marker protocol (Vujovic *et al*., 2019). Two different marker pro-tocols were used with the two educational levels, but the same types of data were used for the final analysis. The first marker protocol was used with the university students and consisted of headbands with five physical markers (reflective spheres), four placed on the sides of the head and one on the top. In the case of the elementary school students, a second marker protocol was used where markers were placed on the hats worn by the participants, with one top marker on each hat. The movement of the markers was captured by eight infrared cameras (BTS Smart-DX 700, 1.5 Mpixels 250 fps BTS S.p.A., Milan, Italy) and translated into coordinates. Using the Smart Tracker and Smart Analyser software tools, which are part of the BTS Smart-DX motion capture system, we extracted distances from the top head markers for the range of movement. The range of movement represents the range of displacement of each student's head and it was calculated as the standard deviation of the distance between learners.

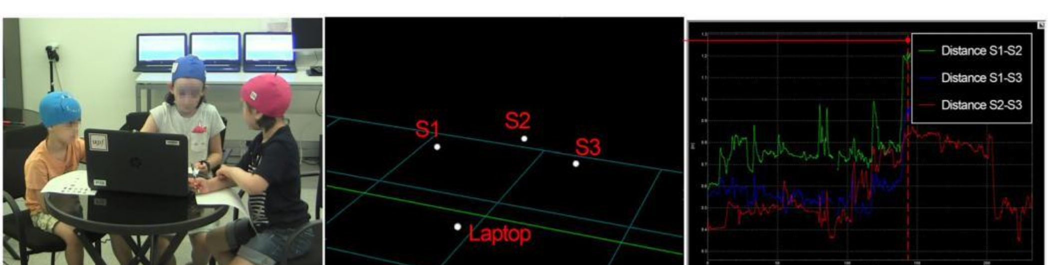


*Figure 4: Detecting physical features with a motion capture system*
*[Colour figure can be viewed at wileyonlinelibrary.com]*

The level of participation was extracted from the video recordings and assessed using the NISPI framework (Cukurova, Luckin, *et al*., 2018), where physical aspects of the interactions were coded. Video recordings were split into segments of 20 seconds and for each segment, each par-ticipant was assigned a score. Based on the coding scheme (Table 1), we used three different scores (0, 1 and 2) for three different levels of participation (Figure 5). Full participation was assigned to a situation in which, for one segment, all participants scored 2. The level of participation for the whole group was calculated as the percentage of segments with full participation compared to the whole session. We focused on the numerical coding of the participation without further interpretation regarding synchrony or physical interactivity, individual accountability, equality and intra-individual variability. We acted this way in order to obtain quantitative data and use them in a statistical analysis prepared prior to the execution of the experiment. Two observers coordinated their criteria by coding the same parts of the recording and comparing and adjusting the scores.

### *Analysis*

In the analysis process, we distinguished three independent variables (table shape, level of edu-cation and group size) and three dependent variables (level of participation, distance between students and range of movement). Therefore, three multifactorial analyses of variance (ANOVAs) were performed. Each ANOVA presents the analysis of the independent variables' influence on one of the dependent variables. Normality tests were conducted in order to verify the normality distribution of the residuals. Also, due to the different table sizes (the rectangular tables were 60 cm wide, while the round tables were 69 cm wide), all measures of distance were normalised by dividing them by the width of the tables and in this way, the data were given the same unit sizes. This was done to avoid biased measurements of the distances between the students and the ranges of their movements. All statistical analysis was performed using SPSS v23 IBM.

The video recordings were qualitatively analysed using visual transcription and open coding (Ramey *et al*., 2016) to identify on-task and off-task actions. The quantitative results were trian-gulated with the qualitative observations to illustrate and help understand the trends indicated by the statistical analysis.

## Results

The results present the output of the applied analysis methods about the effect that the physical environment has on students' behaviour when collaborating in a design problem-solving task. Three multifactorial ANOVA tests generated the results of the individual or simultaneous influ-ences of the tested factors on the dependent variables. Figure 6 shows how many subjects par-ticipated in each level of the independent variables. The three following tables paragraphs show

*Table 1: NISPI coding scheme*

| *Score* | *Description of the activity* |
|---|---|
| 1. | Active participation (interacting with others, working on a laptop, Arduino or design objects) |
| 2. | Semi-active participation (only listening and looking with the engagement in the form of nodding, pointing, etc.) |
| 3. | No participation (participant looking in another direction, distracted, doing another activity) |

the factors and interactions between factors that significantly differ between the levels of the independent variables regarding (1) *the level of participation*, (2) *the distance between learners* and (3) *the range of movement*. The results of statistical analysis are available as open data (see materials in Vujovic, Hernández-Leo, Tassani, & Spikol, 2020 https://doi.org/10.5281/zenodo.3843436). Normality tests (Kolmogorov–Smirnov and Shapiro–Wilk) were conducted and they failed to re-ject the null hypothesis (normal distribution of the residuals) for two out of the three dependent variables (Figure 7).

In the case of the range of movement, we had a deviation from normality (Shapiro–Wilk test, $p$ = .007) and two points were identified as outliers and were, therefore, removed from the anal-ysis. The removed points present the values for two elementary school students that belonged to two different groups, with one value belonging to the triad in session 2 and the other to the dyad in session 5. Therefore, the impact on the overall analysis was minimal in terms of imbalances and we were able to remove them, resulting in a normal distribution (Figure 8).

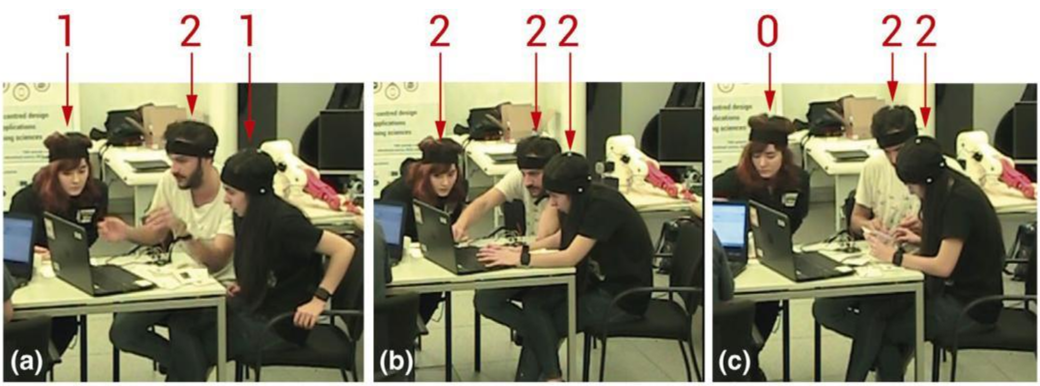


*Figure 5: Explanation from left to right: (a) 1—listening/nodding, 2—talking, 1—listening; (b) 2—talking, 2— working on a laptop, 2—working with Arduino; (c) 0—not participating, 2—working with Arduino, 2—working with Arduino*
*[Colour figure can be viewed at wileyonlinelibrary.com]*

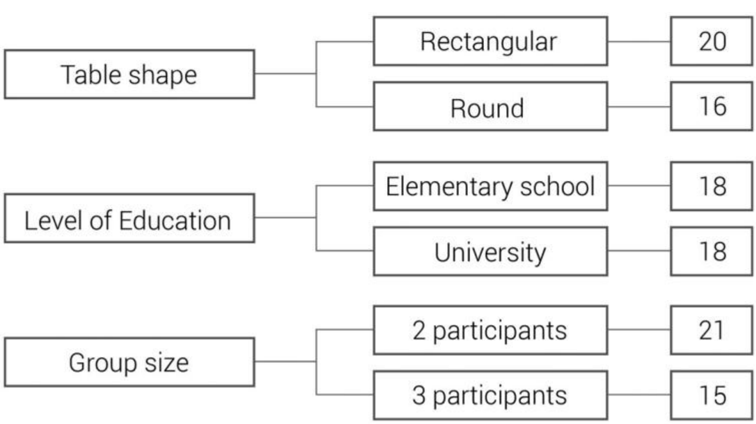


*Figure 6: Number of students per level of independent variable*

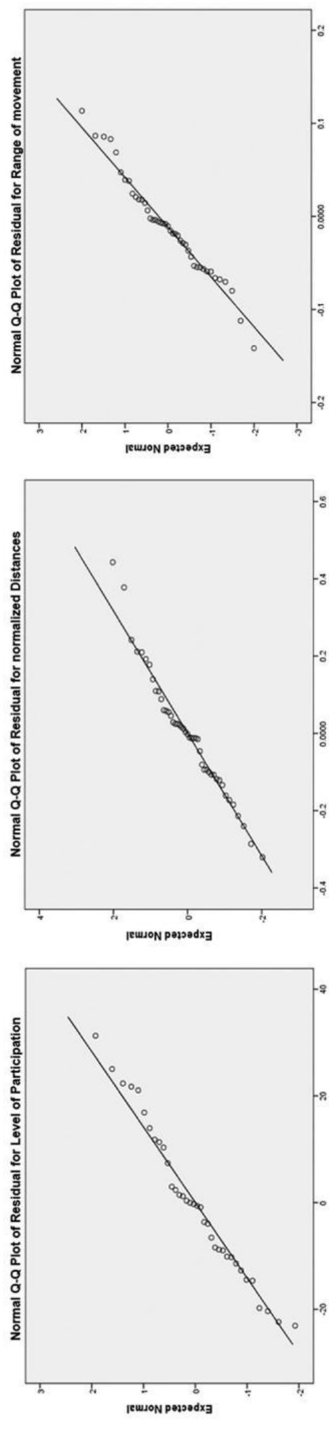


*Figure 7: Q-Q plot of the residuals for the three dependent variables*

*Do different table shapes have different effects on learners' levels of participation for different educa-tional levels and for different group sizes?*

Significant differences were detected in the level of education (*p* value = .040) and in the in-teraction between the shape of the tables and the level of education (*p* value = .019). Another factor that has a *p* value close to the significance level (.073) is the shape of the tables. Figure 9 shows the interaction between the shape of the tables and the level of education, where the blue line presents elementary school students, while the green line presents university students. The significant difference is visually presented and indicates higher levels of participation for elemen-tary school students when using round tables and for university students when using rectangu-lar tables. However, while the higher participation of the university students using rectangular

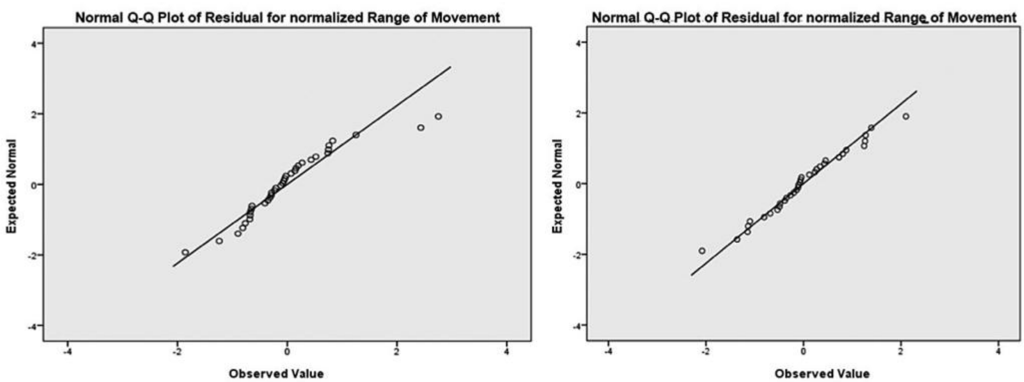


*Figure 8: Normality test with (a) all values and (b) outliers removed (range of movement)*

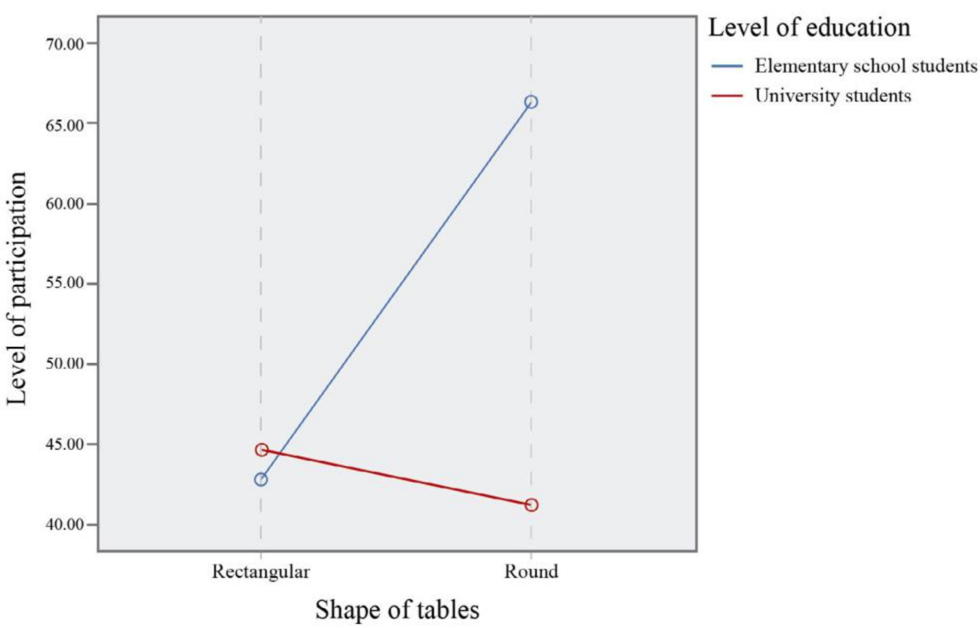


*Figure 9: Compared levels of participation for interaction of levels of education and table shapes [Colour figure can be viewed at wileyonlinelibrary.com]*

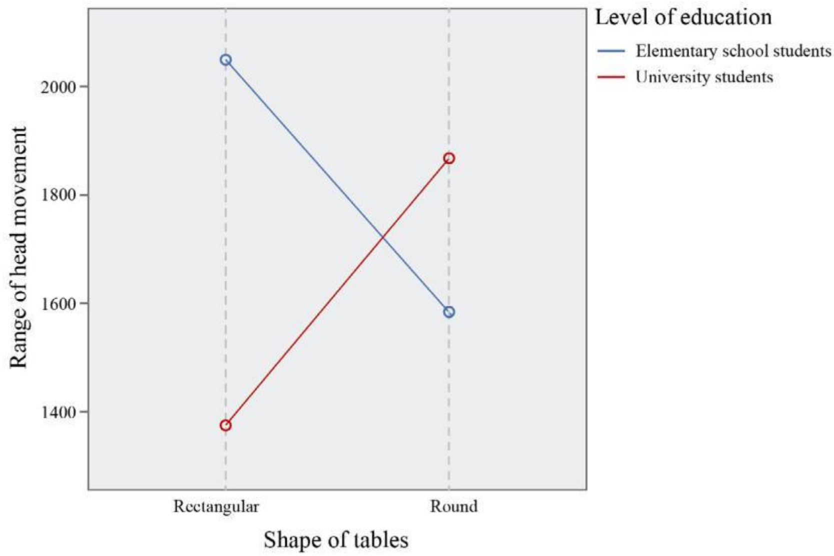


*Figure 10: Compared ranges of movement for levels of education and table shapes [Colour figure can be viewed at wileyonlinelibrary.com]*

tables is not considerably greater than those using round tables, the figure displays a considerably higher level of participation in elementary school students using round tables. The interactions between table shape and group size as well as between the level of education and group size were found to be non-significant.

*Do different table shapes have different effects on the distance between learners for different educational levels and for different group sizes?*

Significantly different distances were detected between different group sizes (*p* value = .006), where shorter distances were noticeable within groups of two participants. No significant differ-ences were found with other factors regarding the distances between learners.

*Do different table shapes have different effects on the learners' ranges of movement for different educa-tional levels and for different group sizes?*

There is a significant difference between groups of two members and three members, where the range of movement is smaller in groups of two. Also, the range of movement significantly differs when we observe the interaction between table shape and the level of education. This means that for elementary school students the range of movement is higher when using rectangular tables. Quite the opposite effect is observed with university students, whose range of movement is higher with round tables (Figure 10).

*Qualitative results and triangulation*

A qualitative analysis of the video recordings provided certain insights that could better explain the findings of the statistical analysis. Examples of the coding performed and the whole anal-ysis is available as open data (see materials in Vujovic *et al*., 2020 https://doi.org/10.5281/ze-nodo.3843436). The main aim of the video data analysis were to identify how students from different levels of education engage in interactions with the learning space in order to shed more light on the results of the statistical analysis, which revealed significant differences between round and rectangular tables in terms of the levels of participation and ranges of movement. The analysis considered distinguishing behaviour related to on-task and off-task actions, where on-task actions included engagement in conversation, actions with artefacts and nodding and pointing, while off-task actions were all actions not directed at the other team members or arte-facts involved in the task.

The qualitative analysis showed that the elementary school students, when engaged in on-task actions, display a significant amount of movement and interaction with elements of the envi-ronment. They tend to lean on the table a lot and hold onto objects that are in their immediate environment ("A participant (pink hat) was kneeling on the chair and leaning on the table with her full body."; "During the discussion, participants came closer to the screen (very close), leaning over the table, pointing more."). When engaged in off-task actions, elementary school students seem to have equal or more contact with the table than when on-task actions are conducted ("Boy that wasn't participating in certain moments was moving a lot on his chair, sometimes standing up and leaning on the table."). However, when engaged in off-task actions, university students have less contact with the table and artefacts than when engaged in on-task actions ("The two uninterested participants were distant from the table, passive, not doing anything."). When managing on-task actions, university students tend to be closer to each other and to the table, having more contact with artefacts used in the task ("Close to each other. Close to the table, but not leaning over, only using artefacts on it."). The presented observable behavioural charac-teristics were qualitatively equally present for both table shapes.

The triangulation of the quantitative and qualitative results implies that the relationship between the physical setting and behaviour is linked to the level of education. As opposed to elementary school students, who show equal or more movement when performing off-task actions, univer-sity students practically do not move when they are off-task. This observation also suggests that the statistical results obtained for university students are essentially focused on on-task actions and that the obtained statistical trend (not very different levels of participation in terms of round vs rectangular tables for university students) is valid. The qualitative observations show that for university students, closeness and interaction with the artefacts are indicators of on-task partic-ipation. Therefore, we can interpret, in the quantitative results, that higher on-task participation (slightly higher with the use of rectangular tables) is not necessarily accompanied by a higher range of movement (observed when round tables are used). In the case of elementary school students, the quantitative results should be interpreted with caution as students' movement is considerable both during on-task and off-task actions. But, the qualitative observations show that on-task actions cause elementary students to be closer to each other and to the table and arte-facts, although they move an equal amount or more when they are off-task. This suggests that the quantitative measurements for levels of participation and their derived findings (round tables support the higher positive participation of elementary students) may be valid. This may also explain why higher levels of on-task participation are not necessarily related to higher ranges of movement, as elementary students move quantitatively more when using rectangular tables, but we observe that they move qualitatively equally or more when they are off-task.

## Discussion

The contribution of this paper is multifaceted and connects to and extends previous research into MMLA by critically examining its potential, while using new data sets. The results highlight the importance of certain aspects of physical environments with a focus on student behaviours and their relationships (Blinne, 2013; Colbert, 1997; Francis & Raftery, 2005). These behaviours and relationships clearly illustrate how table shape plays a significant role in the interactions of elementary school students. This paper also offers insights into the relationship between the fields of learning analytics and learning design, which needs further research.

*Adding evidence about the effects of learning spaces*

Designing for collaboration is not limited to single dimensions of learning design, but rather re-quires researchers, designers and teachers to consider the physical environment. The results in-dicate that round tables have positive effects on elementary school students' behaviour when participating in collaborative learning activities by increasing levels of on-task participation. These results are consistent with findings in the literature that suggest that the developmental level and the physical learning environment have an effect on learners' behaviour (Godwin & Fisher, 2011; Kumar *et al*., 2008; Midgley, 2006; Pai *et al*., 2014). An explanation is found in the qualitative analysis that links this result to students' movement needs and indicates the ability of certain physical forms to facilitate the desired movement more easily and, thus, to promote the comfort of participating in a collaborative activity in the most appropriate way for students. Triangulating the findings of statistical and qualitative analyses, we conclude that elementary school students move more when using rectangular tables, where participation levels are lower. This is in line with research that suggests that forms in the physical environment can cause dis-tractions and increase off-task time for young students (Godwin & Fisher, 2011). These effects are not observed with university students, where table shapes seem to have a limited impact on their levels of participation in CPS.

*Implications for learning designers and MMLA researchers*

Overall, our study adds to the evidence that supports the need for considering the characteris-tics of the physical learning space as a relevant aspect of comprehensive learning design pro-cesses (Goodyear & Carvalho, 2014; Yeoman & Ashmore, 2018). The evidence is clearer in the case of elementary school students and further research is needed in the case of older learners. This conclusion is aligned with research in collaborative learning that points at discrepancies be-tween classroom layouts (external constraints) and pedagogical methods (intrinsic constraints) reflected in learning designs (Dillenbourg *et al*., 2013; Pérez-Sanagustín, *et al*., 2012).

The employment of comprehensive multimodal analysis tools through the use of a motion cap-ture system in conjunction with video analysis has been based on previous research (Cukurova, Luckin, *et al*., 2018) where physical indicators of collaboration were measured. Differing from previous work in the emerging field of MMLA, we used established motion capture tools to collect and analyse the data, which may help provide standards, validity and repeatability for future work (Shankar *et al*., 2018). Our qualitative analysis has shown that closeness is an indicator of on-task behaviour for both elementary school students and university students. This finding implies that the distance between learners, an indicator used in MMLA research, could be more informative if observed in relation to on-task versus off-task actions. Moreover, the study suggests that movement is not necessarily a key indicator of collaboration. Finally, the study shows the relevance of considering mixed methods, in which qualitative analysis can explain and confirm the validity of the trends revealed by quantitative analysis.

In summary, our findings suggest supporting collaboration researchers, learning designers and other stakeholders in their need to understand how the physical space and table shape can be used to support learning in relation to age and the skills of the students. In terms of MMLA sys-tems, the physical interaction between learners (motion) alone is not strong enough to support an understanding of collaboration without the context of on-task and off-task actions and other human modes of communication and collaboration. Lastly, there is a need for richer frameworks, like AL4LD, for research, analysis and visualisation and for learners and teachers that are able to scale both human and machine data in understanding and supporting education.

*Limitations of the study*

Experimenting in laboratory conditions provided the possibility to administer control over fea-tures of the collaborative activity (same space, same light, same instructors, etc.). However, the evident age differences between the elementary school students and the university students im-posed unavoidable limitations on the study. In both cases, the collaborative activity followed a Jigsaw pattern, but tasks were adjusted to the age of the participants. However, their design was kept as similar as possible (both were design tasks that combined the use of laptops and tangibles). Also, within one level of education, age differences could affect the "maturity" of the students. Elementary school students also had occasional help from the instructors. However, the help was kept to a minimum. Also, concerning the removed outliers, it would have been desirable to have a higher number of participants. Although this did not seem to influence the interpretation of the main results, it reduced the number of samples for the range of movement analysis. The univer-sity students came from engineering bachelor's degree programmes, so the generalisability of the findings is not clear and could have been improved by collecting more qualitative data via focus groups and interviews to gain deeper insights into participants' preferences for table shapes.

## Conclusions and future work

This paper examined how table shape (round vs rectangular) has different effects on physical interactions and patterns of participation of students where variables related to learners' pro-files (level of education) and elements of the pedagogical method (group size) were analysed. The statistical analysis has shown significant differences between the levels of independent variables related to table shape and how the effect differs between two different levels of education and this was further supported by a qualitative analysis of the observations obtained from the video recording of the activities.

This study adds evidence, with implications for practice, about the relevance of including the physical space as an important facet of collaborative learning design. The evidence provided is for two different table shapes, a design task and a learning design involving group sizes of two and three students. Further research should tackle similar studies and consider different character-istics of physical space, educational contexts, tasks and learning designs. A variety of methods in MMLA should help study these settings. In our future work, we will further investigate the influence of table shape by expanding the data set, analysing potential gender differences and introducing new modalities (electrodermal activity analysis and voice analysis) to study more dimensions of students' behaviour.

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**Statements on open data, ethics and conflict of interest**

Anonymised data are available in Zenodo (https://doi.org/10.5281/zenodo.3843436).

The study was approved by the ethics committee of University of Barcelona, supporting the INPhINIT programme. Consent was obtained from participants.

There are no potential conflicts of interest in the work.

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# Chapter 4 - On-task actions in collaborative learning spaces

This chapter addresses the interaction of table shape, group size and gender. The paper presented in this section is:

- 'How do table shape, group size, and gender affect on-task actions in collaborative learning activities?' - shows how round and rectangular tables can affect two group sizes and two genders in different ways when conducting on-task actions. Figure 16 presents the relationship between the paper presented in this chapter and the contributions of the dissertation.

## 4.1 How do table shape, group size, and gender affect on-task actions in collaborative learning activities?

The paper in this section discusses the analysis of on-task actions with the aim of establishing the potential of table shape to influence collaboration when group size and gender are also considered.

Vujovic, M., and Hernández-Leo, D. (2021). How do table shape, group size, and gender affect on-task actions in collaborative learning activities? (to be submitted)

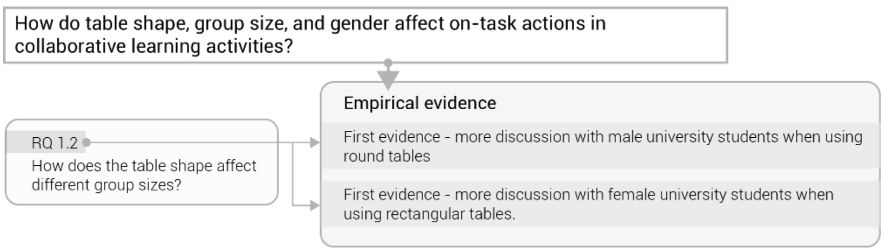


Figure 16. Relationship between the 'How do table shape, group size, and gender affect on-task actions in collaborative learning activities?' paper and dissertation contributions.

# How do table shape, group size, and gender affect on-task actions in collaborative learning activities?

**Abstract**

This paper presents a study that adds evidence to the field of collaborative learning analytics by focusing on the interaction of elements in the physical environment – shapes of tables, group size and gender – and their effects on on-task actions during collaboration. The experimental design is based on a Jigsaw collaborative activity flow and involves the participation of higher education students. The analysis of video recordings followed a coding system with four on-task actions as dependent variables (explanation, discussion, nonverbal interaction, and interaction with physical artefacts). The analysis revealed that decomposition of on-task action and their individual analysis provides detailed insight into students participation. Results show that students engage more in interaction with physical artefacts when collaboration is conducted in dyads. In terms of gender, the analysis shows a tendency of female students engaging more when the activity is conducted in dyads. Furthermore, the combination of dyad structure and a round table resulted in more discussion and nonverbal interaction.

**Notes for Practice**

- Overview: This paper presents a study of how table shape, group size, and gender affect collaborative learning processes in terms of on-task behaviour.
- Contribution: This study contributes by providing a dataset and analytical methodology based on a proposed coding of video recordings. The findings reveal that dyad structures trigger more interaction with task-related physical artefacts, while they also elicit more engagement in female students. Moreover, dyad structures in combination with round tables tend to generate more discussion and more nonverbal interaction.
- Key Implications: Dependencies between table shape, group size, gender, and on-task behaviour during collaborative learning should be further investigated in various contexts in order to closely inform learning design practice.

**Keywords**

Collaborative learning analytics, on-task behaviour, table shape, group size, gender

**Submitted:** 31/05/20

## 1. Introduction

There are multiple factors that can affect student behaviour in collaborative learning activities. Key factors may relate to the design of the learning scenarios or to student characteristics. In terms of learning scenario design, there are factors in the formulation of the epistemic task as well as in the social (group design) and the set (place, tools, artefacts) arrangements (Goodyear & Carvalho, 2014). With respect to student characteristics, examples of factors include sociocultural background, prior knowledge, and gender (Prinsen, Volman, & Terwel, 2007). Research on collaborative learning has provided evidence of how the interplay of different factors affects the processes of collaboration (Janssen & Kirschner, 2020). The main body of evidence along these lines has focused essentially on student, group, task, and technological characteristics. While there is research that considers the influence of factors related to the physical context, the existing findings are inconsistent and are derived from limited trials for data collection (Cukurova, Luckin, & Baines (2018). In this paper, we focus on the shape of shared tables as a specific element in the physical design of collaborative learning environments, and study how it affects students' on-task behaviour in the interplay with group design and gender factors.

The physical environment affects peoples' cognitive processes by influencing dynamic and adaptive interactions between the social and physical planes of human behaviour (Gärling & Golledge, 1989). In other words, the essential aspect of human cognition is perceiving processes in the immediate environment automatically, and those perceptions can, unintentionally or subconsciously, affect the acquisition of skills as well as behaviour (Kaufman, et al., 2010.). Previous research related to the influence of shape and colour on the learning process (Plass, et al., 2014) imply a relationship between the physical environment to emotions and cognition (Ricca, Bowers and Jordan, 2019). A case in point are studies of kindergarten children, e.g. by Godwin & Fisher (2011), that demonstrate children's allocation of attention and learning depend on the classroom visual environment. Studies of older students focus more on the effects of 'places' than on the physical design of the classroom environment. For example, in medical education, research reports evidence of the considerable impact of changes in the physical environment on the overall learning process (Pai, et al., 2014; Midgley, 2006). Switching from a classroom to a clinical setting causes significant amounts of additional stress, where students felt more insecure in the learning process. Furthermore, the observations reported by exploratory co-located collaborative learning studies suggest there are certain physical parameters, such as table shapes and layout, that can encourage desirable on-task social interactions that lead to learning (Brooks, 2012; Croker, Fisher & Smith, 2015; Yee & Park, 2005) Moreover, the relationship between collaborative learning activity and furniture has been researched previously (Healion, et al., 2017), but the body of evidence that explores this topic comprehensively is still not significant.

The design of groups and its effects has generally not been researched in the domain of computer-supported collaborative learning. Both group formation policies (Amarasinghe, Hernandez-Leo & Jonsson, 2017) and group sizes have been shown to have an impact on the collaboration process and its outcomes (Saqr, Nouri, & Jormanainen, 2019). For example, we know that cohesiveness, efficiency, exchange of information and ideas as well as the personal satisfaction of students are aspects that are affected by group size (Liverpool-Tasie, Adjognon, & McKim, 2019; Granados & Wulf, 2007; Kooloos et al, 2011). However, existing research has neglected how the design of the physical space can affect the behaviour of specific group configurations.

Regarding individual student characteristics, gender factors can affect the character of collaboration from the perspective of group composition (Zhan, et al.,, 2015). Moreover, there is evidence that points to behavioural differences between female and male students when collaborating (Stump, et al., 2011; Seymour and Hewitt, 1997). However, it is unclear if the physical space itself may also have an impact on the differences by gender in student behaviour.

In this paper, we provide an empirical study that examines student behaviour when engaged in a collaborative learning activity and analyse the effects of table shape, group size, and gender. The study is designed so that engagement is reflected in physical on-task actions (Thuen & Bru, 2000; Wheldall & Lam, 1987) and student focus on tasks is detectable by observation (Cukurova, et al., 2018).

This study builds on previous research to ground the formulation of relevant on-task actions, such as explanation, discussion, and nonverbal interaction, as well as interaction with physical artefacts. On-task actions are used as dependent variables in the analysis process. Dependent variables are the aforementioned factors of table shape, group size, and gender. Accordingly, the research question of the study is: Do different table shapes have different effects on on-task actions for different groups sizes (2 and 3 participants) and for different genders? To examine the research question, the collaborative sessions were video recorded, analysed by means of a grounded coding system, and Analysis of Variance (ANOVA) done to determine if there are significant differences in each dependent variable with the independent variables.

## 2. Background

In this section we review key previous research regarding the design of learning scenarios in terms of the physical space and group formation as well as gender aspects and their effects on collaborative learning processes. This section also explores the need for an on-task analytical focus based on a grounded (video) coding system.

### 2.1 Collaborative learning spaces

Classroom organisation and seating arrangements are parameters that have a proven impact on the allocation of educational resources and educational opportunities (Yuan, Yunqi & Feng-Kuang, 2017). Furthermore, co-located learning research points to the relevance of the reinforcement of social bonding through shared seating, where educational spaces are also social spaces and spatial structures are used in a way to encourage interaction, which was reported to enhance collaboration and interprofessional rapport (Croker, Fisher & Smith, 2015). Misused spatial features such as non-transparent partitions and grid-organised desks created problems of reduced awareness between participants in co-located learning contexts (Yee & Park, 2005). Furthermore, various aspects of the physical learning environment such as different shapes used in spatial design, colours, and light, influenced student behaviour (Francis & Raftery, 2005; Blinne, 2013; Colbert, 1997). Brooks (2012) reported that classrooms with round tables for multiple students encouraged more on-task student behaviour in the active learning classroom system, while conventional classroom seating, where rectangular tables are positioned in rows, was better for lecture-type activity. Overall, perception of the physical learning environment has been shown to affect student behaviour and involvement, and learning progress (Pai, et al., 2014; Midgley, 2006). Yet, the field recognises the need for more research on actionable knowledge of the connections between the designed environment and quantifiable learning activity analytics (Yeoman & Ashmore, 2018; Cukurova, Luckin, & Baines, 2018)

### 2.2 **Group size**

There is a significant body of research on group formation policies, group size, and interaction dynamics in collaborative learning that focus on the differences between homogeneous vs heterogeneous and large vs small groups. Despite existing findings indicating that smaller groups are more efficient, few studies have investigated the differences between different sizes of small groups. A study that examined collaborative groups with 7-15 participants per group showed that smaller groups encourage a higher level of social interaction, which increases the individual student performance (Saqr, Nouri, & Jormanainen, 2019). Furthermore, smaller groups become more cohesive and communicate more efficiently, while participants in larger groups tend to share less information among themselves and cause some students to be inactive and isolated. In a study of group size and compositions in collaborative learning in an economics class, researchers saw that groups consisting of 5 to 6 participants enhanced learning when compared to larger group sizes (Liverpool-Tasie, Adjognon, & McKim, 2019). In terms of satisfaction and personal preferences, Kooloos et al. (2011) report that students favour smaller groups (5 members instead of 15) and point out that possible larger learning gains due to these circumstances need to be further investigated.

When examining smaller groups in greater detail, studies on the specific numbers of group members are divided on whether dyads or triads generate the most beneficial outcomes for learners. The learning benefits of dyad structures stress the possibility for learners to observe one another while they are encouraged to exchange ideas and strategies to boost their performance (Granados & Wulf, 2007). Furthermore, dyads demonstrate efficiency in practical assignments, due to more optimised use of equipment between two users (Shanks, et al., 2013). However, while Crook & Beier (2010) report that the effectiveness of dyads is demonstrable, it could also depend on the task that is being performed. In terms of collaborative learning, some researchers state that dyads are often considered to be peer learning, while triads imply real collaboration (Pijeira-Diaz, Drachsler, Järvelä, & Kirschner, 2019). Their premise is that triads trigger complexity in terms of majority/minority influence, coalitions, negotiations, and conflict that are beneficial for learning. Also, the expert/novice patterns that are developed in dyads also hold true for triads and are important for collaboration (Edstrom, 2015).

### 2.3 **Gender aspects**

Previous research on gender aspects in collaborative learning demonstrated interesting findings related to their effects on the collaboration process. On the one hand, regarding group formation, the gender structure of the group tends to have an impact on the learning outcome. Zhan, et al. (2015) provide evidence that certain grouping formations, in terms of gender distribution, are more suitable for collaborative learning, where female-only and balanced-gender grouping are shown to be the most suitable.

On the other hand, existing evidence suggests gender may have implications for individual student behaviour when collaborating. For example, in a study by Stump, et al., (2011), female students claimed that they applied more collaborative learning strategies than their male peers. Also, Seymour and Hewitt (1997) found that female students seek help from other students with higher frequency in collaborative activities, even if this leads to their feeling like the group member of lower status. Finally, there are studies that present issues related to female students experiencing bias, as in engineering programmes where they were disrespected by the male students (Vogt, Hocevar & Hagedorn, 2007).

### 2.4 **On-task actions**

In the analysis of the effects of the different factors in collaborative activities, student actions can be categorised into two groups: on-task and off-task. When students engage in actions or interactions that are unrelated to the task, it is considered off-task behaviour (Randolph, 2007), whereas paying attention during instructions or focusing on group or individual work is considered to be on-task behaviour (Thuen & Bru, 2000). Furthermore, on-task behaviour is defined as attending to assigned tasks, focusing on the appropriate materials, manipulating learning objects, and maintaining eye contact with the teacher, team members, or task objects (Wheldall & Lam, 1987). In collaborative learning, these actions are essential for problem solving (Meloth & Deering, 1992) and for generating the social awareness and overall positive perception of group members' interdependence and accountability, which underpin fruitful collaboration (Wood, Mirza & Shaw, 2018). Furthermore, Chiu (2004) reported that when conducting collaborative work in classroom settings, groups of students who were exhibiting on-task actions more often generated better solutions to the problems than other groups.

### 2.5 **Video recording**

Video recording is the common tool used to collect data in co-located collaborative learning settings for the study of student behaviours. The ability to interpret and analyse actions from video is a demanding and challenging job that requires coding and counting as an approach for valid analysis. The literature provides a variety of approaches where the coding of student behaviour in the collaborative process is often associated with a specific task (Malmberg, et al., 2019). Also, some examples have pointed to coding that could be considered generic to some extent (Falcão & Price, 2009). This should be taken with caution, meaning that the usage of the coding elements must be tailored and justified on a case-by-case basis.

As Cukurova, et al. (2018) state in their research on students' physical interactions during collaborative activity, observing the quality of collaboration is a challenging process. In addition to social coordination, the complexity of the collaborative process is reflected in the actions participants take to achieve collective acceptance of a jointly agreed goal related to the task. With this in mind, the literature does provide frameworks built on observable features in a coding process that enables evaluation of collaborative activity using video recordings, but these are often based on verbal interactions (Saleh, Lazonder & de Jong, 2007). Although verbal interaction is undoubtedly a valid tool in collaborative analysis, in some cases nonverbal actions can provide greater insight into the quality of collaboration in specific contexts (Cukurova, Luckin, Millán & Mavrikis, 2018).

In this paper, we use a coding system tailored for our specific study where on-task actions have been recorded and analysed. The formulation of the codes were grounded in the research mentioned previously.

## 3. Methods

The study focused on a collaborative problem-solving activity, where two main conditions were examined: table shape (round or rectangular) and how this interacts with group size (two or three participants) and gender. University students were engaged in design tasks conducted in small groups orchestrated using the widely known Jigsaw pattern (Hernández-Leo et al., 2006; Aronson, 1978). To achieve fruitful learning, this pattern proposes a collaborative learning flow that promotes positive interdependence and individual accountability by allocating students into small groups that change along the flow. Data for the analysis of on-task actions were extracted from video recordings and coded using previously defined codes of types of on-task actions, after which the data were processed and analysed (Figure 1). In order to determine the impact of independent variables (table shape, group size, and gender) on the representation of different types of on-task activity, the two coders coded the videos independently.

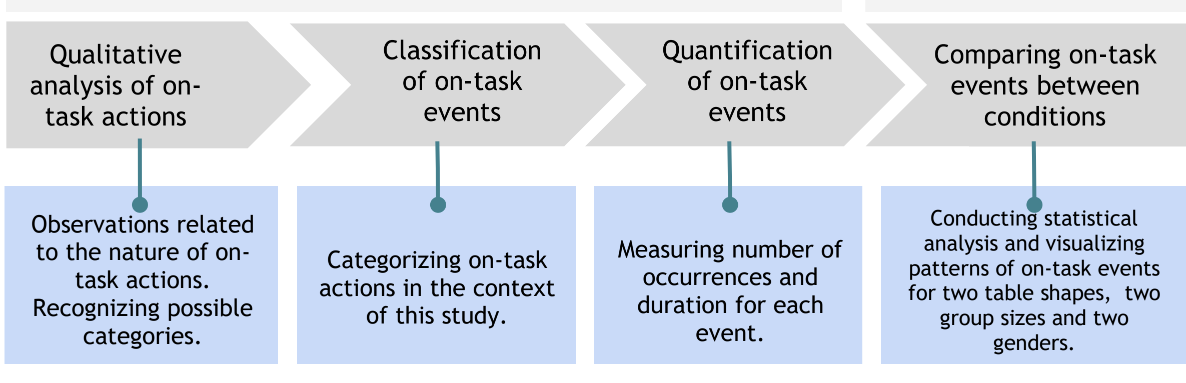


**Figure 1.** Data collection and analysis

### 3.1 **Participants**

University students were invited to extracurricular training focused on design tasks in physical computing. In the recruiting process, of more than 150 volunteers interested in the training, 36 students with no prior knowledge of the topic were selected from different engineering degrees, in different years, and with an equal number of male and female participants. These 36 students (aged 18-24) formed 12 (Jigsaw) groups, from which we analysed the data of 8 groups, which amounts to 24 subjects. The subject selection criteria for analysis was: good camera coverage in order to obtain valid data, balance of gender as much as possible, and balance of table shapes. Of the 24 subjects selected for the data analysis, 12 subjects had used rectangular tables and 12 round ones (Figure 2). Within the analysed dataset of 24 subjects, there were 11 female and 13 male participants.

**Figure 2.** Two seating arrangements that present different conditions in the study

### 3.2 **Materials and task description**

Students participated in a collaborative problem-solving activity where specific artefacts were to be designed. Following a Jigsaw pattern flow structure, each session started with two groups of three members each. After being given instructions on a divisible task, they were organised into three different expert groups of two members (each coming from different initial groups) for a second phase of the activity in which each group specialised on a sub-task. After finishing the sub-task, students returned to their initial Jigsaw group and continued work on the overall task. The task was open-ended, which means that each group could produce a different design. At the end of the activity, each group presented their work. The activity lasted one and a half hours and required no prior knowledge, and was designed in a way so that each group member had close to the same workload when conducting her/his part of the task.

The participants were asked to design, programme, and build an interactive toy that was to be designed using electronics connected to an Arduino board and additional elements such as cardboard and paper. The difficulty level was adapted to the student profiles (who had no experience in Arduino programming) and they were provided with the information necessary for each step of the process. Students were informed of the data collection and analysis that followed this experiment, which was approved by an ethics committee. Informed consent was obtained from the students before the experiment.

### 3.3 **Measurements**

As previously mentioned, three independent variables were identified: table shape, group size, and gender. Two levels were defined for each of these independent variables, and their effect(s) tested on dependent variables related to student behaviour that were relevant to collaborative learning situations. In terms of table shape, two configurations, round and rectangular, were used in this study. Group size was introduced as a relevant pedagogical requirement of the Jigsaw-based collaborative learning design, which considers group transformation during the activity. Part of the activity was conducted in groups of two and part in groups of three. Thus, there were two levels for the independent variable of group size. Regarding gender, all participating students declared as either male or female, which also defined two levels for this independent variable.

Observable elements in student behavior that may be relevant to collaborative learning processes relate to social and physical actions emerging from student activity when completing the epistemic facets of a learning task (Goodyear & Carvalho, 2014; Martinez-Maldonado, et al., 2020; Isohätälä, Näykki & Järvelä, 2020), i.e.

when working on-task. Therefore, the effects of changes in independent variables were measured on dependent variables that present on-task actions (both social – interaction with group members and physical – interaction with physical artefacts).

The data measured and analysed were acquired through the coding of video recordings of the collaborative problem-solving activity. In order to develop a coding system for the specific focus of this study, the intersection of participant behaviour observations was combined with findings from the literature. During the first phase of formulating the coding system, participant behaviour during the activity was observed qualitatively, where certain behavioural categories were detected that were recognisable in all groups and covered the vast majority of on-task actions performed throughout the activity. These include *explanation*, *discussion*, and *nonverbal interaction* as social on-task actions, and *interaction with physical artefacts* as physical on-task action. These categories of on-task actions detected by observation were compared with the methods applied in related work and adjusted to make the coding more valid and meaningful. Table 1 lists the resulting coding system, which aligns with the literature on collaborative learning and multimodal learning analytics.

**Table 1.** Codes of on-task actions

| Source | Code |
|---|---|
| **Explanation** as passive action (Malmberg, et al., 2019) and an indicator that provides lasting and effective problem-solving skills and knowledge (Webb, Troper & Fall, 1995). | **Explaining [E]**<br><br>Passive action (in terms of interaction) - the act or process of making something clear or easy to understand (telling, showing) without active participation from other participants. This is a *social* action that can overlap with *physical* actions (interaction with physical artefacts). |
| **Discussion** facilitates active interaction (Malmberg, et al., 2019) and reinforces equality and mutuality of engagement that are important for building good collaborative skills (Damon & Phelps, 1989). | **Discussion (Joint verbal engagement ) [D]**<br><br>Any type of discussion or quick exchange of words that includes interaction with participants (talking and pointing). This is a *social* action that can overlap with *physical* actions (interaction with physical artefacts). |
| **Nonverbal participation** is equally important to collaboration as verbal forms and in some cases, participants can contribute more when not pressured to talk (Rogers, Lim, Hazlewood & Marshall, 2009). | **Nonverbal participation [NV]**<br><br>When a participant is not talking but is looking at teammates and/or gesturing as a sign of feedback (nodding or short utterances). This is a *social* action that can overlap with *physical* actions (interaction with physical artefacts). |
| **Interaction with physical artefacts** supports collaboration and provides more balanced participation (Falcão & Price, 2009). | **Interaction with physical artefacts [IPA]**<br><br>When participants use artefacts (Arduino, laptop, cards) to work individually or collectively. This *physical* action can overlap with *social* actions (explanation, discussion, and/or nonverbal participation). |

Starting with social on-task actions, we can distinguish two main characteristics: active and passive (Malmberg, et al., 2019; Webb, Troper & Fall, 1995). The action of *explaining* represents a passive action and refers to reading out loud or talking with the objective of clarifying instructions or ideas. This is considered beneficial because it reorganises the material in a new way, develops new perspectives, and resolves inconsistencies, which would not be accomplished as comprehensively when done individually (Webb, Troper & Fall, 1995). *Discussion* is considered an active social on-task action that engages more than one person in dynamic interaction (Malmberg, et al., 2019), reinforces equality and mutuality of engagement (Damon & Phelps, 1989), and coordination of attention (Falcão & Price, 2009). Another on-task action in the social category is nonverbal participation, meaning actions and gestures of listening and observing without extended verbal engagement, which has been shown to be highly significant in collaboration. Rogers, et al. (2009) showed that, in some cases, participants contribute more when they are not under pressure to say something. Regarding physical on-task actions, in this context *interaction with the artefacts* is essential for solving the collaborative activity task. The use of the artefacts indicates engagement with the task and, when used during explanations or discussion, reinforces collaboration and provides more balanced participation (Falcão & Price, 2009). Therefore, we designated four on-task codes (explanation, discussion, nonverbal interaction, and interaction with artefacts) for video analysis, which were considered as the dependent variables.

### 3.4 **Procedure**

For measuring the dependent variables in a laboratory setting, we used video-recording devices. Ambient factors such as light, room temperature, wall colour, surrounding furniture, researchers present, and environmental noise were exactly the same for all groups. Video recordings were made with two cameras positioned at a height of two metres from different angles in order to avoid the occlusion of subjects (Figure 3). Recordings were labelled and saved after each session of the experiment.

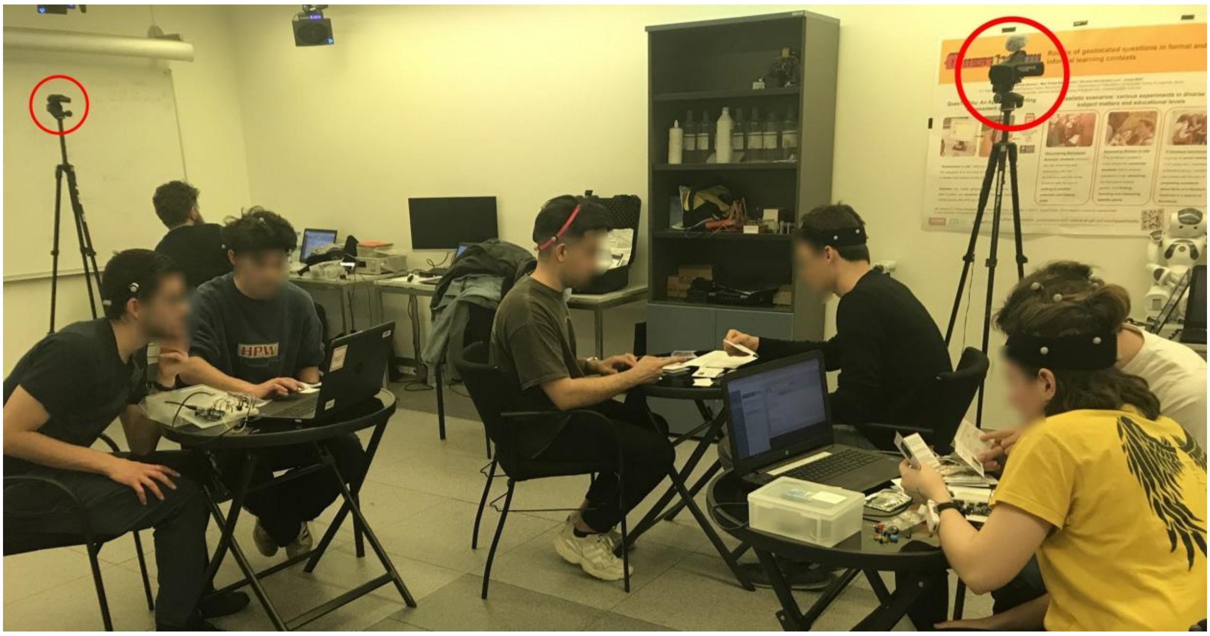

**Figure 3.** Camera positions

Analysis of the recordings was conducted by two coders and the coding criteria were unified through intercoder reliability (ICR) assessment, where ICR was calculated to better understand the extent to which two or more independent coders assign the same rating to the same object (MacPhail, Khoza, Abler & Ranganathan, 2016; Lombard, Snyder-Duch & Bracken, 2010). Four techniques were used to assess ICR, including percent agreement, Scott's Pi coefficient, Cohen's Kappa coefficient, and Krippendorff's Alpha (MacPhail, Khoza, Abler & Ranganathan, 2016). Both coders were assigned to code the same segments of video recordings. Due to the nature of the activity, in which each student participated in both dyad and triad group structures, the coders were allocated five minutes for each group structure from one session. Coding tests were conducted in three iterations, though after the first and second iterations, coders revised the coding table and adjusted definitions in order to apply more coherent coding in the next iteration. Furthermore, different segments of video recordings were analysed in each iteration. The iterative process ended when each of the four assessment techniques provided a satisfactory score (table 2).

**Table 2**. Intercoder reliability assessment - Iteration 3 (final iteration)

| Intercoder reliability assessment | | | | | |
|---|---|---|---|---|---|
| ICR assessment techniques | | Percent agreement | Scott's Pi coefficient | Cohen's Kappa coefficient | Krippendorff's Alpha |
| Group of 2 | D | 92.6% | 0.850 | 0.850 | 0.853 |

| | | | | | |
|---|---|---|---|---|---|
| students | E | 96.3% | 0.647 | 0.649 | 0.654 |
| | NV | 96.3% | 0.926 | 0.926 | 0.927 |
| | IPA | 81.5% | 0.621 | 0.626 | 0.628 |
| Group of 3 students | D | 88.6% | 0.772 | 0.776 | 0.777 |
| | E | 95.5% | 0.774 | 0.776 | 0.779 |
| | NV | 95.5% | 0.904 | 0.904 | 0.906 |
| | IPA | 90.9% | 0.741 | 0.741 | 0.747 |

### 3.5 **Analysis**

As explained above, we identified three independent variables (table shape, group size, and gender) and four dependent variables (the on-task actions of explanation, discussion, nonverbal interaction, and interaction with artefacts). Data for the four dependent variables were extracted from the coded videos and expressed in percentages of total time spent on on-task activity, as in the example presented in Table 3. Three Analyses of Variance (Anova) were performed, excluding analysis of the on-task action explanation due to its non-normal data distribution. Each Anova presents the independent variables' influence on one of the dependent variables. All statistical analyses were performed using SPSS v23 IBM.

**Table 3.** Example of values taken from the coded videos and entered into the analytical process

| Subject | Table shape | Group size | Gender | Explanation* | Discussion* | Nonverbal interaction* | Interaction with the artefacts* |
|---|---|---|---|---|---|---|---|
| Subject 1 | Round | 3 | male | 2.55% | 20.58% | 23.76% | 11.91% |
| Subject 2 | Round | 3 | female | 1.61% | 13.97% | 40.30% | 11.97% |
| Subject 3 | Round | 3 | male | 0.00% | 10.09% | 18.67% | 1.06% |
| ... | | | | | | | |

*Values presented are the percentage of total time spent on on-task actions of the coded activity in certain conditions.

Distribution by factor of the cases analysed is presented in Table 4 and shows how many activities were conducted in each condition for each of the factors. In total, this study analysed 24 subjects, who each participated in two activities, one in dyad and one triad collaborative structure. For three of those who were working at round tables, video recordings for the triad structure were not complete and those data were excluded from the analysis, which resulted in unequal numbers between conditions. For example, the 24 activities analysed for the rectangular table condition included activities of both group sizes and both genders, but for round tables, the number is 21, as the three excluded triad activities all took place at round tables.

**Table 4**. Distribution by factor of the cases analysed

| Between-Subject Factors | | |
|---|---|---|
| Independent variable | Level of independent variable | Number of activities |
| Table Shape | Rectangular | 24 |
| | Round | 21 |
| Group Size | 2 | 24 |
| | 3 | 21 |
| Gender | female | 21 |

| | | |
|---|---|---|
| | male | |

## 4. Results

The results present the output of the analysis methods applied and show the effects that the physical environment, group size, and gender have on students' on-task actions when collaborating on a design problem-solving task. Three multifactorial Anova tests generated the results of the individual or simultaneous influence of the factors tested (*table shape*, *group size* and *gender*) on the dependent variables (*discussion*, *nonverbal interaction*, and *interaction with physical artefacts*). Normality tests (Kolmogorov-Smirnov and Shapiro-Wilk) were conducted and they failed to reject the null hypothesis (normal distribution of the residuals) for one of the four dependent variables (Table 5, Figure 4), *explanation*. This means that the multifactorial Anova test could be conducted on three dependent variables with normal distribution, while *explanation*, as the dependent variable with non-normal distribution, could not. This was due to the low number of occurrences of this action, which in terms of the number of samples processed cannot be considered to provide valid insight.

**Table 5.** Normality test results

| Normality tests | | | | | | |
|---|---|---|---|---|---|---|
| | Kolmogorov-Smirnova | | | Shapiro-Wilk | | |
| | Statistic | df | Sig. | Statistic | df | Sig. |
| Explanation | 0.28 | 45 | 0 | 0.524 | 45 | 0 |
| Discussion | 0.099 | 45 | .200* | 0.987 | 45 | 0.882 |
| Nonverbal | 0.084 | 45 | .200* | 0.974 | 45 | 0.4 |
| Artefacts | 0.11 | 45 | .200* | 0.958 | 45 | 0.105 |
| * This is a lower bound of the true significance. | | | | | | |
| Lilliefors significance correction | | | | | | |

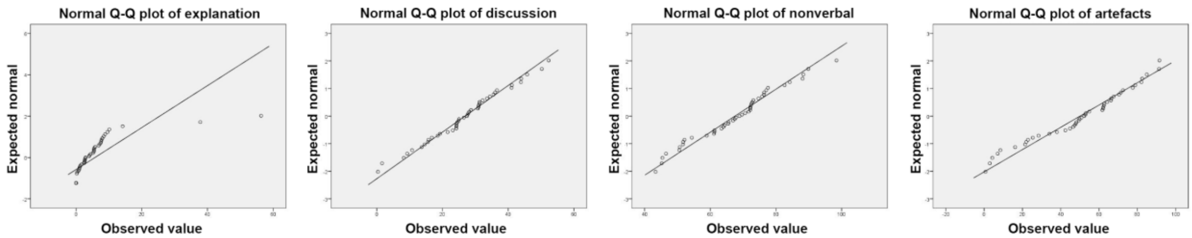


**Figure 4**. Q-Q plot of the residuals for four dependent variables

*Do different table shapes have different effects on on-task discussion for different group sizes and different genders?*

There are no statistically significant differences detected in any of the factors included in the analysis (Table 6), but there are certain trends evident in the graphs (Figure 5) that suggest the potential influence of interaction between the factors on the discussion activity during collaboration. In groups of three, more discussion was generated when students were using rectangular tables, while in groups of two it occurred when using round tables (Figure 5-a). Male students discussed more when using round tables, while female students discussed more when using rectangular tables (Figure 5-c). These individual findings were independent of the gender of the other group members.

**Table 6.** Multifactorial Anova of Discussion

| Tests of between-subject effects |
|---|
| Dependent variable: Discussion |

| Source | Type III sum of squares | df | Mean square | F | Sig. | Partial Eta squared |
|---|---|---|---|---|---|---|
| Table shape | 14.394 | 1 | 14.394 | 0.1 | 0.753 | 0.003 |
| Group size | 147.874 | 1 | 147.874 | 1.031 | 0.316 | 0.027 |
| Gender | 221.636 | 1 | 221.636 | 1.546 | 0.222 | 0.040 |
| Table shape * Group size | 29.482 | 1 | 29.482 | 0.206 | 0.653 | 0.006 |
| Table shape * Gender | 196.692 | 1 | 196.692 | 1.372 | 0.249 | 0.036 |
| Group size * Gender | 328.856 | 1 | 328.856 | 2.294 | 0.138 | 0.058 |
| Table shape * Group size * Gender | 30.766 | 1 | 30.766 | 0.215 | 0.646 | 0.006 |
| Error | 5304.545 | 37 | 143.366 | | | |
| Total | 38623.223 | 45 | | | | |
| Corrected total | 6166.136 | 44 | | | | |
| a R squared = 0.140 (adjusted R squared = -0.023) | | | | | | |

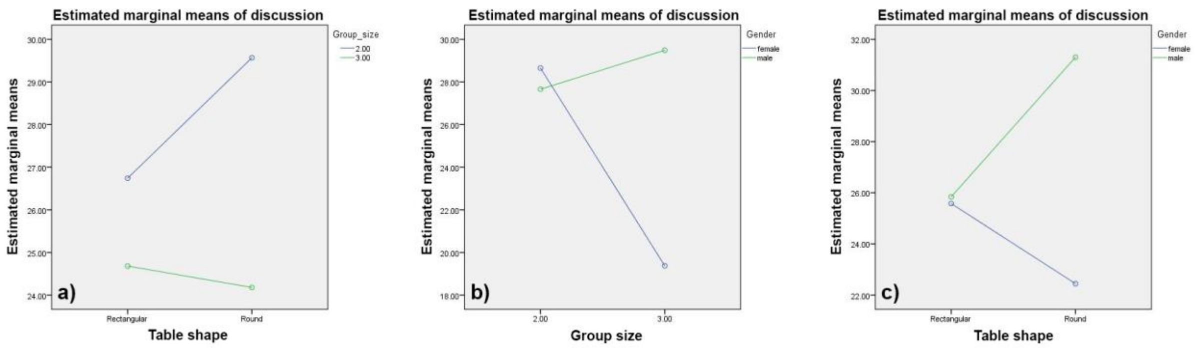


**Figure 5.** (a) Discussion comparing table shape and group size; (b) Discussion comparing table shape and gender; (c) Discussion comparing group size and gender

*Do different table shapes have different effects on on-task nonverbal interaction for different group sizes and different genders?*

Table 7 presents the results of the multifactorial Anova test of the independent variables that affect nonverbal interaction and shows that there is a statistically significant difference between group sizes. Furthermore, a p-value of 0.053 indicates that nonverbal interaction also differs considerably between genders. Figure 6 indicates that students are more likely to interact nonverbally when collaborating in groups of three. Furthermore, male students demonstrate far less nonverbal interaction than female students. Figure 7 presents cases of interaction between factors, where the occurrence of nonverbal interaction differs between levels of independent variables. Students collaborating in groups of two displayed more nonverbal interaction when using round tables (Figure 7a). However, when working in groups of three, more nonverbal interaction took place when rectangular tables were used. When observing the interaction between gender and group size, both female and male students displayed more nonverbal interaction when collaborating in groups of three (Figure 7-b). When considering the relationship between table shape and gender, there is the opposite tendency but with smaller differences, where female students demonstrated more nonverbal interaction while using round tables, as opposed to their male peers, who demonstrated more of this type of interaction when using rectangular tables (Figure 6-c).

**Table 7.** Multifactorial Anova of Nonverbal Interaction

| Tests of between-subject effects | | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable: Nonverbal | | | | | | |
| Source | Type III sum of squares | df | Mean square | F | Sig. | Partial Eta squared |
| Table shape | 0.330 | 1 | 0.330 | 0.002 | 0.963 | 0 |
| Group size | 756.677 | 1 | 756.677 | 4.911 | **0.033** | 0.117 |
| Gender | 615.161 | 1 | 615.161 | 3.992 | **0.053** | 0.097 |
| Table shape * Group size | 59.199 | 1 | 59.199 | 0.384 | 0.539 | 0.010 |
| Table shape * Gender | 36.803 | 1 | 36.803 | 0.239 | 0.628 | 0.006 |
| Group size * Gender | 162.865 | 1 | 162.865 | 1.057 | 0.311 | 0.028 |
| Table shape * Group size * Gender | 48.735 | 1 | 48.735 | 0.316 | 0.577 | 0.008 |
| Error | 5701.105 | 37 | 154.084 | | | |
| Total | 212053.707 | 45 | | | | |
| Corrected total | 7224.907 | 44 | | | | |
| a R squared = 0.211 (adjusted R squared = 0.062) | | | | | | |

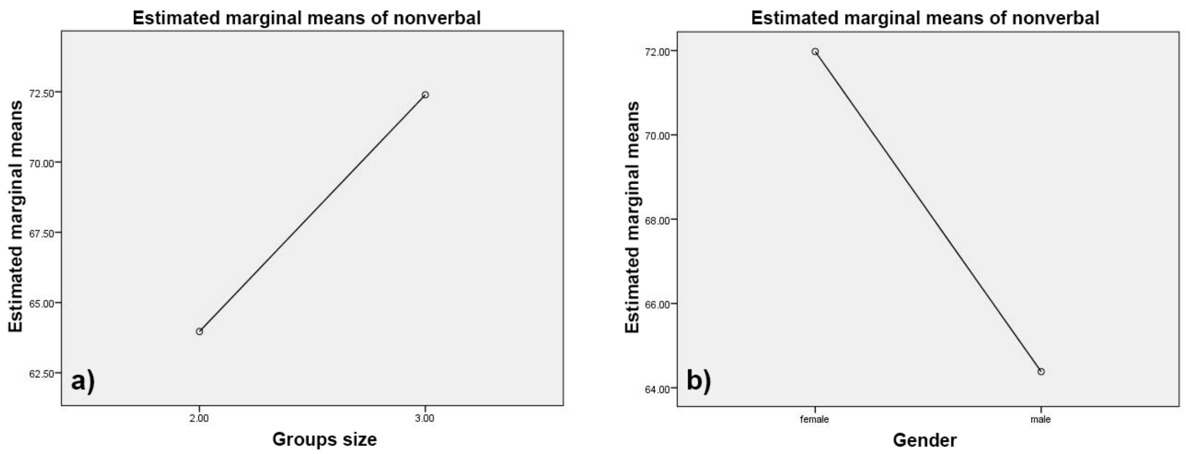


**Figure 6.** Group size (statistically significant) and gender effects on nonverbal interaction

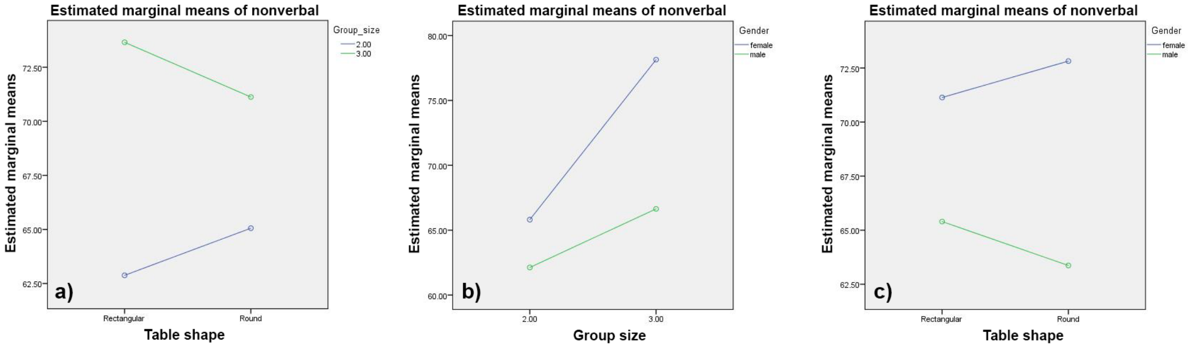


**Figure 7.** (a) Nonverbal interaction comparing table shape and group size; (b) Nonverbal interaction comparing group size and gender; (c) Nonverbal interaction comparing table shape and gender

*Do different table shapes have different effects on on-task interaction with artefacts for different group sizes and different genders?*

A statistically significant difference was found between two different group sizes when considering interaction with physical artefacts (Table 8), with significantly more interaction occurring when students worked in groups of two (Figure 8). Moreover, a p-value of 0.067 in the differences between genders when interacting with physical artefacts suggests that male students engage more in this kind of interaction than female ones. In terms of interaction between factors, there were no noticeable trends in the data that might indicate different tendencies between students in different levels of the independent variables, in which all values suggest that there are similar tendencies (Figure 9).

**Table 8.** Multifactorial Anova of Interaction with Physical Artefacts

| Tests of between-subject effects | | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable: Artefacts | | | | | | |
| Source | Type III sum of squares | df | Mean square | F | Sig. | Partial Eta squared |
| Table shape | 106.345 | 1 | 106.345 | 0.28 | 0.6 | 0.008 |
| Group size | 9092.75 | 1 | 9092.75 | 23.913 | **<.00** | 0.393 |
| Gender | 1351.4 | 1 | 1351.4 | 3.554 | **0.067** | 0.088 |
| Table shape * Group size | 44.681 | 1 | 44.681 | 0.118 | 0.734 | 0.003 |
| Table shape * Gender | 513.868 | 1 | 513.868 | 1.351 | 0.252 | 0.035 |
| Group size * Gender | 311.808 | 1 | 311.808 | 0.82 | 0.371 | 0.022 |
| Table shape * Group size * Gender | 643.701 | 1 | 643.701 | 1.693 | 0.201 | 0.044 |
| Error | 14068.735 | 37 | 380.236 | | | |
| Total | 139528.504 | 45 | | | | |
| Corrected total | 26919.478 | 44 | | | | |
| a R squared = 0.477 (adjusted R squared = 0.379) | | | | | | |

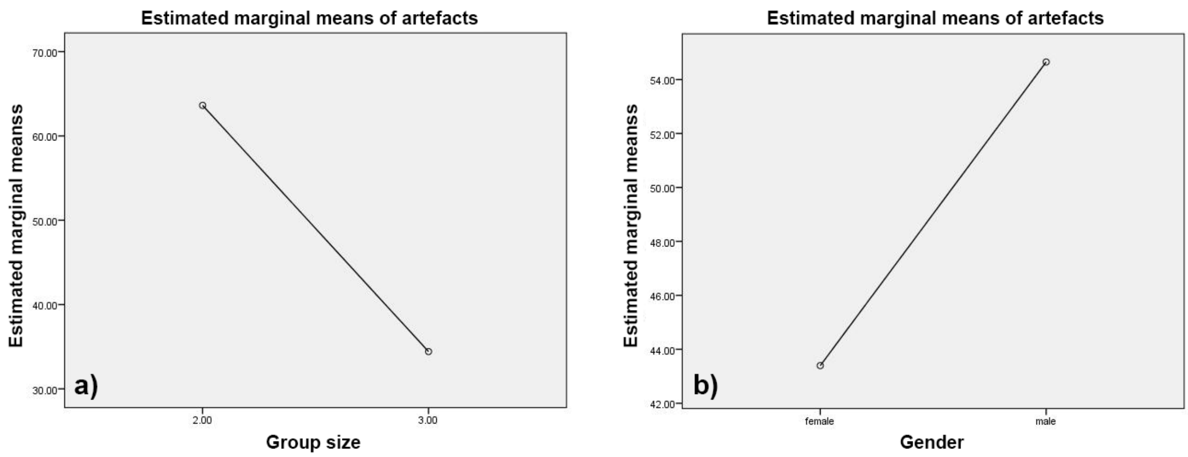


**Figure 8.** Group size (significant) and gender effect on interaction with physical artefacts

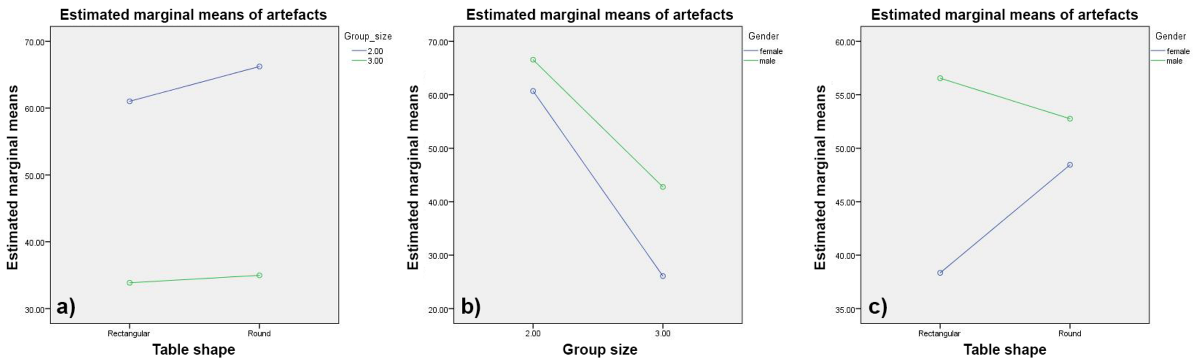


**Figure 9.** (a) Interaction with physical artefacts comparing table shape and group size; (b) Interaction with physical artefacts comparing table shape and gender; and (c) Interaction with physical artefacts comparing group size and gender

# 5. Discussion and limitations

## 5.1 Examining and extending topics from previous research

The aim of this study is to contribute to the field of collaborative learning analytics by examining the association between table shape, group size, and gender with collaborative on-task actions. This study is grounded in and further examines previous research that indicates the impact of the physical environment on learning and collaborative processes and specific relationships that may have implications for future research on face-to-face collaborative learning. It contributes further to studies on the size of collaborative groups and gender differences in the collaborative process. The findings reveal that group size plays an important role in interaction with physical artefacts, even in the case as here in which the learning design reinforced the need to use artefacts to the same degree in both dyad and triad structures. Same statistically significant differences between group sizes was noted in analysing nonverbal interaction. Pijeira-Diaz, et al (2019) argue that there is higher potential for coalitions, negotiations, and conflicts in triads. Interestingly, in this study we have found more nonverbal interaction in triads than in dyads, which could be linked to previous research showing that students sometimes contribute more when they are less verbally engaged (Rogers, Lim, Hazlewood & Marshall, 2009). This dual interpretation of nonverbal interaction, in which students still exhibit on-task behaviour and are engaged in collaborative processes, requires further investigation.

This study has also found certain correlations between gender and group size. As it is more common for female students to be less verbally engaged and to interact with artefacts less in triad structures, it could be questioned whether previous research on group size considered gender perspective sufficiently. Although our study did not focus on the group formation structure itself, research such as that done by Zhan, et al. (2015), who examined how gender distribution within groups affects collaboration, could be further extended with the findings presented here. That is to say, classification of on-task actions and deeper insight into their patterns shows promising results in pointing out the specific causes of why different gender group structures generate different collaboration behaviours and performance.

### 5.2 Adding evidence of the effects of group size and tendencies related to table shape and gender

The results show that group size plays a significant role in interaction with physical artefacts. Statistically more interaction in groups of two students builds on the findings of the literature indicating that dyads, when involved in practical work, use equipment with higher frequency (Shanks, et al., 2013). Furthermore, this study reveals a tendency for students to generate more discussion when working in dyads as opposed to triads. Interestingly, the study shows opposite tendencies when considering table shape in relation to group size. Dyads engage in more discussion, nonverbal interaction, and interaction with physical artefacts when using round tables, while triads do so more when using rectangular tables. If we relate these findings of student behaviour to previous research by Brooks (2012), which reported that students participating in active learning practices such as collaborative learning performed better when using round tables, this study contributes corresponding evidence. On the other hand, Healion, et al. (2017) report that, based on movement measurements, students in triad structures were more engaged in social interaction when using standing-height round tables, rather than rectangular tables with seats. Although this study presents the results for one triad per table shape and does not include other group sizes, the findings could be further challenged on the grounds of including detailed on-task action analysis.

Looking more into the table shape effect on on-task actions in collaborative learning, different tendencies exist between genders as well. The tendency of female participants to discuss slightly more when sitting at rectangular tables, while male students do so at round tables. It would be interesting to further investigate this behavior and understand if it is related to existing findings about gender bias leading to disrespect to female students in engineering programs (Vogt, Hocevar & Hagedorn, 2007). However, female participants employ nonverbal interaction more at round tables, where their male counterparts use it more at rectangular ones, which relates to the previous observation and could indicate that female students, in situations that encourage easier communication (Ge, Yang, Liao & Wolfe, 2015), feel under pressure to say something and contribute more through nonverbal interaction (Rogers, Lim, Hazlewood & Marshall, 2009). Similar tendencies are found when analysing interaction with physical artefacts, although the different preferences between conditions are less pronounced. The effects of table shape, as an element of the physical space, confirm the findings from the literature in which researchers report on the ability of spatial structures to have different effects on students depending on the learning design (Francis & Raftery, 2005; Blinne, 2013; Colbert, 1997), thereby encouraging interaction and enhance collaboration (Croker, Fisher & Smith, 2015).

### 5.3 Limitations

The conditions under which this study was conducted imposed certain limitations. Due to the nature of the Jigsaw pattern applied to the activity, tasks conducted in dyads were not the same for all participants, though they were designed to be as similar as possible. However, tasks in triads were the same for all subjects. The differences between the tasks conducted in dyads should not have affected on-task actions, as all students received the same materials and their instructions differed according to the kind of expertise they were supposed to gain, but none of the on-task actions was restricted by that. As previously stated, for three out of 24 subjects, data for the triad activity were not used in this study due to the incomplete video recording, which resulted in different numbers of samples per condition. This did not affect the application of Anova due to its robustness in terms of different sample size, as the differences in samples per condition are not significantly different. This study relies on video recording data. While this data source is rich and suitable for addressing the targeted research questions, triangulation with additional data sources would have increased the depth of the analysis. For example, interviews with participants could have provided qualitative data useful for interpreting the results further. Additionally, as this study was performed in a particular context (physical computing tasks) and educational level (higher education), additional studies in other contexts are needed to provide further evidence on the phenomena studied.

## 6. Conclusion

This study adds evidence to the field of collaborative learning analytics by providing a setting for data collection and analysis that enables examination of the interplay of elements in the physical environment – table shape, group size, and gender – and their effects on on-task actions during collaboration. It shows that dyad structures lead to higher levels of interaction with task-related physical artefacts, while they also prompt more engagement in female students. Moreover, dyad structures in combination with round tables tend to generate more discussion and more nonverbal interaction. Furthermore, it is interesting that female students were more active in their nonverbal interaction, which opens questions for further research on why this occurs. On the other hand, male students engaged more in interaction with physical artefacts than female students. Altogether, the findings on the three factors examined and their influence on on-task actions in collaborative learning activities call for further research of their effects and interplay in different contexts with different learning designs to offer contrasted guidance for practice.

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# Chapter 5 - Temporal relationships between on-task actions in collaborative learning spaces

In this chapter, Epistemic Network Analysis was used as a tool to explore the effects of the learning space; more specifically, the effect of table shape on student behaviour. The paper presented is:

- ‘Studying collaboration dynamics in physical learning spaces using Epistemic Network Analysis – examines the temporal components of collaboration, modelling co-occurrences of students’ on-task actions.

## 5.1 Studying collaboration dynamics in physical learning spaces: considering the temporal perspective using Epistemic Network Analysis

The paper in this section was submitted to a peer-reviewed journal. Figure 17 shows the relationship between the paper in this chapter and the contributions of the dissertation.

Vujovic, M., Amarasinghe I., Hernández-Leo, D. (2021). Studying collaboration dynamics in physical learning spaces using Epistemic Network Analysis, *Sensors*. (accepted with minor revisions).

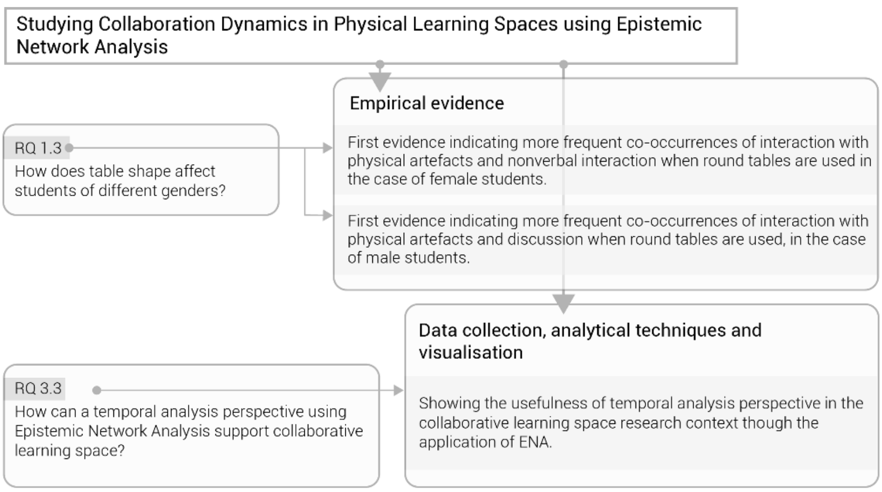


Figure 17. Relationship between the 'Studying collaboration dynamics in physical learning spaces using Epistemic Network Analysis' paper and dissertation contributions.

*Article*

# Studying Collaboration Dynamics in Physical Learning Spaces: considering the temporal perspective through Epistemic Network Analysis

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**Abstract:** The role of the learning space is especially relevant in the application of active pedagogies, for example those involving collaborative activities. However, there is limited evidence informing learning design on the potential effects of collaborative learning spaces. In particular, there is a lack of studies generating evidence derived from temporal analyses of the influence of learning spaces on the collaborative learning process. The temporal analysis perspective has been shown to be essential in the analysis of collaboration processes, as it reveals the relationships between students' actions. The aim of this study is to explore the potential of a temporal perspective to broaden understanding of the effects of table shape on collaboration when different group sizes and genders are considered. On-task actions such as explanation, discussion, nonverbal interaction, and interaction with physical artefacts were observed while students were engaged in engineering design tasks. Results suggest that table shape influences student behaviour when taking into account different group sizes and different genders.

Keywords: learning space, collaborative learning, table shape, group size, gender, epistemic network analysis

## 1. Introduction

In the field of education, there is ongoing discussion about the meaningful effect that learning spaces seem to have in facilitating and supporting learning scenarios and as a relevant element of the learning design [1, 2]. In particular, the collaborative learning approach to pedagogy — as opposed to traditional lectures — has introduced versatile dynamics into the interaction between students, peers, and teachers, but also with the environment [3, 4]. However, how learning spaces support or inhibit the potential of these dynamics has not been sufficiently explored. By understanding the effect of elements of the environment on student behaviour in the collaborative process, significant contributions can be made to inform design for productive collaborative learning.

Indeed, transforming traditional classrooms into spaces that support active learning models, where collaboration plays a major role, requires adapting the space to them [5, 6]. Collaborative spaces, unlike traditional classrooms, feature elements that should support the actions characteristic of collaboration. Therefore, through the examination of these actions and the way in which they are represented in the physical domain, insight may be gained into the relationship students have with the space surrounding them and that directly facilitates collaboration. However, learning analytics methods focused on studying collaboration rarely include spatial aspects as factors influencing collaboration. Although mostly static, space plays a role in the development of collaborative activities by providing a framework within which actions occur. As data science and methods become more sophisticated, new opportunities for exploring this issue are emerging. The investigation of collaborative actions, their evolution over the duration of a learning activity, and the potential impact of the environment on this dynamic require methods of analysis that include the development of actions over time and their interconnections. It is insufficient to focus on coding and counting of actions without monitoring and understanding their interconnectedness [7] through the analysis of the temporal perspective of collaborative activity [8, 9].

A previous study [10] examining the influence of table shape on the behaviour of elementary school and university students found significant differences. The results suggested that elementary school students participate in collaborative activity more, when using round tables. However, the differences between different table shapes were not significant for university students. This study focused on analysing the influence of different table shapes on student behaviour during collaborative activity, but did not consider the temporal dimension of the actions. Yet a temporal perspective is crucial to understanding the development of collaborative processes as they may reveal interactional patterns [11], show how collaborative actions can encourage socially shared planning and regulation [12], and provide more detailed insight into the active learning processes of groups [13].

Temporal perspective analysis has been adopted in a number of studies, in which various techniques such as temporal pattern analysis [14], variable- and event-centred analysis [13], sequential analysis [15], sequence and process mining [16, 17], and dynamic multilevel analysis [18] were applied. Motivated by studies that indicate different possibilities for temporal perspective studies and new techniques enabling the parallel analysis of several parameters, the behaviour of university students was re-examined from a new perspective and incorporating these techniques. With the ability to model and analyse multiple conditions in parallel, as well as to examine the frequency of co-occurrences of actions, Epistemic Network Analysis (ENA) is suitable for studying temporal aspects of the collaboration process in observed context [54].

This paper presents an analysis of the impact of table shape on student behaviour, with a focus on the temporal component of collaboration. Using ENA as a tool that incorporates the temporal component into the analysis of coded actions by modeling co-occurrences of action bypasses the classical approach of coding and counting and provides a deeper understanding of collaborative development over time. In comparing two conditions — round and rectangular tables, and their interaction with group size and student gender — the aim is to identify potential differences. The second section surveys the literature relevant to this study, which includes indicators of collaboration, learning space, group size and gender in interaction with learning space, temporality in the analysis, and ENA. The third section outlines the research aims and questions while the next covers the methods used in applying ENA in this study. The fifth section presents the findings of the analysis, while the sixth section discusses the results. Finally, the seventh and eighth sections consider the limitations and conclusions of the study as well as future work.

## 2. Background

In order to ground the analysis of the learning space in which we examine the student behaviour during collaborative learning activities, it was necessary to blend several different domains that converge in the field of learning analytics. This study referred to previous work on the indicators of high-quality collaborative learning, impact of learning space on behaviour, temporality as the focus of analysis, and finally, ENA.

### *2.1 Indicators of fruitful collaborative learning (in new learning spaces)*

Indicators of productive collaboration can be found in the actions that students perform during collaborative learning activities. Those actions may be categorised into two groups: on-task and off-task. Students engaging in actions or interactions that are unrelated to the task is considered to be off-task behaviour [19], whereas paying attention during instructions or focusing on group or individual work is on-task behaviour [20]. Furthermore, on-task behaviour is defined as attending to assigned tasks, focusing on the appropriate materials, manipulating learning objects, and maintaining eye contact with the teacher, team members, or task objects [21]. In collaborative learning, these actions are essential for problem solving [22] and for generating the social awareness and overall positive perception of group members' interdependence and accountability that underpin fruitful collaboration [23]. Furthermore, it has been reported [24] that when conducting collaborative work in classroom settings, groups of students who exhibited on-task actions more often generated better solutions to the problems.

To define the analysis of on-task actions, the classification of activities based on their characteristics plays a major role. Two main characteristics of on-task actions may be distinguished: active and passive [25, 26]. The literature indicates the actions common to collaborative learning and whose analysis is used in this study to better understand learning space effects. The action of *explaining* represents a passive action and refers to reading out loud or talking with the objective of clarifying instructions or ideas. This is considered beneficial as it reorganises the material in a new way, develops new perspectives, and resolves inconsistencies, which would not be accomplished as comprehensively when done individually [26, 15]. Additionally, *discussion* is considered an active social on-task action that engages more than one person in dynamic interaction [25,] which is beneficial for collaboration. Another on-task action in the social category is nonverbal participation, meaning actions and gestures of listening and observing without extended verbal engagement, which has been shown to be highly significant in collaboration. Webb et al [27] demonstrated that, in certain cases, participants contribute more when they are not under pressure to say something. In physical on-task actions, interaction with the artefacts is essential for completing the collaborative activity task. Artefact use indicates engagement with the task and, when it occurs during explanations or discussion, reinforces collaboration and provides more balanced participation [28]. Overall, the analysis of on-task actions plays a key role in analysing collaboration, and indirectly in the analysis of the space in which collaboration takes place. Grounding the analysis in previously presented findings in the literature that reveal the indicators of good collaboration, this study uses defined on-task actions to assess student behaviour and analyse learning space effects.

### *2.2 Learning Spaces*

Although progress in the development of in-person learning models is evident over recent decades, new learning spaces often neglect the pedagogical vision [5]. With this in mind, the authors [5] stress out that there is a clear need for an integrated design in order to achieve a balance between learning models and the physical environment in which they are implemented. Besides their subtle influence on students, learning spaces possess the power to encourage or inhibit teachers as they create their learning design. Rogers et al [29] presented a study on the learning space preferences of higher education students, in which the general consensus among the students was that learning spaces indeed affect the outcome of learning activities.

Furthermore, Beckers et al [30] found that the informal arrangement of spatial elements encourages more collaboration. Moreover, studies on the physical characteristics of learning space such as colours, light, space shape, and table shape report differences in student behaviour when different conditions are applied [31, 32, 33]. More specifically, tables with curved, organic shapes have been found to reinforce more on-task student behaviour in active learning classroom systems [34]. The application of round tables in active learning classrooms has been shown to encourage active discussion based on group activities [35]. However, a number of students that used informal learning spaces reported that they did not feel comfortable because they did not have their own familiar space to overcome certain difficulties encountered. Carvalho and Yeoman [6] argue that research on learning spaces requires a more contextualised and less generic understanding of tool and space properties and how they can influence learners and their actions.

Newly-configured learning spaces that are becoming more prevalent in practice incorporate recently developed teaching practices and emerging technologies that are dedicated to team-teaching and collaboration between students [36]. These collaborative environments provide opportunities for more interaction and stimulate innovation due to shared reflections and inquiries, which result in robust and constantly developing collaborative practice. However, with all the innovation introduced into classrooms, more research is needed that can corroborate or challenge the benefits of learning space design. In order to do so, this study focuses on two common influential factors on collaboration, group size and gender, that possibly moderate the effects of learning space on collaborative learning. Selection of these factors will be further elaborated upon in the following paragraph.

*2.3 Group size and gender as moderators of the effects of learning spaces on collaborative learning*

Group size and gender have been present in the research of collaborative learning for quite some time as moderators of collaboration. When considering the different group sizes proposed for collaborative learning activities, opinion is divided as to whether dyads or triads develop better collaborative strategies. Carvalho et al [37] point out the benefits of dyads in terms of the possibilities for students to observe each other and exchange ideas and strategies to improve common performance. Another reported benefit of dyads is more optimised use of equipment among two students, which leads to the efficient completion of practical assignments [38].

However, when dealing with collaborative learning, research suggests that dyads should be considered as peer learning, while triads involve real collaboration [39]. In this sense, triads are more likely to foster complex behaviours such as coalitions, negotiations, and conflict, which are all beneficial for learning. A study examining pre-service teachers during teacher preparation programmes found evidence of complexity when working in triads such as benefits from learning from each other, and in support and comprehensive feedback about work being done, as well as limitations in terms of concerns about dependency, loss of individuality, and increased competitiveness [3]. Other benefits that triads have in comparison to dyads are reported [40] to include prompting novel perspectives and enhancing problem-solving abilities, though among the disadvantages are conflicts within groups . Despite the latter, however, triads are more likely to develop various perspectives within collaborative tasks.

When considering another common moderator of collaboration, gender, previous research has yielded interesting findings on the effects of gender on the collaborative learning process. On one hand, the gender composition of groups tends to have an impact on learning outcomes. Wiley and Jensen [41] report that groups which are heterogeneous in terms of both gender and skills benefit more from collaborative learning than those that are homogenous. Later research from Cen et al [42] extended study to female-only groups and provided evidence that certain forms of gender distribution are more conducive to collaborative learning, with female-only and balanced-gender grouping shown to be the most conducive.

On the other hand, existing evidence also suggests gender may have implications for individual student behaviour when collaborating. For example, in a study by Zhan et al [43], female students claimed that they employed more collaborative learning strategies than their male peers. Further, Stump et al [44] found that female students sought help from other students with higher frequency in collaborative activities, even if this made them feel like a group member with less knowledge. Another study examined how students' individual learning performances and knowledge elaboration processes in Computer-Supported Collaborative Learning (CSCL) differed between dyads with different gender distributions [45]. This study found that female-only dyad participants outperformed female peers in mixed-gender dyads, while this was not the case with male-only dyads. Finally, there are studies that present issues related to female students experiencing bias, as in engineering programmes where they were disrespected by the male students [46].

Given the need to explore the impact of learning space in more detail and taking group size and gender as factors through which it may be examined, finding a method that would provide useful results in such a complex context was necessary. A temporal analysis perspective offers an interesting opportunity to examine the development of actions in different conditions over time and the differences that occur in them when different group sizes and genders are considered. Temporality as an element of analysis will be discussed further in the following section.

### *2.4 Temporality as the element of analysis*

The importance of the temporal perspective in learning, as a developmental process, has long been established [47, 48, 49]. However, there is insufficient use of temporal information from learning data and insufficient exploration of temporal concepts [8]. Only recently have the identification, measurement, and analysis of temporal features of learning attracted the close attention of researchers [9]. This attention has focused on various aspects of temporal analysis in the context of learning such as temporal data types, temporal data visualisation, and analytical methods, as well as their practical application [9].

Numerous studies have investigated the development of collaborative learning activity over time and the importance of the order of events in order to better understand the process of collaboration. Reimann [13] points out the relevance of time and order in active learning processes, especially in particularly problematic contexts such as group work. In addressing this issue, when considering the types and processes in regulated collaborative learning, Malmberg et al [12] report that temporal analysis is useful in showing how collaborative actions related to task execution encouraged socially shared planning and regulation. Interesting conclusions were drawn in a study that looked at individual member contributions in a group discussion [11], in which the temporal evolution of interactional patterns revealed the importance of the first phase of the collaborative process on the overall outcome. Furthermore, Molenaar [50] emphasizes the relevance but also the challenges that arise when attempting to forward temporal analysis as part of learning analytics, such as the multidimensionality of time, different analysis techniques, segmentation of time, differences between micro and macro levels, and the need for confirmatory studies. Moreover, temporal analysis requires specific analysis techniques that can provide deeper insight into the connections between actions as they take place over time. To this end, ENA facilitates the modelling of collaborative interactions while focusing on the temporal order and the co-occurrences of events.

*2.5 Epistemic Network Analysis*

Quantitative Ethnography (QE) is an approach that merges quantitative and qualitative approaches to uncover meaningful patterns in data [51]. The large-scale data generation of digital learning environments today creates opportunities to apply QE to gain meaningful insights into learning and teaching processes [51]. ENA is a statistical tool that exemplifies QE and aids in modelling connections among elements in qualitatively coded datasets [52, 53].

ENA generates dynamic network models using discourse data through several steps. First, for a given unit of analysis (which could be a collaborative group, a concept, etc), ENA accumulates the co-occurrences of codes within a defined conversation. This results in the creation of dynamic network models that visualise the structure of connections between coded elements in discourse [52]. Dynamic network models generated using ENA consist of nodes and edges [52]. The nodes represent the codes in discourse data and the network edges connect nodes in the model. The thickness of these network edges represents the relative frequency of the co-occurrences between two codes. Therefore, a thick edge represents a strong connection between nodes and a thinner edge represents a weaker connection.

In the domain of learning analytics, ENA is a tool that provides exceptional opportunities due to its ability to quantify qualitative data and provide an overview of the entire process in terms of the connectivity of its data over a period of time [52]. Current work in this field demonstrates the diversity of the application of ENA and its benefits when it comes to quantitative and qualitative data [54, 55]. For instance, ENA has been applied to understanding students' critical thinking, participation in games, mentoring, and teaching processes. Recent empirical studies have also shown that ENA, in concert with other data analytics techniques such as social network analysis [56] and process and sequence mining [57], can complement each other. The combined methods can provide a complete ontological viewpoint into diverse learning processes such as self-regulated learning and collaborative learning [56, 57].

In the context of CSCL, ENA has been applied for different modelling purposes. For instance, Shum et al [53] have proposed a multimodal matrix inspired by the concepts of QE, producing guidelines on how information presented in a multimodal matrix can be used to deliver feedback to co-located collaborative teams in the context of nursing education. The detection of differences between the connections made by students with high learning gains versus those with low learning gains during collaboration was also the subject of a study that applied ENA [59]. Additionally, in the context of collaborative learning, Andrist et al [54] have employed ENA to analyse dyads and how networks of shared gaze evolve over longer time windows.

3. Research aim and questions

The aim of this study is to investigate to what extent a temporal perspective in the analysis of student behaviours can improve our understanding of the potential influences of learning space elements in collaborative learning activities. We use ENA for the analysis of temporal correlations between students' on-task actions. The aim is not to label one space as better or worse, but rather to investigate whether an analysis of temporal dynamics in collaboration can provide evidence of the potential influences and thus facilitate informed decision making in learning space design that is aligned with a specific pedagogical intent and its related learning design facets.

To achieve this aim, this paper focuses on table shape (round vs rectangular tables) as a relevant element in the design of learning spaces and on group size as a key design facet in collaborative learning. In addition, the paper also explores the gender perspective in a study of the effects of different table shapes.

RQ1) *What can a temporal analytics perspective tell us about the effect of table shape on student behaviour in different group sizes (dyads and triads) during a collaborative activity?*

RQ2) *What can a temporal analytics perspective tell us about the effect of table shape on the behaviour of different genders (female and male) during a collaborative activity?*

## 4. Method

### *4.1 Research setting and participants*

The experimental setup for authentic collaborative learning activity was organised in a motion capture laboratory, where students were invited to participate in an extracurricular activity. In the recruiting process, from more than 150 volunteers who expressed interest in the training, 36 university students with no prior knowledge of the topic were selected from different engineering degrees and different years, with an equal number of male and female participants. These 36 students (aged 18-24) formed 12 Jigsaw groups, from which we analysed the data of 8 groups comprising 24 subjects. The subject selection criteria for analysis was: good camera coverage in order to obtain valid data, balance of gender as much as possible, and balance of table shapes. Of the 24 subjects selected for the data analysis, 12 subjects had used rectangular tables and 12 round ones (figure 1). Within the analysed dataset of 24 subjects, there were 11 female and 13 male participants. All groups were mixed-gender groups and, due to the odd number of members in the home groups (triads), the distribution varied between groups of: a) two female students and one male; and b) two male students and one female.

### *4.3 Materials and task description*

Students participated in a collaborative problem-solving activity in which specific physical computing artefacts were to be designed. Following a Jigsaw method, each session started with two groups of three members each. After being given instructions for a divisible task, they were organised into three different expert groups of two members (each coming from different initial groups) for a second phase of the activity in which each group worked on a sub-task. After finishing the sub-task, students returned to their initial Jigsaw group and continued work on the overall task. Triads and dyads were supported with laptops, although in some cases dyads that were assigned a "design expert" role decided to remove laptops from the table when they did not need them. The task was open-ended, which meant that each group could produce a different design. At the end of the activity, each group presented their work. The activity lasted 90 minutes, required no prior knowledge, and was designed in a way so that each group member had close to the same workload when conducting her/his part of the task. This organisation of the experiment made it possible to conduct an analysis of the interaction between table shapes, group size, and gender, as presented in figure 2.

The participants were asked to design, programme, and build an interactive toy that was to be designed using electronics connected to an open-source electronics platform and additional elements such as cardboard and paper. The difficulty level was adapted to the student profiles (who had no experience with this specific electronic platform) and they were provided with the information necessary for each step of the process. Students were informed of the data collection and analysis that followed this experiment, which was approved by an ethics committee. Informed consent was obtained from the students before the experiment.

**Figure 1. Two seating arrangements representing different conditions in the study**

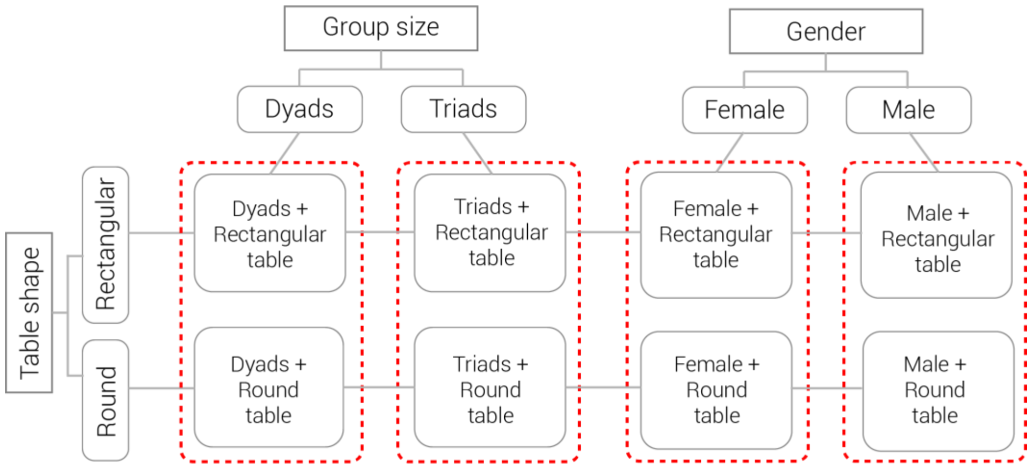


**Figure 2.** Four cases analysed

*4.4 Data collection and analysis*

Data collection was performed with two video cameras used to record the experiments. They were positioned to cover the activity from different angles and at a height of two meters so as to avoid occluding student actions as much as possible. All sessions of the experiment had the same lighting, room temperature, surrounding furniture (except tables used for the activity), researchers present, and sounds in the laboratory (caused by the air conditioning system).

The analysis was based on coding of student actions, where the coding system of on-task activities was established by overlapping information from literature used in similar scenarios and observations of participant behaviour [41, 42, 43]. All actions that were not classified as on-task were recorded under the common category 'off-task actions'. Codes included *explanation*, *discussion*, and *nonverbal interaction* as social on-task actions, and *interaction with physical artefacts* as physical on-task action. Also, the code 'off-task action' was included together with the other codes (table 1). Table 2 presents examples of the defined codes and how they were segmented (when they began and ended) in the specific context that was the subject of the study. Inter-rater reliability was established (values for percentages and Cohen's kappa were greater than 81.5% and 0.626, respectively). After data was collected and coded, ENA was used to model connections in coded data and to represent them using dynamic network models. We chose the Moving Stanza Window method to select the stanzas within which the connection accumulation was required to be modelled. In other words, the stanza window represents a segment with a certain number of codes within which we want to observe the connection. We selected a moving stanza window size of 3. In this case, each code was observed in relation to the adjacent two codes. Since the stanza was shifted by one code and included two adjacent ones for the observed context where the actions followed one another, this approach was informative enough.

Table 1. Coding schema for the analysis of student actions with abbreviations

| Code | Explanation |
|---|---|
| *Explanation (Ex)* | Passive action (in terms of interaction) - the act or process of making something clear or easy to understand (telling, showing) without active participation from other participants. This is a social action that can overlap with physical actions (interaction with physical artefacts). |
| *Discussion (Ds)* | Any type of discussion or quick exchange of words that includes interaction with participants (talking and pointing). This is a social action that can overlap with physical actions (interaction with physical artefacts). |
| *Nonverbal interaction (Nv)* | When a participant is not talking but is looking at teammates and/or gesturing as a sign of feedback (nodding, with 'yes' or 'no'). This is a social action that can overlap with physical actions (interaction with physical artefacts). |
| *Interaction with physical artefacts (IPA)* | When participants use artefacts (Arduino, laptop, cards) to work individually or collectively. This physical action can overlap with social actions (*explanation*, *discussion*, and/or *nonverbal interaction*). |
| *Off-task action (off)* | Any action that is not directed towards the group, table or artefacts |

Table 2. Examples of on-task actions

| **Example of a coded action** | **Image capturing student behaviour** |
| --- | --- |
| Example 1 (group size - dyad):<br><br>Both the student on the left side of the image and the student on the right are working with the artefacts (using instruction cards and writing ideas on the paper) without any verbal interaction. The action is coded in the following way:<br>Student 1 (left side): **nonverbal interaction (Nv), interaction with physical artefacts (IPA)**<br>Student 2 (right side): **nonverbal interaction (Nv), interaction with physical artefacts (IPA)** |  |
| Example 2 (group size - dyad):<br><br>The student on the left side of the image and the student on the right are talking to each other. They are not using artefacts and they exchange short sentences followed by words of agreement and nodding. The action is coded in the following way:<br>Student 1 (left side): **discussion (Ds)**<br>Student 2 (right side): **discussion (Ds)** |  |
| Example 3 (group size - triad):<br><br>Student on the left side is presenting the idea while the student in the middle and student on the right look at him and the paper he is showing, and react verbally with head nodding. The action is coded in the following way:<br>Student 1 (left side): **explanation (Ex), interaction with physical artefacts (IPA)**<br>Student 2 (in the middle): **nonverbal interaction (Nv)**<br>Student 3 (right side): **nonverbal interaction (Nv)** |  |
| Example 4 (group size - triad)<br><br>All three students are connecting elements and testing the Arduino system. The student on the left and the one in the middle are discussing something. The student on the right is also working with the Arduino system, but he is not talking. The action is coded in the following way:<br>Student 1 (left side): **discussion (Ds), interaction with physical artefacts (IPA)**<br>Student 2 (in the middle): **discussion (Ds),** |  |

| | |
|---|---|
| **interaction with physical artefacts (IPA)**<br>Student 3 (right side): **nonverbal interaction (Nv), interaction with physical artefacts (IPA)** | |

5. Results

ENA was used to model student behaviour in two different learning environments, which were defined by the shape of the table that students used during the collaborative activity. Two group sizes (dyad and triad) as well as two genders (female and male) were observed in both conditions. Student activities were coded and epistemic networks were generated for each of the cases analysed. In order to examine the differences between conditions, a difference network was generated by subtracting the average connection strengths for actions in each condition. The sections below present the results for the four cases analysed, with two considering the effects of table shape on different group sizes and two considering the effects of table shape on different genders.

In each of the cases analysed and presented, the networks nodes represent each coded action, while the edge weights represent the relative amount of mutual co-occurrence of each of the actions. Table 3 shows the naming convention for network nodes and their meaning. The network centroids can be described as something similar to the centre of the mass of an object [60] and each condition has its own centroid in this case. To be more specific, the centroid is observed in the context of the projection space and represents the arithmetic mean of all edge weights for the observed network model in that space [60, 61]. In this way, the centroid summarises the whole network. With multiple centroids in the ENA model, differences between networks of different conditions are made visible.

*5.1 Effect of table shape on different group sizes*

Figure 3 presents the difference networks of co-occurrences of actions for triads in two different conditions (rectangular and round tables). The network models the correlation structure of the five listed actions cumulatively for all triads that participated under each of the conditions. The networks of round tables are presented in blue, while those of rectangular tables are in red. The centroids for round and rectangular table conditions are located at different positions on the x-axis, indicating differences in the arithmetic mean of the edge weights for both conditions. This denotes an overall difference in edge weights suggesting that the most frequent co-occurrences between actions under these two conditions are not the same. The strength of the connections between the actions in the case of triads is different between round and rectangular tables. It should be noted that, for round tables, stronger edges exist between interaction with physical artefacts (IPA) and discussion (Ds). This implies that students took turns performing these two actions more often than taking turns with other actions. The proximity of the centroid also confirms an overall prevalence of action co-occurrences under this condition, favouring the alternation of two actions (interaction with physical artifacts (IPA) and discussion (Ds)) that are positioned on the far edge of the projection space.

The position of the centroid for rectangular tables is closer to the centre of the projection space than that for round tables, which indicates less pronounced co-occurrences of a certain pair of actions. However, difference networks show how certain co-occurrences of actions are more present than that of others. For rectangular tables, the most frequent co-occurrence was between the action of nonverbal interaction (Nv) and discussion (Ds) (see figure 3). This shows that students tend to be more engaged in alternating between those two actions than between any other actions when rectangular tables are used. Furthermore, as shown in figure 3, off-task action (off) is more connected to other actions when rectangular tables are used, which suggests this event is more common under this condition. Under both conditions, discussion (Ds) is the most common co-occurring action. With round tables, discussion alternates with interaction with physical artifacts (IPA), while with rectangular ones it alternates with nonverbal interaction (Nv).

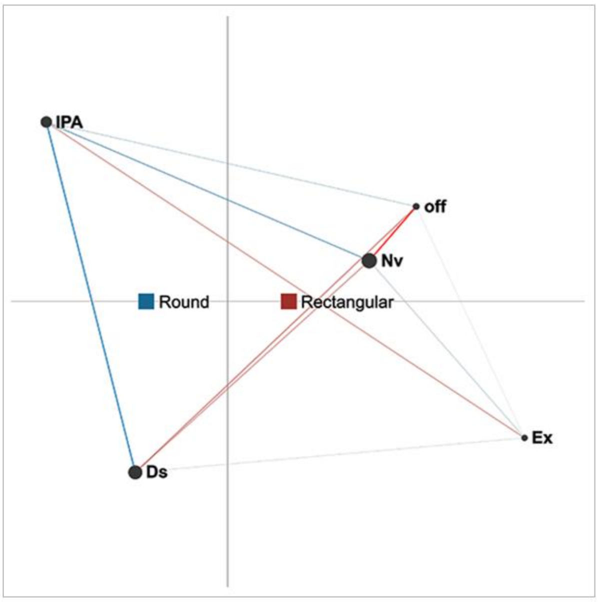


**Figure 3.** Difference network for triads under two conditions (round and rectangular tables)

In the case of dyads (figure 4), the network centroids under the two conditions studied, as with triads, are located in different places in the projection space. The centroid for round tables, shown in blue, is located closer to the border of the projection space, which is defined by the actions of interaction with physical artefacts (IPA) and nonverbal interaction (Nv). This indicates that these co-occurrences between these two actions are more common when compared to other conditions. The centroid for rectangular tables, shown in red, is located closer to the opposite border of the projection space, which is defined by the discussion action, demonstrating that, in the case of rectangular tables, discussion is the action that occurs most frequently. When it comes to the co-occurrences of specific actions, co-occurrences between nonverbal interaction (Nv) and interaction with physical artefacts (IPA) is higher with round tables. This suggests that when using round tables, students communicate less with each other if they are engaged in working with artefacts than is the case with rectangular tables. On the other hand, with rectangular tables, co-occurrences between interaction with physical artefacts (IPA), explanation (Ex), and discussion (Ds) are more frequent than with round tables. This indicates more interpersonal verbal communication (both discussion and explanation) while working with artefacts when dyads use rectangular tables.

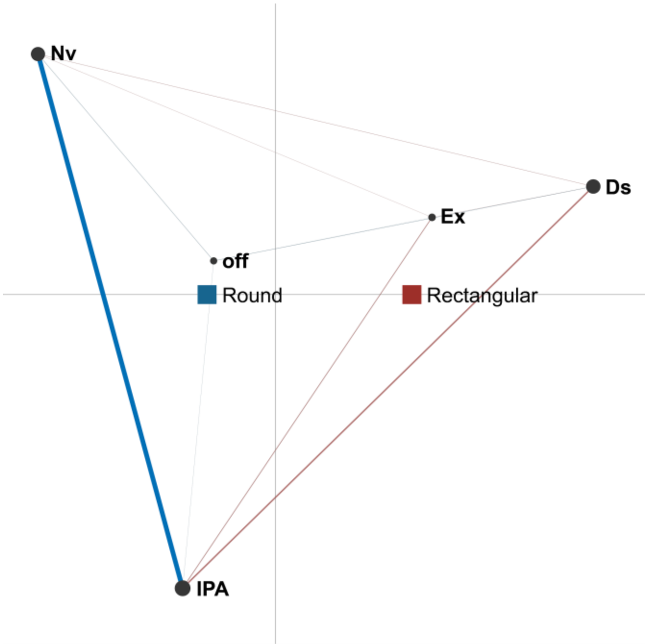


**Figure 4.** Difference network for dyads under two conditions (round and rectangular tables)

*5.2 Effect of table shape on gender*

Further analysis focused on the influence of table shape on the behaviour of students of different genders when working in groups of two or three members. Figure 4 shows the ENA network for female students' actions under both conditions. The differing position of the centroids evinces the difference between the two conditions. The centroid and co-occurrences of actions that are more frequent with round tables is shown in blue. The centroid is located closer to the border of the projection space formed by nonverbal interaction (Nv) and interaction with physical artefacts (IPA), meaning that these actions co-occur more often under this condition. This is confirmed by the pronounced blue line representing the edge between these two actions. On the other hand, the centroid for rectangular tables (in red) is located closer to the border of the projection space defined by nonverbal interaction (Nv), discussion (Ds), and off-task actions (off). Together with a pronounced red line, the network suggests that co-occurrences between nonverbal interaction (Nv) and off-task actions (off) are more frequent with rectangular tables. Furthermore, as shown in figure 5, other nodes in the network are connected to the 'off' node, indicating that female students are more engaged with off-task actions when they use rectangular tables.

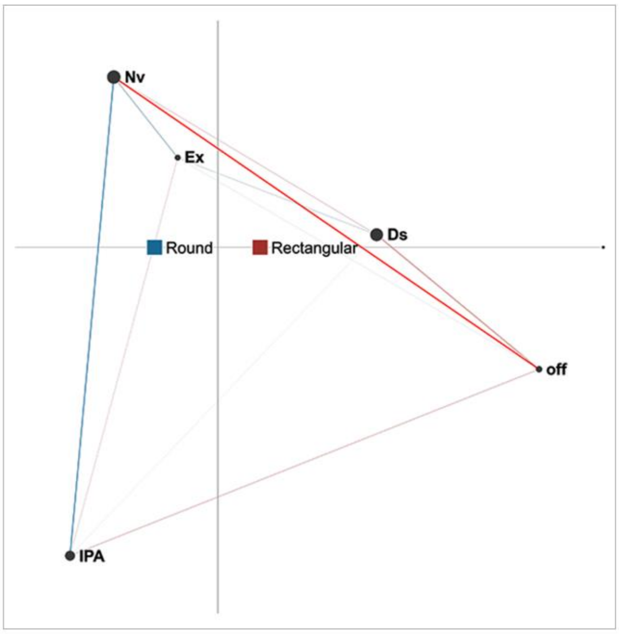


**Figure 5.** Difference network for female students under two conditions (round and rectangular tables)

In the case of male students, as in the previous cases, the positions of the centroids for both conditions also indicate differences between the conditions (figure 6). The round table centroid, shown in blue, is located close to the node that represents interaction with physical artefacts (IPA). Furthermore, when observing the weight of the edge between interaction with physical artefacts (IPA) and discussion (Ds), it is evident that male students are more frequently engaged in alternations between these actions with round tables than with rectangular ones. Also, co-occurrences between nonverbal interaction (Nv) and discussion (Ds) are more prevalent when male students use round tables. The centroid for rectangular tables, located close to the border of the projection space defined by nonverbal interaction (Nv) and discussion (Ds), together with the pronounced edge weight between these two nodes, shows that these actions co-occur more frequently when rectangular tables are used.

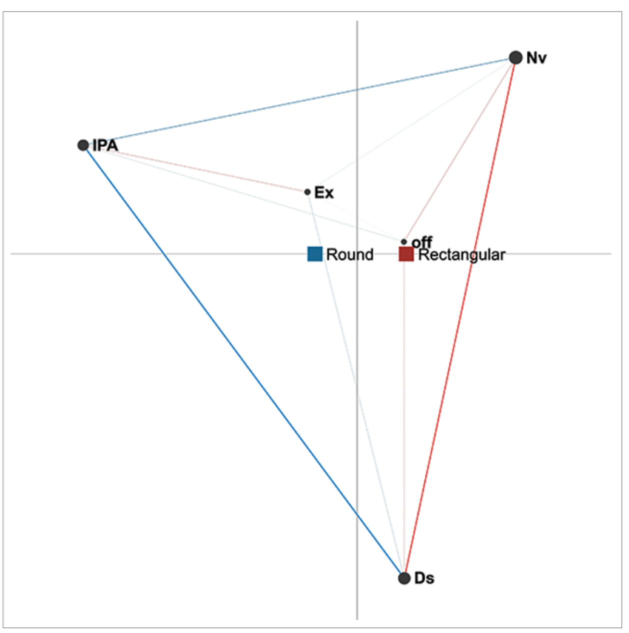


**Figure 6.** a) Difference network for male students under two conditions (round and rectangular tables)

The overall aim of this study was to evaluate if the adoption of the temporal perspective in the analysis offers insights into how different table shapes affect collaboration with different group sizes and different genders. More specifically, the study aimed to answer two research questions: (1) *What can a temporal perspective tell us about the effect of table shape on student behaviour in different group sizes (dyads and triads) during a collaborative activity?* and (2) *What can a temporal perspective tell us about the effect of table shape on the behaviour of different genders (female and male))?* To answer the research questions, the study focused on using ENA in order to better understand the effects of the learning space through modelling of co-occurrences of actions, given the limitations of traditional coding-and-counting approaches [7]. Our findings suggest that, in this data collection scenario, the two learning spaces affected triads and dyads, as well as female and male students, differently.

This study presents a different approach from previous ones adopted to date in the analysis of learning spaces. ENA has been employed in collaborative learning as well as in other areas [54, 56], but the authors are not aware of this specific application in existing research on learning spaces. The findings on the co-occurrences of actions cannot be obtained using traditional coding-and-counting methods, which support the use of ENA in analysing learning spaces and contribute to the field of learning space design. The paragraphs below include discussion on the findings on the influence of table shape on students' on-task actions during collaboration when considering two different group sizes and two different genders. Figure 7 is an overview of the ENA results, showing more prevalent co-occurrences of on-task actions in each case analysed.

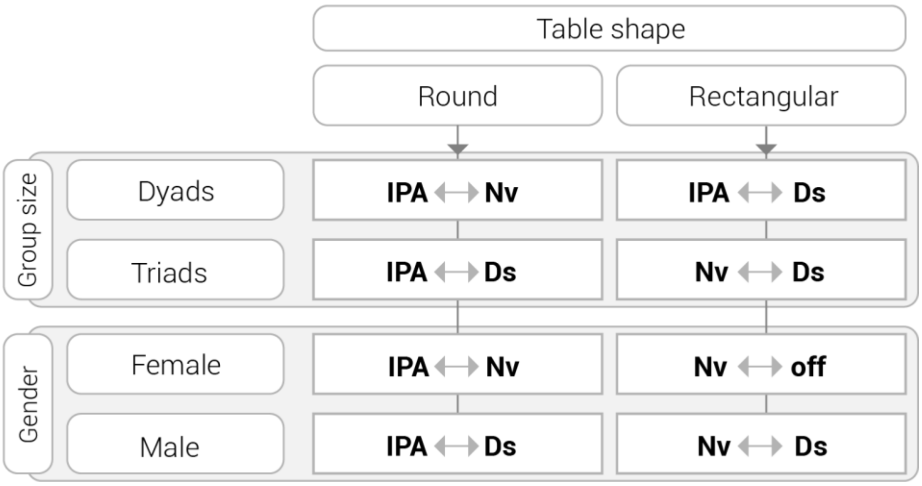


**Figure 7.** Summary of the ENA results of more prevalent co-occurrences of on-task actions for each case analysed

### *6.1 Table shape and group size*

Starting with the first research question, the differences between conditions are visible both with dyads and triads, with a more pronounced difference in the case of dyads. Interestingly, the temporal analysis perspective yields different findings for these two group sizes. In dyads, students combine physical artefacts and nonverbal interaction more frequently when using round tables, as opposed to engaging in explanations and discussion while interacting with physical artefacts when working at rectangular tables. On the other hand, in triads, the round tables tend to foster more alternations between discussion and use of physical artefacts, and rectangular ones induce more co-occurrences of discussion and nonverbal interaction. While it cannot be said that the effects are explicitly opposed, **it can be seen that the effect of more frequent co-occurrences between discussion and interaction with physical artefacts is caused by rectangular tables with dyads and by round tables with triads.** Building on existing studies on the differences between dyads and triads, this study contributes by adding another explanatory factor that may shed light on previous findings on these differences and how the affordances of the space play a role in their behaviour [38, 40]. The claim that triads are more likely to promote complex behaviours such as coalitions, negotiations, and conflict in discussions involving collaborative problem solving is more strongly substantiated in our scenario when round table shapes are used. The exchange of ideas and strategies that are shown to improve common performance also seem to be expressed differently in dyads in the two environments studied. The findings therefore support the hypothesis, based on the literature, that different table shapes can cause different student behaviour [32, 35, 62].

It should be observed that dyads and triads do not behave in the same way when the same table shape is used. The results, which show behavioural differences between dyads and triads, can expand previous research on this topic. Specifically, studies that deal with the differences between these two group sizes and report on the potential effect of the educational context [41, 64] may be updated with the findings presented here. The physical context, indeed, is part of the educational context and should be considered when differences between dyads and triads are examined [64]. Therefore, by focusing on learning space, and more specifically table shapes, in identifying differences between dyads and triads, this study extends previous research by contributing with new insights about group size. In terms of table shape, the findings indicate varying student behaviour according to group size. However, our results show that previous reports of the promotion of active discussion when round tables are used [65] can be confirmed only with triads.

Furthermore, the findings that the use of physical artefacts, which co-occurs more frequently with some actions (discussion and nonverbal interaction) when both round and rectangular tables are used in dyads, as opposed to the same action's co-occurrences with discussion in triads only when round tables are used, align with the literature [41]. That is to say, the hesitation that emerges in triads may have contributed to the reluctance of some group members to use artefacts. Furthermore, the literature establishes that dyads use equipment at a higher frequency when they are involved in practical work [39]. Additionally, a possible explanation for interaction with physical artefacts not being one of the actions that most often co-occur is the potential development of coalitions and conflicts, as stated in the literature [40], which leads to less use of artefacts by some students and dominance by others.

### 6.2 *Table shape and gender*

Considering the second research question and the effects of table shape on genders, the results suggest differences under varying conditions. The findings in the case of female students show more frequent co-occurrences of interaction with physical artefacts (IPA) and nonverbal interaction (Nv) when round tables are used. Conversely, male students at round tables exhibit more alternation between interaction with physical artefacts (IPA) and discussion (Ds). This behaviour of male students contrasts with the lack of verbal communication among female students under the same conditions, which indicates that the learning space exerts a different influence depending on gender. This difference may also be observed with rectangular tables, at which there are frequent co-occurrences between nonverbal interaction and off-task actions with female students, while more co-occurrences between nonverbal interaction and discussion occur with male students. Once again, the differing influences of table shape can be noted.

The behaviour of female students confirms the findings of previous studies, in which the inequality between male and female group members engaged in engineering tasks like this one was evident [47]. Observations detected a lower frequency of changes in the actions of female students while using certain artefacts, such as the Arduino, which may be attributed to the aforementioned uncertainty and the widespread belief that male team members possess greater knowledge. In contrast to male students, female students behave more passively but consistently during collaborative learning, which was also previously reported in the literature [44, 45]. Although this study did not focus on group structure itself, it could be further extended by examining issues such as how gender distribution within groups affects collaboration, which has already been considered to some extent in the literature [43].

## 7. Limitations of the study

The study has several limitations. One, common to studies in the field of educational technology in complex contexts [63], is the sample size. Organising studies with complex experimental setups in collaborative learning contexts, together with students' potential time limitations and ethics (data sharing) concerns, places constraints on participant recruitment. Increasing the number of subjects in future studies will be especially important to further explore these questions from the perspective of gender, thereby leading to a greater understanding of gender differences with different group sizes and group composition. In the present study, a certain number of participants were removed from the analysis due to occlusion, which is a limitation in the analysis of collaborative activities with multiple participants when video recordings are used. More video cameras would help solve this problem in future studies.

Another limitation is that the activity was specifically designed with a Jigsaw collaborative script that makes it difficult to generalise the findings to other collaborative learning designs. However, the activity was open-ended, which is common to a wide variety of collaborative activities. Furthermore, the Jigsaw scrip allowed for the possibility to test dyads and triads during the same experiment in a structured way, while balancing each students' load to provide the most similar conditions for each student as possible. Even so, collecting additional surveys from students on aspects such as the workload and emotional stress they experienced would be beneficial. Furthermore, pre- and post-surveys would be useful for understanding to what extent their behaviour was influenced by previously acquired experiences.

## 8. Conclusion and future research lines

This study adds evidence to the fields of learning space design and collaborative learning by providing a setting for data collection and an analysis that enables observation of the interplay between table shape, group size, and gender, and their effects on on-task actions during collaboration. The results indicate the influence of table shape on student behaviour with different group sizes and different genders. Based on the ENA results, the different effects that different table shapes have on the course of student actions during collaboration have been identified. This study supports previous findings in the literature and extends them by providing further evidence that, due to its impact, the learning environment should not be overlooked as an important part of learning design.

The temporal analysis perspective of collaborative behaviour adopted in this paper has been shown to be useful and meaningful in examining the varying effects of table shapes on different group sizes and genders. With this approach, the study contributes by applying known analysis methods in a new context. Regarding practical implications, more experimental research of table shape should be conducted in order to further clarify its role in the field of learning space research.

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# Chapter 6 - Towards extending modalities with electrodermal activity and visual analytical approaches

This chapter discusses the examination of new techniques with the aim of expanding existing research by including electrodermal activity analysis as well as the use of data visualisation as an analytical method. The papers presented in this chapter are:

- ‘Shall we learn together in loud spaces? Towards understanding the effects of sound in collaborative learning environments’ - initially examined the sound effects of the environment on students’ electrodermal and voice activity and visualising the data obtained. The objective was to create a visualisation suitable for researchers to conduct further analysis.

- ‘Towards teacher orchestration load-aware teacher-facing dashboards’ - application of electrodermal activity in understanding changes in teachers’ affective states when different dashboards are used. Assessment of affective states aimed to better understand teachers’ orchestration loads.

### 6.1 Shall we learn together in loud spaces? Towards understanding the effects of sound in collaborative learning environments

The paper in this section was presented at the International Conference on Computer Supported Collaborative Learning. Figure 18 shows the relationship between the paper presented in this chapter and the contributions of the dissertation.

Vujovic, M., Hernández-Leo, D. (2019). Shall we learn together in loud spaces? Towards understanding the effects of sound in collaborative learning environments, International Conference on Computer Supported Collaborative Learning, Lyon, France, pp.891-892.

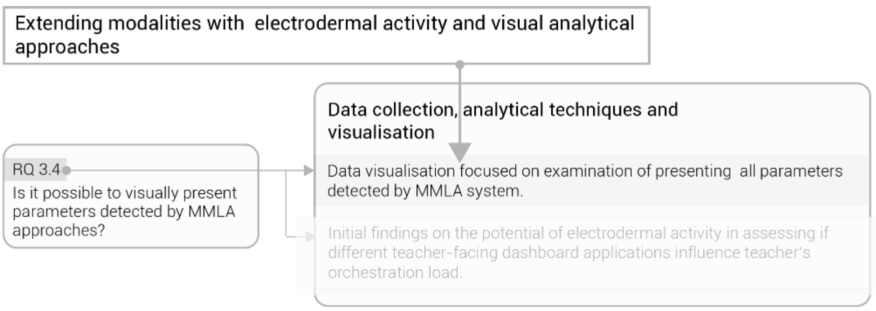


Figure 18. Relationship between the 'Shall we learn together in loud spaces? Towards understanding the effects of sound in collaborative learning environments' paper and dissertation contributions.

# Shall we learn together in loud spaces? Towards understanding the effects of sound in collaborative learning environments

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**Abstract:** In this paper we question the role of environmental sound on the process of CL. The first pilot study is presented where we investigated effects of environmental sound on EDA and voice VA of the participants. The created visualization presents the dependence between mentioned parameters and serves as an awareness tool for participants in CL. Preliminary results are provocative; there seems to be mentioned dependences and participants accept the proposed visualization as a useful tool to support self-regulation during CL.

## Introduction

Investigating the process of collaboration in learning remains challenge due to many unclear aspects of socio-emotional and cognitive interactions (Pijeira-Díaz, Drachsler, Järvelä & Kirschner, 2016). Additionally, broad application of collaborative learning finds its challenges in implementation because it is "so noisy" due to participants' interaction that can hinder learning (Graetz & Goliber, 2002). As in any other activity, interactions are tightly related to the environment (Malmberg, et al. 2018), and successful learning should be supported by the space where it takes place (Yeoman, 2008). The effect of environmental sound on CL has been underexplored in the sense of its effect on aspects of collaboration such as cognitive and socio-emotional interactions, that are reflected through physiological changes and conversation. Electrodermal activity (EDA) and voice activity (VA) measurements could help us understand and further explore connection between the environmental sound and collaborative learning process. Examples in the literature show different ways of visualizing physiological data with graphical user interface such as SLAM-KIT (Noroozi et al, 2018) and voice data with Reflect, a reactive table that monitors the collaborative interaction based on voice activity of participants (Bachour, Kaplan & Dillenbourg, 2010). We focus on loud spaces within university campus, used for collaborative activities, given their pedagogical interest, orchestration complexity and their direct relation to the sound footprints of learning spaces. We present a pilot study that opens the question of the role of environmental sound in Collaborative Learning (CL), using multimodal learning analytics (MMLA), that supports CL in many ways (Ochoa et al, 2013; Spikol, Ruffaldi & Cukurova, 2017). We also propose visualization of the changes of EDA and VA and their relation to sound footprints of learning spaces.

## Understanding the effect of sound in CL through a pilot study

We have conducted a first pilot study, measuring EDA and VA, where qualitative data is also collected through interviews with participants. Two types of environments were identified (a quiet room where only the participants stayed and a loud space with many people). The same type activity was carried out in both spaces, with the same level of difficulty and duration of activity. The first group performs activity first in the loud environment, then in a quite one, while the other group first performs activity in a quiet environment, and then in a loud one. Activity is based on learning a set of words in Swahili language (Carpenter, et al, 2008), where participants receive a list of English-Swahili pairs of words from where they should learn. Participants had no prior knowledge of Swahili.

## Visualization and discussion of preliminary results

We propose a visual representation (Figure 1) that aims to clearly present two measured parameters from participants (EDA and VA) and characteristics of environmental sound, where it is possible to understand the changes that occur in time. The level of sound from the environment was expressed by means of decibels, EDA by number of peaks in the signal occurred above the certain threshold that indicates arousal, while the voice activity was presented by time periods during which the speech occurred. Results indicate that there may be a dependence between the environment and the behaviour of the participants as shown in the Figure 1, where the EDA and VA values greatly differ in two environments. The visualization of the data was shown to all participants in order to understand if it can be used as an awareness tool. All participants stated that the visual representation is an effective way to look at all the parameters at the same time as it can be used as a tool for determining interdependence of collaboration parameters.

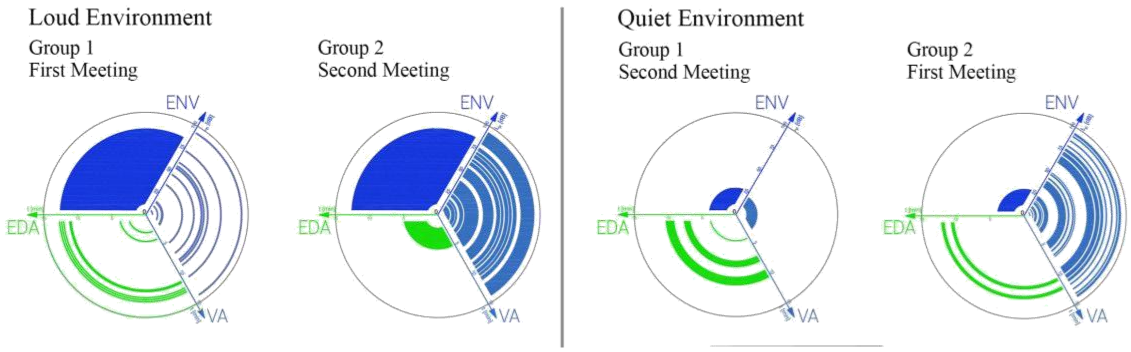


**Figure 1. Visualization – unique graphic presentation for three measured parameters**

## Conclusion

**Based on the pilot study, we cannot make clear conclusions because of the small sample in which the experiment was conducted, but we can see that there are differences in EDA and VA measured in different environments. This tells us that it is necessary to expand the study to a larger number of samples in order to see how and to what extent the sound from the environment affects the aspects of collaborative learning. The future work implies the extension of the study towards understanding what kind and level of environmental sound can be beneficial for collaboration, as well as the further development of visualization and its implementation in the process of collaboration as a conscious tool.**

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## 6.2 Towards teacher orchestration load-aware teacher-facing dashboards

The paper in this section was presented at the workshop of the 10th International Learning and Analytics Conference (LAK 2020). Figure 19 shows the relationship between the paper in this chapter and the contributions of the dissertation.

Amarasinghe, I., Vujovic, M., & Hernández Leo, D. (2020). Towards teacher orchestration load-aware teacher-facing dashboards. In Giannakos M, Spikol D, Molenaar I, Di Mitri D, Sharma K, Ochoa X, Hammad R, editors. *Proceedings of CrossMMLA in practice: Collecting, annotating and analyzing multimodal data across spaces co-located with 10th International Learning and Analytics Conference (LAK 2020*); 2020 Mar 24. Aachen: CEUR; 2020. p. 7-10. CEUR Workshop Proceedings.

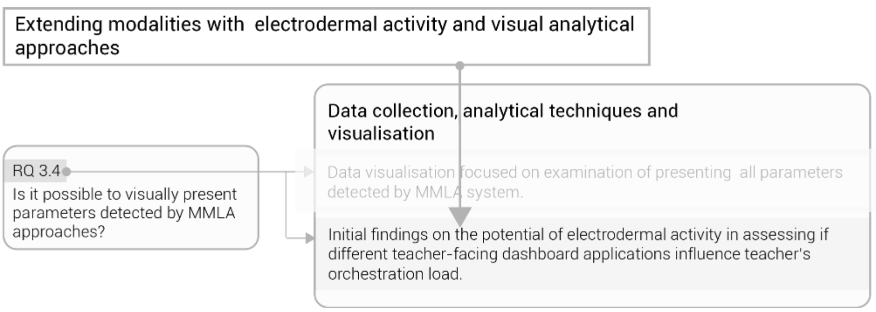


Figure 19. Relationship between the 'Towards teacher orchestration load-aware teacher-facing dashboards' paper and dissertation contributions.

# Towards Teacher Orchestration Load-aware Teacher-facing Dashboards

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

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

## 1 INTRODUCTION

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

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

# 2 STUDY DESIGN

## 2.1 Participants

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

## 2.2 Procedure

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

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

## 2.3 Data collection and analysis

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

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

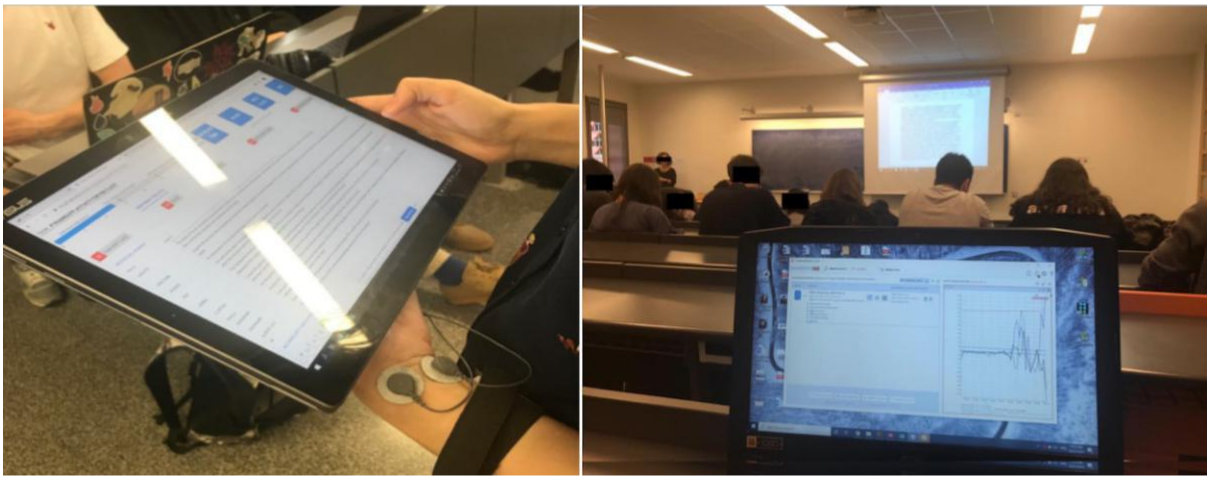

**Figure 1: A teacher wearing the Shimmer3 GSR+ sensor during a classroom session (left) and data collection in a co-located collaborative learning setting (right)**

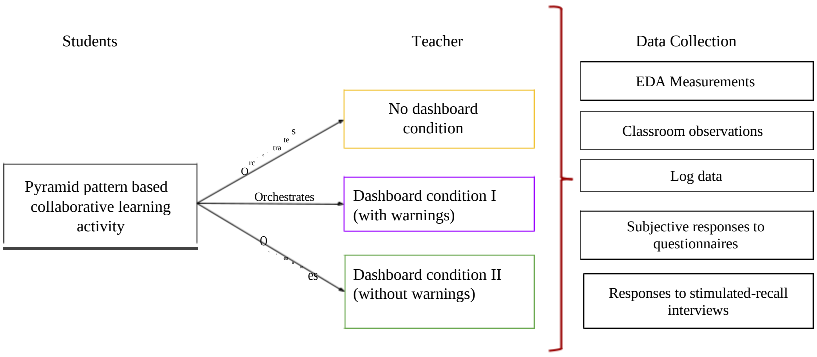


**Figure 2: Different experimental conditions and data collection**

## 3 CONCLUSIONS & FUTURE WORK

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

## ACKNOWLEDGEMENTS

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# Appendices

## Appendix A - About ethics in MMLA

The paper presented in this section was published in the *British Journal of Educational Technology (BJET).* It focuses on the ethical aspect of MMLA and the enhancement of consent form applied in the MMLA research.

Beardsley, M., Martínez Moreno, J., Vujovic, M., Santos, P., & Hernández-Leo, D. (2020). Enhancing consent forms to support participant decision making in multimodal learning data research. *British Journal of Educational Technology*, *51*(5), 1631-1652.

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# *Enhancing consent forms to support participant decision making in multimodal learning data research*

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**Abstract**

Advances in the field of multimodal learning analytics (MMLA) research is often accomplished by actively exploring new technologies and techniques related to the collection and analysis of data. Exploration of ethical principles and procedures for governing the use of new technologies and techniques, however, is not as readily pursued. As collected data grow in complexity and invasiveness, potentially, a growing need is arising to scrutinize ethical aspects of MMLA research. In our study, we introduce an informed consent comprehension test for educational technology research and assess the effects of enhancing MMLA consent forms on comprehension of informed consent and on rates of enrollment in a MMLA study. One form is written from a researcher perspective and the other from a participant perspective. Results of the study involving first-year undergraduate students suggest that the overall level of comprehension did not differ between conditions. Yet, the participant-oriented consent form resulted in significantly lower rates of enrollment. Implications for MMLA researchers are discussed.

## Introduction and related work

Advances in the field of multimodal learning analytics (MMLA) research is often accomplished by actively exploring new technologies and techniques related to the collection and analysis of data. However, the exploration of the ethical principles and procedures for governing the usage of the new technologies and techniques is not as readily pursued. For example, a recent paper examining the body of research emerging from MMLA workshops, published proceedings and journals did not mention topics related to ethics (Worsley, 2018). As MMLA data grow in com-plexity, and potential invasiveness, a need is arising to scrutinize the ethical aspects of MMLA research.

The process of informed consent may be an appropriate starting point as the results of bioeth-ical research suggest that many informed consent processes do not adequately support partici-pant comprehension of the studies they consent to (Falagas, Korbila, Giannopoulou, Kondilis, &

**Practitioner Notes**

What is already known about this topic

- Data collected in multimodal learning analytics (MMLA) research are growing in complexity and invasiveness.
- Informed consent is a process to enable individuals to make voluntary decisions about participating in research based on an understanding of a study's purpose, procedures, risks and benefits.
- Studies in related fields such as Bioethics show that many informed consent processes do not adequately support participant comprehension and decision making.

What this paper adds

- A discussion of the need to scrutinize the ethical aspects of MMLA research with a focus on supporting adequate participant understanding without discouraging par-ticipation in research.
- An approach to measure the effects of enhancing MMLA consent forms on comprehension and rates of enrollment in a MMLA research study.

Implications for practice and/or policy

- MMLA researchers may need to determine what level of learner comprehension is necessary for ethical participation in research studies.
- More research is needed to discover a balanced approach that can adequately inform participants without significantly affecting rates of enrollment.
- Further work is needed to establish adequate ethical protocols that can be applied by researchers, policy makers and institutional managers to facilitate a trusted implementation of MMLA.

Peppas, 2009; Flory & Emanuel, 2004; Nishimura *et al*., 2013; Tam *et al*., 2015; Tamariz, Palacio, Robert, & Marcus, 2013) and may fail to fulfill the requirements of valid consent. Further, recent societal shifts indicate that a greater onus is being placed on data collectors to adequately sup-port the autonomous decision making of individuals with regard to giving of consent and shar-ing of data. These shifts are evidenced by recent revisions to the Common Rule (Department of Homeland Security *et al*., 2017) and the enactment of the General Data Protection Regulation (EU General Data Protection Regulation, 2016), both of which are described later in the paper.

The field of MMLA research could benefit from demonstrating its efforts toward better support-ing potential research participants in autonomously making decisions about sharing their data, especially, as both the complexity of the work being done, and potential invasiveness of the data being collected increase. Studies such as this one attempt to contribute to the demonstration of such efforts. We introduce an informed consent comprehension test for educational technology research and assess the effects of enhancing MMLA consent forms on participant comprehension of informed consent and on rates of enrollment in a MMLA study.

### *Multimodal complexity and invasiveness*

MMLA is an elaboration of learning analytics (Blikstein & Worsley, 2016). Corrin *et al*. (2019) write that learning analytics "aims to provide meaningful ways of using data to support stu-dent learning within learning environments" (p. 7). Whereas learning analytics materialized in online learning environments, MMLA extended the tracking and quantification of learning to offline environments (Ochoa & Worsley, 2016). MMLA can be thought of as the learning traces extracted from log-files or digital documents combined with data from "recorded video and audio, pen strokes, position tracking devices, biosensors and any other modality that could be useful to understand or measure the learning process" (Ochoa, Lang, & Siemens, 2017, pp. 129–141).

The adoption of techniques such as machine learning, and text mining paired with the increas-ing accessibility of collecting and storing massive amounts of data (Blikstein, 2011) has shifted the collection of student data from more discrete, activity-focused exchanges of data to ongo-ing monitoring both within and outside of the classroom (Beardsley, Santos, Hernández-Leo, & Michos, 2019). Along with the increased complexity of the data being collected, the data are becoming more invasive as the collection of electrophysiological data in MMLA research grows. Measures of electrodermal activity (Pijeira-Díaz, Drachsler, Järvelä, & Kirschner, 2019), heart rate (Larra *et al*., 2014) and neural oscillations via an electroencephalogram (EEG) (Sun & Yeh, 2017) are more frequently being used. This biometric data are considered sensitive health data (Chassang, 2017).

*Informed or uninformed consent*

As MMLA research adds layers of complexity to participant understanding of studies, and begins to converge with health research, one can look to the field of bioethics for ideas about how to face the forthcoming challenges via informed consent. Obtaining informed consent is a key compo-nent of upholding the ethical value of participant autonomy (Nishimura *et al*., 2013) and is a process to enable individuals to make voluntary decisions about participating in research based on an understanding of the purpose, procedures, risks, benefits and alternatives (Beskow, 2016). It is grounded in the ethical principle of respect for persons (Kass, Taylor, Ali, Hallez, & Chaisson, 2015) and aims to respect and promote participants' autonomy and protect them from poten-tial harm (Jefford & Moore, 2008). Obtaining informed consent is "widely regarded as central to ethical social science research practice" (Heath, Charles, Crow, & Wiles, 2007, p. 403). In MMLA research, informed consent is regularly obtained via a written consent form signed by the poten-tial research participant. The participant's signature is a visible act of signifying the decision of participating in the research (Alderson & Morrow, 2004). The presentation and signing of the consent form enable research participants to "express their own agency within the research pro-cess"—an agency which "arises from their competency at decision making" (Heath *et al*., 2007, p. 404).

Kass *et al*. (2015) argue that informed consent "rests on an assumption that individuals con-sidering research participation have adequately understood the information provided to them" (p. 2). The requirement of understanding is echoed by many (Buccini, Iverson, Caputi, Jones, & Gho, 2009; Hadden *et al*., 2017; Hallinan, Forrest, Uhlenbrauck, Young, & McKinney, 2016; Joffe, Cook, Cleary, Clark, & Weeks, 2001; Muravyeva, Janssen, Dirkx, & Specht, 2018; Tait, Voepel-Lewis, Robinson, & Malviya, 2002; Young, Hooker, & Freeberg, 1990). Buccini *et al*. (2009) write that "to treat potential research participants as autonomous agents, it is imperative to ensure understanding of the consent information has actually occurred, thereby, enabling them to make autonomous decisions about participation" (p. 7). Wendler and Grady (2008) add that individu-als need to comprehend the information that is needed "to determine whether participation in a given study is consistent with their interests" (p. 205). In other words, it is critical to understand "how their prospective experience will differ if they choose to enroll" (p. 207) and unless they do, their consent is unlikely to be valid.

Meta-analyses and systematic reviews from bioethics suggest that many research participants struggle to understand what they are consenting to (Falagas *et al*., 2009; Flory & Emanuel, 2004; Nishimura *et al*., 2013; Tam *et al*., 2015; Tamariz *et al*., 2013). In a recent survey related to collecting and storing of biospecimens, Beskow, Lin, Dombeck, Gao, and Weinfurt (2017) found that one-third of their survey sample failed to demonstrate adequate comprehension. MMLA research may not reach the level of complexity involved in biomedical research. However, the collection and storage of biospecimens is already underway with the use of biological samples to measure changes in stress response in educational contexts (Schonert-Reichl *et al.*, 2015) and MMLA research is increasingly making use of electrophysiological data. Further, studies on informed consent comprehension related to MMLA research are few and far between but sug-gest that participant understanding could be better supported. For example, a recent study by Muravyeva *et al*. (2018) on informed consent regarding an e-assessment system that used bio-metric data for identity verification found that up to one-quarter of participants did not find the information presented clear enough. Moreover, the results of a study by Beardsley *et al*. (2019) suggest that teacher and learner knowledge of data sharing risks may be deficient thus limit-ing the effectiveness of commonly used consent forms in being used alone to communicate such risks. Jefford and Moore (2008) observe that current informed consent practices in research seem "to have been shaped by emphasis on the legal duty of disclosure" (p. 486) rather than the ethical duty to inform potential participants. Thus, comprehension may be costly to achieve in terms of effort, time, resources and, possibly, rates of participation in research studies, as improving comprehension may require making changes to how things are currently being done in MMLA research.

### *Enhancing MMLA consent forms*

Bioethical studies have shown that enhancing consent forms can improve participant compre-hension and contribute to validating the consent received. In a systematic review of informed consent interventions, Flory and Emanuel (2004) found that 6 out of 15 trials of enhanced con-sent forms showed significant improvements in understanding, but the authors raised concerns about the quality of the trials. In a more recent meta-analysis of informed consent interventions, Nishimura *et al*. (2013) found that 41% of trials of enhanced consent forms led to significant improvements in understanding. Table 1 presents recommendations from biomedical literature toward enhancing consent forms for comprehension.

Based on these bioethical studies, enhancing MMLA consent forms may offer an unburdened approach to improving understanding as it requires few changes to the current practices of MMLA researchers. However, efforts are needed to improve on the success rate of enhanced con-sent forms and overcome certain challenges presented by MMLA research. For example, grasp-ing what data are being collected and how they can be used often requires a basic knowledge of human psychology, physiology and even signal processing. As a result, potential research par-ticipants may underestimate the risks associated with the data they agree to share as they are unaware of how such data could be used to potentially identify them, their traits (eg, race, gen-der, age), and medical conditions (Mordini & Ashton, 2012; Swanlund & Schuurman, 2018). Further, MMLA research not only incorporates terminology from diverse fields but also from new technologies it adopts. As a result, the language used to explain a study can be unfamiliar to participants. To address these issues, efforts should be made to simplify the language used, avoid acronyms and specialized terms commonly used in MMLA, and offer further clarification of concepts that cannot be presented in simpler forms. Finally, the sequence of the informa-tion presented should be logical from the point of view of the interests of the receiver (Bjørn, Rossel, & Holm, 1999)—this can help participants reach an understanding of what interpreta-tions can be made from their data and better assess the obligations, benefits and risks of their participation.

*Table 1: Recommendations for enhancing consent forms from biomedical literature*

| *Item* | *Suggestion* | *References* |
|---|---|---|
| Reduce required reading level | Target a 9th-grade level and use readability checkers to estimate reading level (Jefford & Moore, 2008) | Young *et al*. (1990); Villafranca, Kereliuk, Hamlin, Johnson, and Jacobsohn (2017) |
| Use simple language | "Modify the vocabulary used, making it more familiar, short, and easy to visualize" (Villafranca *et al*., 2017) | Young *et al*. (1990); Bjørn *et al*. (1999); Wittenberg and Dickler (2007); Jefford and Moore (2008); Hallinan *et al*. (2016); Kadam (2017) |
| Use shorter and simpler sentences | Break longer sentences that contain several ideas into shorter sentences that contain only one (Jefford & Moore, 2008) | Young *et al*. (1990); Bjørn *et al*. (1999); Wittenberg and Dickler (2007) |
| Shorten blocks of text and explanations | Keep paragraph length below seven lines (Kadam, 2017) | Bjørn *et al*. (1999); Jefford and Moore (2008); Lorenzen, Melby, and Earles (2008); Villafranca *et al*. (2017) |
| Bold section headings | Describe information on types of data in a separate paragraph, under a separate header, to attract proper attention (Muravyeva *et al*., 2018) | Bjørn *et al*. (1999); Lorenzen *et al*. (2008); Manta, Ortiz, Moulton, and Sonnad (2016) |
| Include bulleted lists, graphics, lists, summaries | Use bullet points to break-up long explanations (Jefford & Moore, 2008) | Wittenberg and Dickler (2007); Lorenzen *et al*. (2008); Kass *et al*. (2015); Manta *et al*. (2016) |
| Use more white space and line spacing | "To make the forms more readable, both high and low literacy patients asked for more white space" (Lorenzen *et al*., 2008) | Wittenberg and Dickler (2007); Villafranca *et al*. (2017) |
| Organize information based on relevance to participant | Restructure information into a sequence that is logical as seen from the point of view of the receiver (Bjørn *et al*., 1999) | Young *et al*. (1990); Tait *et al*. (2002); Kass *et al*. (2015); Hallinan *et al*. (2016); Dranseika *et al*. (2017); Karbwang *et al*. (2018) |

### *Ethical responsibilities*

Recent societal shifts, as evidenced by revisions to the Common Rule and enactment of the General Data Protection Regulation (GDPR), suggest a greater onus is being placed on data col-lectors to adequately support the autonomous decision making of individuals with regard to giv-ing consent and sharing data. For example, the Common Rule which is the "overarching policy governing research with human subjects conducted and supported by most federal agencies and departments in the United States" (p. 22) strongly emphasizes "efforts to promote understanding and comprehension during the consent process" (Sugarman, 2017, p. 23). The GDPR defines consent as any freely given, specific, informed and unambiguous indication of the data subject's wishes by which he or she signifies to the processing of personal data relating to him or her. Further, the notion of imbalance between the controller and the data subject is also taken into consideration by the GDPR (Article 29 Working Party, 2018, p. 5). In the field of educational technology research, recent articles have discussed ethical and privacy issues related to the usage of learning analytics at various scales from teacher-led classroom usage (Rodríguez-Triana, Martínez-Monés, & Villagrá-Sobrino, 2016) to institutional usage of learning analytics (Pardo & Siemens, 2014). In a European Commission publication (2014) on learning and teaching in higher education, the requirement of student consent with regard to learning analytics was put forth as "the full and informed consent of students must be a requirement" (p. 50).

This study attempts to demonstrate efforts in MMLA research toward better supporting potential research participants in autonomously making decisions about sharing their data; and is situated in the understanding that researchers face challenges and costs in having an acceptable num-ber of participants for their research. Our research question is: **How can MMLA researchers comply with the obligation of ensuring adequate participant understanding without discouraging participation in research?**

To explore this question, we assess the effects of enhancing MMLA consent forms on comprehension of informed consent and on rates of enrollment in a MMLA study. Two enhanced consent forms are used. One consent form is written from a researcher perspective and the other from a participant perspective. We hypothesize the following:

- *The rates of enrollment will be the same for both enhanced MMLA consent forms* as in the previously mentioned meta-analysis by Nishimura *et al*. (2013), the authors concluded that "there is little evidence that a participant's satisfaction or a study's accrual rates would be negatively altered by attempts to improve the informed consent process, which should be reassuring to investigators" (p. 12).
- *The participant-oriented consent form will lead to better comprehension of informed consent* as the information is presented in a manner that better aligns with the decision under consideration by the potential participant.

## Methods

### *Participants*

In total, 201 first-year university students enrolled in a computer engineering course at a Spanish university were eligible to participate in the study. The course was offered either in English or Spanish/Catalan. Of the 201 eligible participants, 13 were absent and 6 arrived late to the session and did not sign a consent form. Their data have been removed. Thus, a total of 182 students were potential participants in the study: 97 in the researcher-oriented condition and 85 in the participant-oriented condition.

### *Materials*

#### A classroom lesson on data sharing risks

A two-hour classroom lesson on data sharing benefits and risks was used as formative material to present the main topics covered by the study to the students. A previous publication (Beardsley *et al*., 2019) provides an outline of the lesson content.

#### Enhanced MMLA consent forms

The enhanced MMLA consent forms were constructed following best practices from bioethics with one form written from a researcher-orientation and the other from a participant-orientation utiliz-ing a question and answer format. The best practices were derived from research articles and fall into two broad categories: (1) improving readability via the formatting of the text, the language used, and the length of the form; (2) improving the relevance of the text to the participant via the selection of content and perspective from which the text is written. Both enhanced MMLA consent forms comprised a two-page information sheet and a single consent page (see materials in Zenodo; Beardsley, Vujovic, Martinez-Moreno, Santos, & Hernández-Leo, 2019). The information sheet but not the consent page differed between conditions. With regard to improving readability, both consent forms were enhanced by applying the items highlighted in Table 1. Readability was evalu-ated using the Flesch reading ease (Kincaid, Fishburne, Rogers, & Chissom, 1975) and the Flesch– Kincaid grade level (Flesch, 1948) measures which are available in Microsoft® Word and have been used in similar studies evaluating readability of consent forms (Fortun, West, Chalkley, Shonde, & Hawkey, 2008; Jefford & Moore, 2008; Paasche-Orlow, Taylor, & Brancati, 2003). The readability of the Spanish versions of the documents was assessed with a scale proposed by Barrio-Cantalejo *et al*. (2008) and is an adaptation of the scales proposed by Flesch and Szigriszt (Flesch-Szigriszt Index). A comparison of the information sheets is shown in Table 2 (English) and Table A1 (Spanish).

The researcher-oriented form included brief summaries under each subheading title whereas the participant-oriented form used questions as subheadings (see Table 2). With regard to improving the relevance of the text to the potential participant in the participant-oriented consent form, the information was restructured into a sequence that is logically seen from the point of view of the interests of the receiver (Bjørn *et al*., 1999; Dranseika, Piasecki, & Waligora, 2017). For exam-ple, elements that participants identified as being most important such as major risks (Karbwang *et al*., 2018) and obligations (Wendler & Grady, 2008) were moved to appear earlier in the sequence of information presented.

### *An informed consent comprehension test for educational technology*

To assess comprehension of informed consent in the MMLA study, we created a comprehension test for potential participants. The test is an adaptation of similar tests in bioethics such as the Quality of Informed Consent (QuIC) measure (Joffe *et al*., 2001), Informed Consent Questionnaire (Guarino, Lamping, Elbourne, Carpenter, & Peduzzi, 2006) and the Brief Informed Consent Evaluation Protocol (Sugarman *et al*., 2005). Our approach follows closely that of Joffe *et al*. (2001) in assessing both subjective and objective understanding of participants but differs in that it integrates questions from all three tests previously mentioned and adds questions to comply with GDPR requirements on disclosure related to data collection. The GDPR disclosure require-ments incorporated include clearly identifying the purpose, type of data, risks of data transfer, the identity of the data controller and the existence of the right to withdraw consent (Article 2018 Working Party, 2018, p. 13). The approach to measure both subjective and objective understand-ing was taken as bioethical researchers have argued that individuals contemplating participa-tion “should both *be* well informed and *feel* well informed about the study under consideration” (Guarino *et al*., 2006, p. 140).

*Table 2: A comparison of the English MMLA consent form information sheets*

| *Variables* | *A. Researcher-oriented consent form* | *B. Participant-oriented consent form* |
|---|---|---|
| Word count | 1505 | 1394 |
| Flesch reading ease score | 54.1 | 54.4 |
| Flesch–Kincaid grade level | 9 | 8.9 |
| Passive sentences | 35.2% | 32.9% |
| Perspective | Researcher | Participant |
| Subheadings in order | 1. Motivation and Objectives<br>2. Methodology<br>3. Collected Data<br>4. Risks and Privacy<br>5. Benefits<br>6. Voluntary Participation<br>7. Data Subject Rights | 1. If I participate in the study, what will I be asked to do?<br>2. If I participate in the study, what are the risks?<br>3. Can I trust you with my data?<br>4. Why do you want to collect my data?<br>5. Do I benefit from participating in the study?<br>6. What if I change my mind?<br>7. What if I feel my rights have been violated? |

Part A of the test measures subjective understanding of informed consent (see Table B1) whereas Part B measures participants' objective understanding (see Table B2). The grouping of ques-tions in Part B is based on constructs taken from GDPR's definition of consent (EU General Data Protection Regulation, 2016). The B1 grouping of items relates to consent being freely given (eg, consent is given without coercion or pressure); B2 relates to consent being specific (eg, the obligations, expectations and procedures are clear); B3 relates to consent being informative (eg, the purpose, risks and benefits of participation are clear); and B4 relates to the identity of the controller (eg, the participant is aware of who to contact for the research and their subject rights).

As with the QuIC measure, a 3-point scale was used for both the subjective (Part A) and objective (Part B) sections of the test. In the pilot testing of the QuIC, a 3-point scale was deemed more appropriate as "intensity of agreement did not seem meaningful for statements of fact" (Joffe *et al*., 2001). Further, best practices from similar measures created in biomedical Fresearch were followed such as varying the direction of the statements to avoid agreement bias (Beskow *et al*., 2017; Joffe *et al*., 2001); including a neutral option of "not sure" to reduce participant guessing (Beskow *et al*., 2017; Joffe *et al*., 2001); and devising objective scoring algorithms to prevent inves-tigator bias (Joffe *et al*., 2001). For the scoring of Part A, 1 point was assigned for a positive sub-jective evaluation (ie, Yes), 0 points for a neutral answer (ie, Not sure) and −1 point for a negative subjective evaluation (ie, No). For the scoring of Part B, 1 point was assigned for a correct answer, 0 points for a neutral answer (ie, I'm not sure) and −1 point for an incorrect answer. Participants completed the test online via a Google Form. Both Spanish and English versions of the test were created and reading levels assessed (English: Flesch reading ease 61%, Flesch–Kincaid grade level of 8.1; Spanish: Flesch-Szigriszt grade level 54.87).

*Design*

A quasi-experimental design with two conditions was used to assess the effects of the type of enhanced MMLA consent form on rates of enrollment in the study and on participant compre-hension of informed consent. This study was conducted in conjunction with a separate MMLA research study which involved the use of an online collaborative learning application and the collection of different types of data (observations, online artifacts, survey responses, video and audio recordings). Six separate groups (ie, classes) were eligible to participate in the study: 2 of which were in English and 4 of which were in Spanish. Half of the groups (2 Spanish and 1 English) were given an enhanced MMLA consent form written from a researcher perspective (researcher-oriented). The other half of the groups were given an enhanced MMLA consent form written from a participant perspective (participant-oriented).

*Procedure*

As the study took place in an educational setting, we adopted a formative approach that treated consent as an ongoing process. Heath *et al*. (2007) write, "process consent provides a useful mechanism for updating participants involved in studies with emergent research designs, and allows existing participants to decide whether or not to remain involved" as consent "should not be assumed on the basis of initial consent only" (p. 409). At the start of the class, students were presented with the consent form and indicated their initial consent decision; they then took a comprehension test on informed consent, and finally completed a classroom lesson on data shar-ing risks (Figure 1). At the end of the course, once the study had been completed, students read a debriefing of the study and reviewed their consent. Further, on each data collection instrument, students were asked to explicitly mark whether they wanted the data to be shared with research-ers or not.

*Analyses*

To assess the effects of the type of consent form on study enrollment rates, the rate of enrollment was calculated by using the number of consenting participants and number of eligible partic-ipants per condition. To assess the effects of the type of consent form on participant compre-hension of informed consent, two steps were taken. The first step involved conducting a factor analysis to assess the validity of the variables (ie, the questions in the comprehension test). The second step of the analysis consisted of running t-tests to investigate the difference in compre-hension test performance between conditions. The factor analysis was performed on the grouping of questions (A1, A2, B1, B2, B3 and B4 as shown in Appendix B). All statistical analyses were performed using SPSS v.23.0 (IBM Corp., 2015).

## Results

4. *The rates of enrollment will be the same for both enhanced MMLA consent forms*. In total 182 partici-pants completed the MMLA consent forms with 134 consenting to the study ($M$ = 73.63%). In the researcher-oriented condition, 83 out of 97 ($M$ = 85.57%) eligible participants consented to participating in the study compared to 51 out of 85 ($M$ = 60%) in the participant-oriented condition. There was a statistically significant difference between conditions ($p < .001$, two-tailed Fisher's exact test, Cramer's $V = 0.289$).
5. *The participant-oriented consent form will lead to better comprehension of informed consent*. Firstly, the factors analysis could not be run on the B1 grouping of questions due to the nature of the


*Figure 1:* *Schema of the procedure*

answers within it but was run on the other groupings (ie, for the results of the A1 grouping of questions see Tables C1, C2 and C3; for A2 see Tables C4, C5, and C6; for B2 see Tables C7, C8, and C9; for B3 see Tables C910, C11, and C12; and for B4 see Tables C13, C14, and C15). The factor analysis showed that 61.7% of variance or less was explained by components (ie, the ques-tions in the grouping A1, A2, B2, B3 and B4). As the size of $R^2$ coefficients did not differ greatly among questions in each grouping the initial groupings could be maintained (Tables C2, C5, C8, C11 and C14) and a comparison of comprehension scores using all questions could be conducted.

As a process consent approach was followed, participants were afforded the opportunity to re-consider their consent decision within the informed consent test form. In total, 162 participants consented to sharing the data from their tests with 7 participants withdrawing their consent and 35 changing from not consenting to consenting. In the researcher-oriented condition, 89 (80 yes, 9 no) consented to sharing their results. In the participant-oriented condition, 73 (47 yes, 26 no) consented to sharing their results. In comparing comprehension test scores by con-dition, no difference was detected in the scores on the subjective portion (Part A) of the informed consent comprehension test ($M_{\text{researcher}}$ = 5.64, *SD* = 1.89, 95% CI [−1, 7]; $M_{\text{participant}}$ = 5.29, *SD* = 2.34, 95% CI [−5, 7]; *U* = 3013, *p* = .404, two-tailed Mann–Whitney U-test, 95% CI [−5, 7], *d* = 0.272). Further, no difference was detected between conditions in the scores for the objective portion (Part B) of the informed consent comprehension test ($M_{\text{researcher}}$ = 10.97, *SD* = 3.54, 95% CI [4, 19]; $M_{\text{participant}}$ = 11.4, *SD* = 3.61, 95% CI [1, 18]; *U* = 2928.5, *p* = .279, two-tailed Mann–Whitney U-test, 95% CI [1, 19], *d* = 0.314).

*Per question comparison between conditions*

In exploring the data further, we compared the responses to each question between conditions and found that there was a significant difference on the following questions:

*B2.3. The study will not collect my personal data*. ($M_{\text{researcher}}$ = −0.067, *SD* = 0.94; $M_{\text{participant}}$ = 0.52, *SD* = 0.80; *p* < .001, Test, 95% CI [−1, 1]). *B2.4. Because I am participating in a research study, it is possible that others not directly involved in my education may access my data from this class* ($M_{\text{researcher}}$ = 0.00, *SD* = 0.96; $M_{\text{participant}}$ = 0.53, *SD* = 0.78; *p* < .001, Test, 95% CI [−1, 1]). The results of the comparison of each question can be found in Tables B1and B2.

## Discussion

Contrary to the findings of Nishimura *et al*. (2013) and Hallinan *et al*. (2016), the type of consent form affected the rates of enrollment in the MMLA study. The participant-oriented forms which reflected our efforts to better support potential participants' decision making via the consent form resulted in a much lower rate of enrollment in the study. The cause of the lower rate of enroll-ment in the participant-oriented group is unclear. A possible explanation is that those receiving the participant-oriented forms were more aware of the risks of the study as reflected by the dif-ferences between conditions on the questions related to risk (B.2.3 and B.2.4). Question B2.3 re-lated to whether participants understood that personal data would be collected. This question is a gauge for participant understanding of risk as personal data are commonly understood to be risk-ier than non-personal data for individuals. Question B3.4 referred to whether identifiable data would be collected and serve a similar purpose. Even though a statistically significant difference between conditions was not found for question B3.4 (*p* = .105), the results trended in a direction similar to that of B2.3 with the participant-oriented condition showing a greater understanding of the riskiness of the data. Question B2.4 related to data access is an indirect gauge for partici-pant understanding of risk as an interpretation can be made that the more the people who have access to the data the greater the risk. Question B2.5 served a similar purpose but no statistically significant difference was found on B2.5 ($p$ = .56). It is possible that the participant-oriented condition had a greater awareness of the risks of the study which dissuaded them from enrolling in the study, but further investigations are needed.

Consistent with past studies (Beskow *et al*., 2017; Flory & Emanuel, 2004; Stunkel *et al*., 2010), the type of consent form did not affect participant comprehension of informed consent. Also, consistent with the findings of Stunkel *et al*. (2010), we did not find a correlation between pre-vious research participation and greater comprehension (see Appendix D). However, these past findings typically came out of comparisons between short and long consent forms and did not compare two types of enhanced consent forms. As noted above, differences were identified on specific questions on the objective measure related to understanding of risk.

*Limitations of the study*

Participant subjective and objective understanding of informed consent was assessed by a test created for the study. We modeled the test after similar measures created in biomedical research and followed suggested practices. Nonetheless, the comprehension test should be further refined and validated. The results of the factor analyses suggest that while questions should not be re-moved, they could be rephrased to better explain the differences among the questions that appear to be in the same component. Moreover, all questions have been weighted equally which may not aptly reflect the comparative importance of the questions. It may also be worthwhile to have criterion experts and potential participants assess the accuracy and readability of measure; and to assess its test–retest reliability (Guarino *et al*., 2006; Joffe *et al*., 2001).

Kass *et al*. (2015) noted that most informed consent intervention studies used simulated research conditions. We assessed individuals' understanding of informed consent in an actual MMLA research study. Despite having the study begin in 6 different groups and in 2 different languages, we managed to hold all groups in the same week and with the same teacher. However, we were not able to access all of the data relevant to the study as we had to omit the data from those who did not enroll in the study. We attempted to mitigate the data lost by following an ongoing process of consent which enabled potential participants to reflect upon and change their decision regard-ing consent in each data collection instrument. Still we ended up with less data from participants that did not give consent on the initial consent form (72.92%) compared to those that gave con-sent on the initial consent form (94.78%). Moreover, as the study was conducted in a first-year course of a computer science bachelor's degree program, the generalizability of the findings is not clear and could be improved by collecting more qualitative data via focus groups and interviews to gain deeper insights into participants' understanding of informed consent and the rationale for their decisions.

*Implications for MMLA researchers*

Recent MMLA research is showing a greater interest in ethical issues related to user/participant understanding of data acquisition and use. For example, Cowling and Birt (2020) discuss ethical concerns related to data storage, privacy and security when applying MMLA to innovative learn-ing scenarios such as those involving mixed reality. Schneider, Reilly, and Radu (2020) point out concerns related to the increasing amount of fine-grained data that are infiltrating educational environments. However, recent MMLA studies collecting physiological data (eg, Echeverria, Martinez-Maldonado, & Buckingham Shum, 2019; Pijeira-Díaz *et al*., 2019) may promote the use of responsible practices, but do not make explicit the importance of informed consent and en-suring adequate understanding of the study and its risks by participants. The results of our study point to deficiencies in our informed consent process for MMLA research. The average score on the subjective portion of the test was 78.29% ($M$ = 5.48, $SD$ = 2.10) whereas the average score on the objective portion of the test was only 53.17% ($M$ = 11.17, $SD$ = 3.57). Further, the scores for a number of questions identify specific concerns related to a lack of participant understanding of the type and riskiness of the data being collected (B2.3, B2.4, B2.5, B3.4). As there is a lack of publications related to informed consent and ethics in the MMLA research, it is unclear how common researcher-oriented consent forms are and whether our results could be indicative of the field. If comprehension is required for valid consent, then those conducting MMLA experiments may need to determine what level of comprehension is deemed adequate, what instruments are appropriate for measuring it and what steps need to be taken if adequate comprehension is not demonstrated. For example, Beskow *et al.* (2017) had participants review the sections of the con-sent form that corresponded to the items they answered incorrectly, and then had them complete a retest on the same topics.

Beyond the issues related to understanding, additional ethical concerns emerged out of partici-pant test responses. A number of participants noted feeling pressure to participate in the study (A2.6)—marking they were unsure (18 out of 162) or felt pressure (7 out of 162) to participate in the study. Further, some participants were not sure if their participation in the study would appear on their student records (B1.2: 30 out of 162) nor if their teacher would be disappointed in them if they did not join the study (B1.3: 20 out of 162). Such results could invalidate con-sent in formal educational settings in which there is an unequal distribution of power among parties—and much of MMLA research takes place in such settings. A sharing of best practices among researchers could help address these concerns but an initial step involves collecting data to see if such a problem exists or not. Buccini *et al.* (2009) suggest that instruments such as informed consent comprehension tests are useful in identifying gaps in knowledge and pointing to where additional education is necessary.

## Conclusions

We introduced an informed consent comprehension test for educational technology research and assessed the effects of enhancing MMLA consent forms on comprehension of informed consent and on rates of enrollment in a MMLA study. The MMLA consent form written from a partici-pant perspective resulted in higher levels of comprehension on test questions related to risk, yet lower rates of enrollment. Tait *et al.* (2002) write that "it is every investigator's goal to maximize recruitment rates in order to provide a representative sample of sufficient size to achieve statis-tical power" but the authors add that investigators must achieve this goal "through the design of ethically sensitive protocols involving complete and honest disclosure" (p. 335). Our study suggests that more work is needed to discover a balanced approach that can adequately inform participants about risks and benefits without significantly affecting rates of enrollment, espe-cially as MMLA research data increase in complexity and invasiveness. Overall, our work high-lights potential weaknesses in the informed consent process of MMLA research conducted in a formal educational setting (eg, participant understanding of risk, feeling of pressure, feelings of not being adequately informed); provides evidence that the manner in which studies are commu-nicated to participants via consent forms can affect enrollment rates; and introduces an approach for MMLA research, derived from bioethics, to evaluate participant understanding of consent.

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**Statements on open data, ethics and conflict of interest**

The study was approved by the ethics committee of Universitat Pompeu Fabra, Barcelona.

Consent was obtained from participants. Anonymized data excerpts are available in Zenodo (http://doi.org/10.5281/zenodo.3557272).

There are no potential conflicts of interest in the work.

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## APPENDIX A

The readability of the Spanish versions of the enhanced consent forms was assessed with a scale proposed by Barrio-Cantalejo *et al*. (2008) and is an adaptation of the scales proposed by Flesch and Szigriszt (Flesch-Szigriszt Index). A comparison of the information sheets used as part of the consent forms is shown in Table A1.

*Table A1: A comparison of the Spanish consent form information sheets*

| *Variables* | *A. Researcher-oriented consent form* | *B. Participant-oriented consent form* |
|---|---|---|
| Word count | 1980 | 1835 |
| Flesch-Szigriszt Ease Score* | 51.34 | 52.16 |
| Average syllables-word | 2.37 | 2.36 |
| Average words-sentence | 8.02 | 7.94 |
| Perspective | Researcher | Participant |

*Flesch-Szigriszt Ease Score [51–65] Normal. Popular texts. General and sports press.

## APPENDIX B

Part A of the Informed Consent Comprehension Test for Educational Technology measures subjective understanding of informed consent (Table B1). Part B of the test measures participants' objective understand-ing of informed consent (Table B2).

*Table B1: Comparison between conditions of answers to Part A of the consent test*

| *Question* | *Researcher oriented: M (SD)* | *Participant oriented: M (SD)* | *p-value (U)* |
|---|---|---|---|
| A2.1. Did you sign a consent form and mark your choice on whether to participate in the study or not? | 0.97 (0.24) | 0.85 (0.52) | .079 (3052.5) |
| A2.2. Did you read the entire consent form given to you for the study? | 0.8 (0.59) | 0.66 (0.73) | .161 (2991.5) |
| *A2.3. Did you find the consent form difficult to read? | 0.85 (0.47) | 0.85 (0.46) | .874 (3223.5) |
| A2.4. Did you understand the study when you decided to participate? | 0.85 (0.36) | 0.81 (0.46) | .697 (3176) |
| *A2.5. Did you feel any pressure to participate in the study? | 0.62 (0.7) | 0.67 (0.67) | .578 (3125) |
| A2.6. Did you understand what type of personal data will be collected from you? | 0.87 (0.4) | 0.73 (0.58) | .094 (2936) |
| A2.7. Did you feel that you had all the information you needed to make a good decision about participating in the study? | 0.69 (0.6) | 0.73 (0.58) | .564 (3121) |

*Reversed statements.

*Table B2: Comparison between conditions of answers to Part B of the consent test*

| *Question* | *Researcher oriented: M (SD)* | *Participant oriented: M (SD)* | *p-value (U)* |
|---|---|---|---|
| B1.1. The study is voluntary. It is my choice to join or not | 1.0 (0.00) | 1.0 (0.00) | 1.000 (3248.5) |
| *B1.2. My decision about joining the study will appear on my student records | 0.8 (0.48) | 0.73 (0.58) | .501 (3113.5) |
| *B1.3. My teacher will be disappointed with me if I do not join the study | 0.89 (0.32) | 0.84 (0.44) | .5952 (3158.5) |

| | | | |
|---|---|---|---|
| B1.4. I am free to leave this study without giving a reason for wanting to leave | 0.84 (0.46) | 0.9 (0.41) | .154 (3035.5 |
| *B1.5. If I agree to join the study, I cannot leave the study early even if I want to | 0.88 (0.39) | 0.92 (0.4) | .171 (3064) |
| B2.1. The consent form states how long my participation in the study is likely to last | 0.83 (0.51) | 0.78 (0.58) | .616 (3163.5) |
| *B2.2. The consent form does not state how long my data will be kept by researchers | 0.79 (0.53) | 0.71 (0.68) | .768 (3192.5) |
| ***B2.3. The study will not collect my personal data** | **−0.07 (0.94)** | **0.52 (0.80)** | **<0.0001 (2178.5)** |
| **B2.4. Because I am participating in a research study, it is possible that others not directly involved in my education may access my data from this class** | **0.00 (0.97)** | **0.53 (0.78)** | **.0003 (2312.5)** |
| *B2.5. My data that are collected in the study will not be shared with anyone outside of the research team | −0.24 (0.9172) | −0.33 (0.8669) | .56 (3095.5) |
| B2.6. I will not receive any monetary compensation for taking part in the study | 0.99 (0.11) | 1.00 (0.00) | .365 (3212) |
| *B2.7. The study requires that I perform tasks that other students in this course do not have to perform | 0.64 (0.71) | 0.36 (0.92) | .052 (2796) |
| B2.8. I am given the option to share the data with researchers or not for each survey I submit | 0.56 (0.72) | 0.34 (0.82) | .07 (2786) |
| B3.1. By agreeing to join the study, I would be joining a research study about how educational approaches affect a class of students in which I am a member | 0.83 (0.51) | 0.67 (0.69) | .097 (2938.5) |
| *B3.2. The main reason educational research studies such as this one are done is to improve the quality of my education | −0.91 (0.32) | −0.89 (0.39) | .912 (3233) |
| B3.3. The experimental technology and learning methodologies being researched in this study have not yet proven to be the best for supporting student learning | 0.39 (0.63) | 0.33 (0.69) | .612 (3112.5) |
| *B3.4. The data collected in this study do not include identifiable data such as my name and email, so it is not risky | −0.28 (0.9) | −0.04 (0.95) | .105 (2816.5) |
| B3.5. The researchers will anonymize my data before analyzing it to reduce risk | 0.94 (0.28) | 0.85 (0.46) | .116 (3036.5) |
| B3.6. There may not be direct benefits to me in terms of improved learning or wellbeing from my participation in this study | 0.36 (0.86) | 0.53 (0.82) | .125 (2870) |

Table B2: (Continued)

| Question | Researcher oriented: M (SD) | Participant oriented: M (SD) | p-value (U) |
|---|---|---|---|
| B4.1. The consent form lists the name of the person I should contact if I have any questions or concerns about the study | 0.89 (0.44) | 0.89 (0.39) | .755 (3206.5) |
| *B4.2. The consent form does not list the name of the agency I should contact if I feel my rights have been violated | 0.84 (0.52) | 0.75 (0.62) | .2457 (3056) |

*Reversed statements.

## APPENDIX C

A factor analysis was performed on the grouping of questions (A1, A2, B1, B2, B3 and B4) to test the coding of questions—providing clarification on whether the number of questions could be reduced; and to enable us to examine whether the initial grouping of questions were supported by the data.

Table C1: Factor analysis for questions in Part A1, total variance explained

| Component | Total | % of Variance | Cumulative % |
|---|---|---|---|
| 1 | 1.35 | 45.14 | 45.14 |
| 2 | 0.98 | 32.54 | 77.68 |
| 3 | 0.67 | 22.32 | 100 |

Table C2: Factor analysis for questions in Part A1, communalities

| Question | $R^2$ |
|---|---|
| A1-1 [Did you consent to participating in the study?] | 0.65 |
| A1-2 [Did you have a chance to ask questions about the study and have them answered?] | 0.45 |
| A1-3 [Did you ask any questions about the study?] | 0.25 |

Table C3: Factor analysis for questions in Part A1, component matrix

| | Component |
|---|---|
| Question | 1 |
| A1-1 [Did you consent to participating in the study?] | 0.81 |
| A1-2 [Did you have a chance to ask questions about the study and have them answered?] | 0.67 |
| A1-3 [Did you ask any questions about the study?] | 0.5 |

*Table C4: Factor analysis for questions in Part A2, total variance explained*

| *Component* | *Total* | *% of Variance* | *Cumulative %* |
|---|---|---|---|
| 1 | 2.27 | 32.48 | 32.48 |
| 2 | 1.08 | 15.4 | 47.88 |
| 3 | 0.99 | 14.20 | 62.08 |
| 4 | 0.91 | 12.97 | 75.05 |
| 5 | 0.75 | 10.76 | 85.81 |
| 6 | 0.56 | 7.97 | 93.78 |
| 7 | 0.44 | 6.22 | 100 |

*Table C5: Factor analysis for questions in Part A2, communalities*

| *Question* | $R^2$ |
|---|---|
| A2.1. Did you sign a consent form and mark your choice on whether to participate in the study or not? | 0.39 |
| A2.2. Did you read the entire consent form given to you for the study? | 0.47 |
| *A2.3. Did you find the consent form difficult to read? | 0.36 |
| A2.4. Did you understand the study when you decided to participate? | 0.40 |
| *A2.5. Did you feel any pressure to participate in the study? | 0.62 |
| A2.6. Did you understand what type of personal data will be collected from you? | 0.64 |
| A2.7. Did you feel that you had all the information you needed to make a good decision about participating in the study? | 0.47 |

*Reversed statements.

*Table C6: Factor analysis for questions in Part A2, rotated component matrix*

| | *Component* | |
|---|---|---|
| *Question* | *1* | *2* |
| A2.1. Did you sign a consent form and mark your choice on whether to participate in the study or not? | 0.60 | |
| A2.2. Did you read the entire consent form given to you for the study? | 0.67 | |
| *A2.3. Did you find the consent form difficult to read? | 0.60 | |
| A2.4. Did you understand the study when you decided to participate? | | 0.62 |
| *A2.5. Did you feel any pressure to participate in the study? | | 0.79 |
| A2.6. Did you understand what type of personal data will be collected from you? | 0.68 | 0.42 |
| A2.7. Did you feel that you had all the information you needed to make a good decision about participating in the study? | | 0.65 |

*Reversed statements.

*Table C7: Factor analysis for questions in Part B2, total variance explained*

| *Component* | *Total* | *% of Variance* | *Cumulative %* |
|---|---|---|---|
| 1 | 1.42 | 17.8 | 17.8 |
| 2 | 1.31 | 16.41 | 34.21 |
| 3 | 1.16 | 14.43 | 48.64 |
| 4 | 1.04 | 13.04 | 61.68 |
| 5 | 0.93 | 11.6 | 73.28 |
| 6 | 0.9 | 11.17 | 84.45 |
| 7 | 0.73 | 9.09 | 93.54 |
| 8 | 0.52 | 6.46 | 100 |

*Table C8: Factor analysis for questions in Part B2, communalities*

| *Question* | $R^2$ |
|---|---|
| B2.1. The consent form states how long my participation in the study is likely to last | 0.70 |
| *B2.2. The consent form does not state how long my data will be kept by researchers | 0.61 |
| *B2.3. The study will not collect my personal data | 0.5 |
| B2.4. Because I am participating in a research study, it is possible that others not directly involved in my education may access my data from this class | 0.74 |
| *B2.5. My data that are collected in the study will not be shared with anyone outside of the research team | 0.64 |
| B2.6. I will not receive any monetary compensation for taking part in the study | 0.8 |
| *B2.7. The study requires that I perform tasks that other students in this course do not have to perform | 0.41 |
| B2.8. I am given the option to share the data with researchers or not for each survey I submit | 0.54 |

*Reversed statements.

*Table C9: Factor analysis for questions in Part B2, rotated component matrix*

| | *Component* | | | |
|---|---|---|---|---|
| *Question* | *1* | *2* | *3* | *4* |
| B2.1. The consent form states how long my participation in the study is likely to last | | | 0.78 | |
| *B2.2. The consent form does not state how long my data will be kept by researchers | | −0.36 | 0.61 | 0.31 |
| *B2.3. The study will not collect my personal data | −0.54 | | | 0.44 |
| B2.4. Because I am participating in a research study, it is possible that others not directly involved in my education may access my data from this class | | 0.71 | 0.4 | |
| *B2.5. My data that are collected in the study will not be shared with anyone outside of the research team | | 0.79 | | |
| B2.6. I will not receive any monetary compensation for taking part in the study | | | | 0.88 |

| | |
|---|---|
| *B2.7. The study requires that I perform tasks that other students in this course do not have to perform | 0.59 |
| B2.8. I am given the option to share the data with researchers or not for each survey I submit | 0.73 |

*Table C10: Factor analysis for questions in Part B3, total variance explained*

| *Component* | *Total* | *% of Variance* | *Cumulative %* |
|---|---|---|---|
| 1 | 1.38 | 23.03 | 23.03 |
| 2 | 1.14 | 18.99 | 42.03 |
| 3 | 1.01 | 16.89 | 58.92 |
| 4 | 0.98 | 16.28 | 75.2 |
| 5 | 0.82 | 13.65 | 88.85 |
| 6 | 0.67 | 11.15 | 100 |

*Table C11: Factor analysis for questions in Part B3, communalities*

| *Question* | $R^2$ |
|---|---|
| B3.1. By agreeing to join the study, I would be joining a research study about how educational approaches affect a class of students in which I am a member | 0.64 |
| *B3.2. The main reason educational research studies such as this one are done is to improve the quality of my education | 0.46 |
| B3.3. The experimental technology and learning methodologies being researched in this study have not yet proven to be the best for supporting student learning | 0.59 |
| *B3.4. The data collected in this study do not include identifiable data such as my name and email, so it is not risky | 0.65 |
| B3.5. The researchers will anonymize my data before analyzing it to reduce risk | 0.63 |
| B3.6. There may not be direct benefits to me in terms of improved learning or wellbeing from my participation in this study | 0.58 |

*Reversed statements.

*Table C12: Factor analysis for questions in Part B3, rotated component matrix*

| *Question* | *Component* 1 | 2 | 3 |
|---|---|---|---|
| B3.1. By agreeing to join the study, I would be joining a research study about how educational approaches affect a class of students in which I am a member | | | 0.75 |
| *B3.2. The main reason educational research studies such as this one are done is to improve the quality of my education | | | −0.62 |
| B3.3. The experimental technology and learning methodologies being researched in this study have not yet proven to be the best for supporting student learning | | 0.73 | |
| *B3.4. The data collected in this study do not include identifiable data such as my name and email, so it is not risky | −0.73 | 0.33 | |
| B3.5. The researchers will anonymize my data before analyzing it to reduce risk | 0.78 | | |
| B3.6. There may not be direct benefits to me in terms of improved learning or wellbeing from my participation in this study | | 0.69 | |

*Reversed statements.

Table C13: Factor analysis for questions in Part B4, total variance explained

| *Component* | *Total* | *% of Variance* | *Cumulative %* |
|---|---|---|---|
| 1 | 1.2 | 59.79 | 59.79 |
| 2 | 0.8 | 40.22 | 100 |

Table C14: Factor analysis for questions in Part B4, communalities

| *Question* | $R^2$ |
|---|---|
| B4.1. The consent form lists the name of the person I should contact if I have any questions or concerns about the study | 0.6 |
| *B4.2. The consent form does not list the name of the agency I should contact if I feel my rights have been violated | 0.6 |

*Reversed statements.

Table C15: Factor analysis for questions in Part B4, component matrix

| | *Component* |
|---|---|
| *Question* | *1* |
| B4.1. The consent form lists the name of the person I should contact if I have any questions or concerns about the study | 0.77 |
| *B4.2. The consent form does not list the name of the agency I should contact if I feel my rights have been violated | 0.77 |

*Reversed statements.

**APPENDIX D**

As part of demographic data collected, participants were asked to select how many research studies they had previously participated in: 0, 1, 2, 3 or more. We evaluated whether there was a relation between experience in research studies and scores on the Informed Consent Comprehension Test.

## Past research experience and comprehension scores

However, no difference was found in performance on the test and experience related to research participation. Part A: $M_0$ = 5.79, $SD$ = 1.63; $M_1$ = 5.16, $SD$ = 2.54; $M_2$ = 5.7, $SD$ = 1.42; $M_{>3}$ = 5.19, $SD$ = 2.48; $X^2(3)$ = 1.61, $p$ = .657, Kruskal–Wallis One-way ANOVA, 95% CI [−5, 7]; Part B: $M_0$ = 11.59, $SD$ = 3.37; $M_1$ = 11.02, $SD$ = 3.58; $M_2$ = 10.7, $SD$ = 5.57; $M_{>3}$ = 10.29, $SD$ = 3.74; $X^2(3)$ = 2.92, $p$ = .404, Kruskal– Wallis One-way ANOVA, 95% CI [1, 19].

In comparing the responses to each question based on participant past experience related to research participation, a significant difference was found on questions:

*A2.2. Did you read the entire consent form given to you for the study?* ($M_0$ = 0.87, $SD$ = 0.48; $M_1$ = 0.58, $SD$ = 0.8; $M_2$ = 0.3, $SD$ = 0.95; $M_{>3}$ = 0.9, $SD$ = 0.44; $X^2(3)$ = 12.21, $p$ = .007, Kruskal–Wallis One-way ANOVA, 95% CI [−1, 1]).

*B1.3. My teacher will be disappointed with me if I do not join the study*. ($M_0$ = 0.84, $SD$ = 0.44; $M_1$ = 0.91, $SD$ = 0.29; $M_2$ = 0.6, $SD$ = 0.52; $M_{>3}$ = 0.95, $SD$ = 0.22; $X^2(3)$ = 8.72, $p$ = .033, Kruskal–Wallis One-way ANOVA, 95% CI [−1, 1]).

*B2.5. My data that are collected in the study will not be shared with anyone outside of the research team*. ($M_0$ = −0.11, $SD$ = 0.92; $M_1$ = −0.47, $SD$ = 0.83; $M_2$ = 0.1, $SD$ = 0.99; $M_{>3}$ = −0.52, $SD$ = 0.81; $X^2(3)$ = 8.98, $p$ = .03, Kruskal–Wallis One-way ANOVA, 95% CI [−1, 1]).

# Appendix B - About self-reported data

Papers presented in Appendix B concern self-reported data and a tool used for self-report of moods called ClassMood app. This type of self-reported data has the potential to complement the data collected with MMLA systems in collaborative learning space research and provide further understanding of the obtained findings. Two papers are featured in this appendix:

- ‘ClassMood app: a classroom orchestration tool for identifying and influencing student moods’ - introduction to the ClassMood app for self-reporting student moods.
- ‘The challenge of gathering self-reported moods: Cases using a classroom orchestration tool’ - reports on the challenges of students’ individual understandings of moods.

## B.1. ClassMood app: a classroom orchestration tool for identifying and influencing student moods

The first paper in the Appendix was presented at the European Conference on Technology Enhanced Learning.

| |
|---|
| Beardsley, M., Vujovic, M., Portero-Tresserra, M., & Hernández-Leo, D. (2019, September). ClassMood app: a classroom orchestration tool for identifying and influencing student moods. In *European Conference on Technology Enhanced Learning* (pp. 723-726). Springer, Cham. |

# Class Mood App: a classroom orchestration tool for identifying and influencing student moods

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**Abstract.** Certain affective states are less conducive to learning than others. Moreover, results from studies suggest that a classroom's social-emotional climate affects student motivation and performance; and that moods can be automatically transferred among individuals in a group. The Class Mood App is an online classroom orchestration tool for social emotional learning that identifies the aggregate mood of a class and suggests classroom activities for educators to help shift the class mood to one that is more conducive to learning. Suggested activities are categorized based on how they aim to impact students' internal state of arousal. The application aims to facilitate learner and educator development of self-awareness and self-management competencies consistent with the CASEL framework for systemic social and emotional learning. Preliminary results, conducted as part of an iterative designed-based research process, suggest that the tool is perceived as being easy-to-use for both educators and undergraduate students.

**Keywords:** Learning Design, Learning Analytics, Orchestration Tool, Social Emotional Learning, Self-regulated learning, Mindfulness

## 1 Pedagogical background

Studies about the relationship between affective states and student performance suggest that certain physiological states or moods are less conducive to learning than others [1][2]. Study results also suggest that the emotional climate of a class affects student motivation, conduct, and performance [3][4]; and that moods can be automatically transferred among individuals in a group [5]. A classroom emotional climate can be described as "the extent to which teachers promote positive emotions and make students feel comfortable" [3]. Further, investigations have found that immediate interventions such as mindful breathing are able to induce a change in the affective state of individuals, specifically in reducing test anxiety and in increasing positive automatic thoughts [6].

Arguments to better support student social-emotional learning (SEL) in formal education have been put forth [7][8] and interventions supporting the social-emotional learning of students have been found to positively impact student wellbeing and their academic outcomes [9][10]. Weissberg et al., 2015 propose a framework, the CASEL framework for systemic social and emotional learning, to help educators identify the core SEL competencies to prioritize. The Class Mood App has been conceptualized to facilitate learner and educator development of two of the prioritized competencies: self-awareness and self-management.

Therefore, it is important for teachers to consider the classroom emotional climate when orchestrating the activities proposed to their students, both to reach the best possible emotional conditions for their students to learn and to facilitate the development of the related competencies. The concept of classroom orchestration refers to “how a teacher manages, in real time, multi-layered activities in a multi-constraints context” [11]. Several orchestrations tools have been proposed in the literature to support teachers in classroom real-time management considering the the specific needs and constraints of a given context. However, these tools have focused on cognitive and social aspects [12] and there is a lack in addressing the emotional facet. The Class Mood App aims to fill this gap.

## • Technological Background

The Class Mood App is a standalone, web-based, social and emotional learning orchestration tool that provides teachers with real-time data that identifies the aggregate mood of a class and suggests classroom activities to help teachers guide learners to moods that are more conducive to learning. The application is compatible with mobile, tablet and laptop devices. Students insert a unique code and are prompted to select their current mood from a graphical interface that plots a selection of moods. The U-shaped graphical interface is based on an interpretation of the affective circumplex model [13][14] (see Fig. 1). After selecting their current state, students have the opportunity to submit a comment to notify the teacher of the cause of their mood. Student data and comments are collected anonymously.


**Fig. 1.** Screenshots of the Class Mood App (https://classmood.upf.edu/). (a) Student mood selection interface & (b) Teacher dashboard displaying an aggregate class mood.

Teachers start by creating a mood measuring event. The creation of the event results in teachers receiving a code to share with their students. As students enter their mood selections, teachers can monitor the submissions in the teacher’s dashboard. The learning analytics are displayed with differing levels of granularity (see Fig. 1). The first level categorizes the mood of the class based on aggregated categories of valence (e.g. happy or sad) and arousal (e.g. awake or sleepy). The second level presents a count of students per mood – to provide a more detailed mood mapping of the class. The final level displays the individual comments entered by students to explain their moods. The dashboard data is updated every 8 seconds. When ready, teachers can generate an activity suggestion from the dashboard. Suggested activities are categorized based on how they aim to impact students' internal states of arousal (see Table 1). The aggregate mood is calculated based on the ratio of happy-to-sad and awake-to-sleepy ratings with greater weight given to low arousal ratings. Activities are evidence-based or have been contributed by collaborating educators.

**Table 1.**Categories of suggested activities to impact student moods.

| Category | Arousal | Sample Activity Names |
|---|---|---|
| Energize | Increase | Mindful walking |
| Calm | Decrease | Progressive muscular relaxation [15] |

## • Use case, preliminary results and future work

As part of an iterative designed-based research process, the Class Mood App was presented to individual educators to elicit feedback and was tested in an undergraduate university class. In the class, the application was used to gauge the mood of the class and suggest an activity for the teacher to run for students as a warm-up activity prior to a regular lesson. Preliminary results suggest that the tool is perceived as being useful and easy-to-use for educators and undergraduate students. Future work is needed to validate and expand the offering of suggested activities, to refine the interface for younger students, and to facilitate teacher-adoption of the tool with formative training.

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## B.2. The challenge of gathering self-reported moods: Cases using a classroom orchestration tool

The second paper presented in this Appendix B was presented at the 20th International Conference on Advanced Learning Technologies (ICALT).

Beardsley, M., Vujovic, M., Theophilou, E., Hernández-Leo, D., & Tresserra, M. P. (2020, July). The challenge of gathering self-reported moods: Cases using a classroom orchestration tool. In *2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT)* (pp. 355-359). IEEE.

# The challenge of gathering self-reported moods: Cases using a classroom orchestration tool

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***Abstract*—Self-reports of affective states are increasingly being collected in educational settings. However, individual definitions and usage of emotion and mood terms are often subjective despite objective definitions becoming more widely accepted. We explore whether the variation among individual learners in how mood terms are defined presents an obstacle to using self-reported mood data for group comparison studies. Following a design-based research methodology, we ran two case studies to explore the use of ClassMood App in a multimodal learning study and the validity of the self-reported mood data it collected. During the first case, 24 primary school students experienced difficulty understanding the words used to describe the moods in ClassMood App. In the second case, involving 77 university students, we explored whether the misunderstanding of mood words persisted with older students. Participants were asked to rate their familiarity with and match definitions to a set of 8 mood words. We found that levels of familiarity with the mood words varied greatly and 17.9% of all definition matching attempts were incorrect. The results suggest that the variation in subjective definitions of mood terms is likely to affect the validity of the data collected by the ClassMood App for group comparison studies.**

***Keywords-Emotion measurement, data validation, social and emotional learning, user interface design, orchestration tool***

## I. Introduction

Instruments that incorporate self-reports of affective states are increasingly being used in educational settings [1, 2]. The self-report data collected can potentially be used to assess the effectiveness of educational interventions [3]. However, individual definitions and usage of emotion and mood terms are often subjective despite objective definitions becoming more widely accepted [4]. A difference in how mood terms are defined and applied may affect the validity of self-report mood data when used for group comparison studies – and such studies are commonplace when assessing educational interventions.

Validated self-report instruments for measuring affective states in educational settings include the Medical Emotion Scale (MES) [1] and Achievement Emotion Questionnaire (AEQ) [2]. MES presents participants with words representing affective states and asks them to rate the intensity of the state. AEQ presents statements that include words representing affective states and asks participants to rate their level of agreement with the statements. The words representing affective states are consistent with the circumplex model of affect [5]. It is becoming more widely accepted that objective mood definitions can be represented in the circumplex model of affect. The x-axis of the model is the continuum between emotions considered pleasant and unpleasant, like happiness and sadness respectively. The y-axis is the continuum between high and low levels of arousal. Each of these emotional categories tend to correlate with specific physiological changes in the body [6] and specific neural structures and pathways [7, 8]. In this context, measures of affective state that are independent of individual perception, such as physiological measures, pattern recognition or brain states, are often found to be more accurate and objective than self-reported states [9]. Thus, the variation among individuals in how emotions are defined and applied can affect the validity of self-reported mood data. For example, if my definition of sad is intense while yours is placid, then it is difficult to state that we are referring to the same mood. Nevertheless, self-reports of emotion are useful to the extent that they relate to an individual's perception of their currently experienced emotions [10] and can contribute to better self-regulated behavior [11].

The importance of improving self-regulated behaviors of learners is evidenced by results of interventions focused on developing students' social and emotional skills in school education settings. Such interventions have resulted in lasting positive effects on student "skills, positive attitudes, prosocial behavior, and academic performanceS [12]. To help teachers integrate social and emotional learning (SEL) activities into their classes, we developed an online, classroom orchestration tool called the ClassMood App [13]. The objective of the ClassMood App is to provide teachers with a tool that can scaffold student development of self-regulatory practices over time. The application focuses on supporting learner development of self-awareness and self-management competencies. These competencies have been identified as priorities in the framework for systemic social and emotional learning proposed by the Collaborative to Advance Social and

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Emotional Learning (CASEL) [14]. Developing these competencies involve improving learner proficiency at recognizing one's emotional state, labelling it accurately (i.e. selecting an appropriate word to describe it), and being able to influence it with self-regulatory practices [15]. These competencies have been selected as understanding emotions strongly relates to wellbeing and academic performance. MacCann et al. (2020) [16] write, "knowledge about the causes and consequences of emotions and a vocabulary of emotions words, along with knowing how to manage emotional situations are potentially the most important parts of Emotional Intelligence for academic performance.S In short, the ClassMood App anonymously collects students' self-reported moods via a U-shaped graphical interface. As self-reported moods are collected, the tool determines an aggregate class mood and suggests a classroom activity to the teacher in order to influence the mood of the class. Most of the suggested activities model evidence-based self-regulatory practices such as mindful breathing and have been shown to induce changes in the affective states of individuals [17].

Beyond use within the tool to generate an aggregate class mood, the data collected by the ClassMood App is envisioned to be used to assess the effects of the 'mood-changing' activities (i.e. self-regulatory activities) suggested by the tool; as an impact measure for intervention programs such as the Spotlighters project (http://spotlighters.eu) that of which the tool is an output of; and as a source of data for multimodal learning research. Moreover, identifiable data could be collected and used in the future to track changes to student moods over time. This richer data could more accurately measure the effectiveness of the learning activities and interventions based on student profiles; and possibly be used as multimodal training data (e.g. combined with physiological measures, auditory and visual modalities) for emotion recognition systems. For these purposes the validity of the data is crucial. Previous studies have validated the use of self-report instruments for measuring affective states in educational settings [1, 2]. Yet these studies did not test participant understanding of the words used to describe the affective states. Our study, which is framed within a design-based research iterative cycle focused on improving interface designs for gathering self-reported moods, provides an investigation into whether the variation among individual learners in how mood terms are defined presents an obstacle to using the self-reported mood data collected by the ClassMood App for group comparison studies. In the section that follows, we present two case studies interceded by a description of the iterative improvements made to the ClassMood App interface.

## II. Approach

As the goal of the ClassMood App is to make it applicable to multiple educational contexts from primary school to higher education; and available in multiple languages, we follow a multiple case study approach [18]. The cases are framed in a design-based research methodology [19], which allows iterative feedback cycles of developing and testing

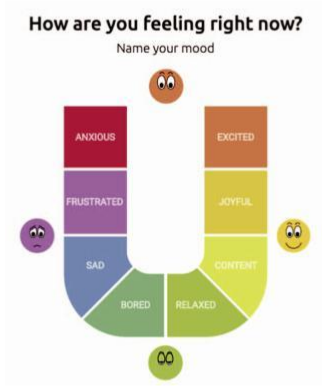


Figure 1. The ClassMood Mood Measure Interface.

increasingly satisfying solutions to problems. As part of this approach, we report two case studies and focus our analyses on the ClassMood mood measure interface that is used to collect the self-reported moods of participants (see Fig. 1).

The main purpose of the mood measure interface is to collect actionable data for the educator rather than accurately represent the spectrum of moods a student may be experiencing in class. In other words, the goal is to have students pick a positive or negative valence and high or low arousal mood rather than a neutral mood to better facilitate an activity suggestion.

Consequently, the initial design of the interface is limited to 8 moods to limit the choices presented to students (see Fig. 1). The U-shaped graphical interface combines concepts of the Yerkes-Dodson Law [20, 21] and affective circumplex model

7. The affective circumplex model has been used to inform other instruments and applications that incorporate self-report mood interfaces [1, 2, 22]. The final selection of mood words was made by collaborating neuroscientists who selected the words that most accurately represented their placement on the U-shaped interface. Further, the words were translated into Catalan by a neuroscientist to match the local context in which the studies were to be run. Finally, the colors used in the interface were derived from research that suggests the link between emotions and colors is rooted in biology [23].

### A. Case 1: Elementary School Students

In the first case, four separate groups of six school children (*n* = 24; 4 male and 20 female; Ages 6 to 9) participated in an observational study exploring the collection and interpretation of multimodal learning data. The study, conducted in Catalan, involved the collection of physiological data (e.g. galvanic skin response); video, audio and motion capture recordings; qualitative data from researcher and instructor observations; and ClassMood data. The ClassMood data was mainly being explored for its suitability as a before-and-after measure for detecting the effects of the mood changing activities being considered for integration into the tool.

During the first case, the young participants experienced difficulty in understanding the mood measure interface the first time they were asked to use the tool. Specifically, they were unfamiliar with some of the words used to describe the moods and required an explanation of what the words meant.

Documented comments by observers (i.e. researchers and instructors) can be summarized as follows: students found the interface to be easy to use but found it challenging to understand the words used to define some expressions, especially AnsiNs (Anxious) and Frustrat (Frustrated). Further, the words Alegre (Joyful) and Entusiasmat (Excited) were too similar to be distinguishable.

### *B. Updates to the ClassMood Mood Measure Interface*

After the first case study experience, efforts were made to improve the mood measure interface. The selected mood words were revised in an attempt to better facilitate the capturing of the category of the mood or core affect [24] rather than trying to accurately capture a more narrow and specific mood. To facilitate the capturing of core affect, the graphical interface design changed from a U-shape representation to a grid structure (Fig. 2) with the x-axis representing valence and y-axis representing arousal. Half of the moods are of positive valence and half of negative valence. Further, half of the moods are positive arousal (i.e. high energy moods) and half are negative arousal (i.e. low energy moods). The selected words feature antonyms along the x-axis to make it easier to distinguish the moods and to better provide a context for understanding the definitions of the mood words.

### *C. Case 2: First-Year Undergraduate Students*

In the second case study, we set out to explore whether the problem of understanding mood words persisted with university students. To do so we conducted a survey study involving first-year undergraduate students (*n* = 77; 21 female and 56 male) at a university in Barcelona, Spain. Participants were presented Catalan translations of the updated mood words in an online survey form and asked to rate their level of familiarity with the words; and then match definitions to them. Participants were able to select multiple definitions for each word. The definitions were derived from theories on Core Affect [21]. The evaluation of the definition responses was based on Table I. The table presents the exact match for a word and definition; and the close matches. The close matches are the words that have similar but not identical definitions. The words that do not appear as exact or close matches were deemed to be incorrect. A 5-point Likert scale was used to collect ratings of familiarity.


Figure 2. A proposed update to the ClassMood mood measure interface

TABLE I. MATCHES OF MOOD DEFINITIONS WITH MOOD TERMS

| Definition | Exact Match | Close Match |
|---|---|---|
| Having lots of energy with unpleasant feelings. | Agitated | Upset |
| Having lots of energy with pleasant feelings | Excited | Happy |
| Having energy with unpleasant feelings. | Upset | Agitated, Sad |
| Having energy with pleasant feelings. | Happy | Excited, Content |
| Having little energy with unpleasant feelings | Sad | Upset, Tired |
| Having little energy with pleasant feelings | Content | Happy, Sleepy |
| Having no energy with unpleasant feelings. | Tired | Sad, Sleepy |
| Having no energy with pleasant feelings. | Sleepy | Content,Sad, Tired |

## III. RESULTS

Upon completing the study, it was determined that 'contingut' was a mistranslation of the English word 'content' and the subsequent analysis is of the remaining 7 words.

### *A. Analyses of words*

To assess the familiarity of each mood word, we calculated the average rating per word and, also, determined the number of participants that selected 4 or 5 on the 5-point familiarity scale. The results are shown in Table II. The average rate of familiarity across all words was 72.3% and ranged from a low of 44.2% for Agitat (Agitated) to a high of 93.5% for Cansat (Tired).

To assess how well the mood words were defined, we determined whether the matching definitions selected by participants were exact or incorrect matches (see Table I). For the exact match analysis, we assigned 1 point for each correct match. For instances in which participants had a correct match but had selected multiple definitions for a single mood, their 1 point was divided by the number of responses given (e.g. 1 correct and 2 incorrect answers resulted in a score of 0.33). The results are presented in Table II and show that across the 7 mood words, an exact match of the word to its definition occurred in 51.37% of the responses with the highest rate of exact matches being 74.7% for Emocionat (Excited) and lowest being 31.9% for Cansat (Tired). To determine the incorrect matches, 1 point was assigned for exact or close matches (see Table I) and 0 points for the remaining answers deemed to be incorrect. Overall 18.9% of responses were incorrect with the highest rates of incorrect answers occurring in words representing unpleasant states (e.g. Trist, Agitat, Cansat).

### *B. Analyses of participants*

The scoring approach described above was maintained for the per participant analyses. The rates of familiarity by participant can be found in Table III and range from a low of being familiar with 1 out of 7 mood words (1.3% of participants) to a high of being familiar with all 7 mood words (31.2% of participants).

TABLE II. PER WORD FAMLIARITY RATINGS

| Word | Familiarity | | Correctness | |
|---|---|---|---|---|
| *Catalan (English)* | *Average Rating* | *Familiar with* | *Exact match* | *Incorrect* |
| Agitat (Agitated) | 3.21 | 44.2% | 51.9% | 34.6% |
| Emocionat (Excited) | 3.94 | 74.0% | 75.3% | 7.8% |
| Molest (Upset) | 3.66 | 58.4% | 53.0% | 12.0% |
| Content (Happy) | 4.22 | 85.7% | 60.5% | 13.6% |
| Trist (Sad) | 3.66 | 62.3% | 41.7% | 19.0% |
| Contingut (Content) | 3.18 | 37.7% | 25.3% | 66.3% |
| Cansat (Tired) | 4.38 | 93.5% | 30.3% | 23.6% |
| Adormit (Sleepy) | 4.30 | 88.3% | 41.4% | 14.9% |
| *Average(ignoring Contingut) | 3.91 | 72.3% | 50.6% | 17.9% |

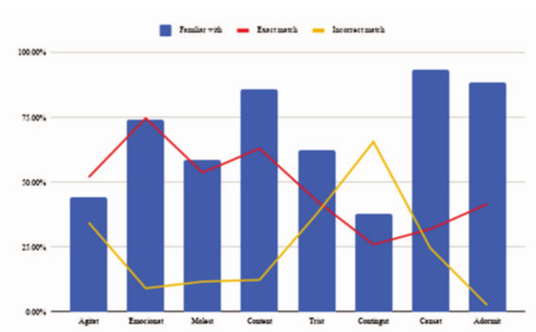


Figure 3. Ratings per word by familiarity and correctness

Further, 40 (52%) of participants rated being familiar or highly familiar with at least 6 of the 7 words; while 21 (27.3%) rated being familiar or highly familiar with less than half of the words. The average across all participants was a rating of being familiar or highly familiar with 3.9 of the 7 words.

Seven participants (9.1%) were able to exactly match all words to their definitions; 23 (29.9%) matched at least 6 words; while 41 (53.2%) matched less than half of the words with their exact definitions. The average across participants was exactly matching 3.6 of the 7 words with their definitions. In looking at the rate of incorrect answers given, 17 (22.1%) gave no incorrect answers; 66 (85.7%) gave two or fewer incorrect answers; while 5 (6.5%) gave 4 or more incorrect answers. The average across participants was a rate of 1.3 incorrect definition matches out of 7 possibilities.

### C. Familiarity and Correctness

A Spearman's rank-order correlation was run to determine the relationship between familiarity ratings and exact matching definitions ($r$ (75) = -.32, $p$ = .48) and incorrect definitions ($r$
9. = -.04, $p$ =.94). No significant correlations were found (see Fig. 3).

## I. DISCUSSION

In relation to whether the variation among individual learners in how mood terms are defined presents an obstacle to using the self-reported mood data collected by the ClassMood App for group comparison studies, we looked at how familiar participants were with the mood words selected for the interface; how well they could match the words with objective definitions; and how many incorrect matches participants made. Incorrect matches were determined in such a manner that an incorrect match would involve the selection of a definition that was outside of the range of a correct answer and was clearly incorrect. The study found that 60 (77.9%) participants produced at least 1 incorrect answer, and 17.9% of all responses given were incorrect. Additionally, the accuracy of the data collected seemed to depend largely on the specific mood word. The rate of incorrect answers ranged from a high of 34.6% for Agitat (Agitated) and a low of 7.8% for Emocionat (Exciting). Overall, the rate of errors would affect the usefulness in terms of accuracy and comparability of the data collected. Further, on average, participants rated being familiar or highly familiar with only 3.9 out of 7 words; and 28 participants (36.4%) were familiar with 4 or fewer words. Low ratings of familiarity suggest that we did not select or translate words correctly. For example, Contingut (Content) was mistranslated and resulted in the majority of participants (66.3%) incorrectly defining the word. In general, the results suggest that the problem of misunderstanding words to describe affective states, brought to light in the first case study with elementary school children, persisted with university students. Also, there was a wide range in the rate of incorrect responses given among participants from a high of 5 out of 7 (2 participants) to a low of 0 (17 participants). This suggests that there may not be a straightforward solution and supports the notion that there is a need to improve student understanding and recognition of affective states (i.e. self-awareness).

TABLE III. AGGREGATION OF PARTICIPANT FAMILIARITY RATINGS AND DEFINITION SCORES

| Word count | Familiarity | Exact Matches | Incorrect |
|---|---|---|---|
| 7 | 31.17% | 9.09% | 0.00% |
| 6 | 20.78% | 5.19% | 0.00% |
| 5 | 11.69% | 15.58% | 2.60% |
| 4 | 9.09% | 16.88% | 3.90% |
| 3 | 15.58% | 22.08% | 7.79% |
| 2 | 10.39% | 19.48% | 22.08% |
| 1 | 1.30% | 9.09% | 41.56% |
| 0 | 0.00% | 2.60% | 22.08% |

### A. Limitations

The main limitation of the study is its generalizability. The study was conducted in Catalan. The participants in the survey study were first-year university students in an engineering degree program. It is important to explore whether similar results emerge in studies conducted in other languages and contexts. Furthermore, the low levels of familiarity of participants in the second case study with some of the translated words suggest that a couple of the words were poorly selected. Improvements could include changing the words being evaluated from Contingut (Content) to Satisfet; Content (Happy) to Alegre; and Agitat (Agitated) to NerviNs or Inquiet.

## II. Conclusion

We explored the possibility of using the student self-report mood data collected by the ClassMood App for multimodal learning research. The application could serve as both a practical tool for educators and as a validated instrument for research. The results of our exploratory study suggest that the variation in subjective definitions of mood words by participants is likely to affect the validity of the data collected by the ClassMood tool. For example, if one participant defines a mood word much differently than another, then it cannot be assumed that these participants are referring to the same construct. Further work is needed to improve the accuracy of the self-reported moods collected via the ClassMood App.

## III. Future Work

As instruments that incorporate self-reporting of affective states are increasingly being used in educational settings, there is a need to operationalize the variation in how words are used to describe affective states in such instruments and explore approaches that allow self-reported states to be calibrated to the individual to facilitate more accurate comparisons within and between groups. Further, it would be beneficial to explore factors that may influence the discrepancy in defining affective states such as language, demographics and context. Efforts to improve the validity of the self-report mood data collected via the ClassMood App could be pursued through complementary research and student training related to self-awareness (i.e. recognition and labelling of affective states); interface design; or even through the creation of an application that can facilitate the assessment and comparison of items used for self-reported mood interfaces be they words, emoticons, or colors.

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