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Where Are You? Exploring Micro-Location in Indoor Learning Environments

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ABSTRACT Classroom teaching methodologies are gradually changing from masterclasses to active learning practices, and peer collaboration emerges as an essential skill to be developed. However, there are several challenges in evaluating collaborative activities more objectively, as well as to generate valuable information to teachers and appropriate feedback to students about their learning processes. In this context, multimodal learning analytics facilitate the evaluation of complex skills using data from multiple data sources. In this work, we propose the use of beacons to collect geolocation data from students who carry out collaborative tasks that involve movement and interactions through space. Furthermore, we suggest new ways to analyze, visualize, and interpret the data obtained. As a first practical approach, we carried out an exploratory, collaborative activity with sixteen undergraduate students working in a library, with bookshelves and work tables monitored by beacons. From the analysis of student movement dynamics, three types of well-differentiated student roles were identified: the *collectors*, those who go out to collect data from the bookshelves, *ambassadors*, those who communicate with other groups, and the *secretaries*, those who stay at their work desk to shape the requested essay. We believe these findings are valuable feedback for the enhancement of the learning activity and the first step towards MMLA-driven Teaching Process Improvement method.

INDEX TERMS Beacon, collaborative learning, geolocation device, multimodal learning analytics.

I. INTRODUCTION

The exponential growth of technology has driven the creation of new and innovative forms of information management. In education, integrating technologies to improve the quality of learning represents a growing challenge. In fact, different technological tools are being developed for this purpose [1], [2]. The use of devices in the classroom provides quantitative information to teachers about how the teaching-learning process is being developed [3]. One of the main challenges in education is the development of essential skills, such as communication, collaboration, and knowledge in information and communication technologies (ICT) [4].

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Moreover, collaborative learning is one mechanism used to assess the development of these types of skills in students [5].

Multimodal learning analytics (MMLA) is a set of techniques that can be used to collect data from multiple sources in high frequency (video, logs, audio, biosensors, gestures), synchronize and code the data, and examine learning in realistic, ecologically valid, social, mixed-media learning environments [6]. Furthermore, MMLA seeks to quantify what was not quantifiable before and understand people’s behavior from the measurement of specific skills. MMLA techniques have recently been used to evaluate the collaboration of individuals in learning environments [3], [7], in programming tasks [8] and in the training of agile practices [1], [9].

According to Worsley [3], one of the MMLA techniques that has been less explored and developed is micro-location. Micro-location [10] refers to the use of sensors to locate the

position of objects or individuals in an indoor environment. Beacons are low-cost, proximity detection devices. Although it is an emergent technology, there are several applications currently in the market, but also broad possibilities to explore creative ways of use, such as micro-location in educational settings. Although the micro-location works are quite recent, they have already shown progress in educational aspects such as interactive applications among students or with the teacher [8], [11]–[13].

In the literature, it is possible to identify interesting alternative proposals to carry out people's location in indoor environments. Some authors [14], [15] use WiFi to determine the position of an individual, while Nakamori *et al.* [16] perform the internal location using radio-frequency identification (RFID). There are also proposals that combine multiple positioning technologies to improve location accuracy when the moves are indoors and outdoors [17], [18]. In addition, GPS is not considered here since it is not suitable for indoor environments [19]. Despite the above, none of these technologies have yet been successfully used in learning environments. Beacons have several comparative advantages over the previous technologies used for indoor location [20], [21], especially in learning environments prepared to promote collaborative learning. Accordingly, beacons technologies use Bluetooth low energy (BLE), a version of the Bluetooth protocol designed to use much less energy and send more compact information [22]. The wide use of mobile devices compatible with this technology facilitates its implementation while the low energy consumption of the beacons provides high availability guarantees for micro-locations. Thus, integrating micro-location technologies with MMLA techniques can help obtain new data from students and their interactions in collaborative environments, information that the teacher today cannot quantify and evaluate. The analysis of these new data will allow observing the development of the teaching-learning processes from a different perspective, and also to explore the development of professional skills [23].

In this article, we propose different ways to analyze and visualize data obtained through beacons in collaborative learning environments. As a first exploratory approach, we carried out a collaborative activity developed by 16 undergraduate students from the second year of Computer Engineering at the University of Valparaíso, Chile. Students were organized in groups of three to five people. The activity consisted of each group writing an essay on social networks, moving through the shelves of the Library of the Faculty of Engineering of the University to find the information they need. The data generated by the students' movements were collected by seven beacons located in the library and by a mobile application on each student's cell phone. Through this case study, we were able to identify three well-differentiated student roles: the *collectors*, those who go out to collect data from the bookshelves; *ambassadors*, those who communicate with other groups; and the *secretaries*, those who stay at their work desk to shape the requested essay.

The article continues as follows. In Section II, we present related work regarding the use of geolocation devices for collaborative learning in closed spaces. In Sections III–IV we present the problem description, followed by the developed solution. After that, Sections V–VI explain our case study, followed by the analysis, visualizations and results. We finish in Section VII, by presenting our main conclusions and future work.

II. RELATED WORK

In accordance with the above, MMLA deals with data gathered from non-traditional sources through different sensors and systems, which can be collected from different and diverse learning settings (e.g. individual, collaborative, formal, informal, professional) and may consist of a myriad types and combinations, such as: facial expressions [24], gestures [25], movements [2], talking [9], vision [26] and heartbeats [27], among others [28]. Furthermore, professional competencies are the ultimate way of applying knowledge and skills at workplace environments, normally involving collaborative activities. The availability of a whole new generation of sensors allows the experimentation of a wide range of complex situations such as those involving collaboration and location. Therefore, MMLA offers a unique opportunity in such contexts as it provides ways of quantitatively observing and analyzing behavior and attitudes that, until very recently, were not possible to dissect [9].

According to Worsley [3], GPS/Bluetooth technologies are one of the least explored in investigations involving group-working so far. Micro-location sensors are a specific kind of devices that can pinpoint specific indoor/outdoor placements with higher precision than a GPS, but with limitations of covering only a small area. Indoor location [29] refers to tracking objects/persons in an indoor environment and determining/estimating its location according to a specific dimension (e.g. 2-dimensions, 3-dimensions). In terms of MMLA, indoor location is related to knowing the exact position of a given stakeholder (student, teacher) or object of interest (table, bookshelf) in the context of a given learning setting. Its importance lies on the fact that, in many cases, the development of certain skills is determined or influenced by the interactions of the stakeholders with the environment surrounding them [30].

Micro-location has already been used in marketplaces to offer products and promotions to customers accordingly to their proximity in the outlet and to target specific audiences (“Micro-Location Technology Market”), and Beacons have already been used in the literature to track location and duration of indoor spots visited by users [31]. However, the application of micro-location in educational settings is still incipient. A recent review [32] shows only 33 studies exploring the use of Bluetooth Beacon in teaching and learning physical spaces. The majority of those studies are focused on location-based dissemination of educational information (15), while others on the use of beacons for monitoring (7) and implementation of smart services in

the campus. This is most likely due to the many difficulties to deal with multimodal data in ubiquitous learning settings, such as: the heterogeneity of the data sources, the dynamism and emergence of the location of the activities, the need for contextualized analysis, and the need for integrating and synchronizing different pieces of evidence [33]. Moreover, dealing with data collected from students devices also poses ethical dilemmas related to privacy, surveillance, and the avoidance of information misuse [34]. Despite all these challenges, a number of works found in the related literature use micro-location and physical spaces in learning settings.

Beacons have been applied to enable automatic class check-ins in higher education by Huang *et al.* [35]. The authors developed a mobile app that records students attendance when connected to the beacons located in the classroom.

Martinez-Maldonado *et al.* [36] present three prototypes for physical Learning Analytics tasks. The first is focused on the proximity analysis of the teacher while attending small groups in a classroom session. The resulting data could be used to uncover patterns of teachers' attention (through position and expended time) to the distinct groups and to assess how teachers' feedback impacted students' learning. Another prototype was focused on providing feedback to dance students during their practice. Accordingly, sensors were used to track dancers' movements and detect if they were dancing according to the beats of the music. The third prototype was a system of location sensors to improving workgroup strategies in healthcare. While nursery students executed a given set of procedures, a reflection tool provided individual feedback to team members after completing the exercise.

Wake *et al.* [37], developed a tool called FireTracker using a set of Bluetooth Low Energy (BLE) beacons on a cell phone to collect location data of firefighters during smoke diver training. Even though beacons' precision was considered inaccurate (due to the smoke), the system was considered as an important tool by instructors who claimed visualizations could serve as a good starting point for discussions with trainees. The idea is to further investigate the use of more techniques to identify patterns of good and bad movement (including places and moments they stopped) during a fire and that can be used to warn instructors and firefighters.

Moreover, the work of Griffiths *et al.* [32] described the use of Bluetooth beacons to create an intelligent campus at the Hong Kong Polytechnic University. In order to improve learning in physical spaces, location sensors were used to foster students meeting during their free time, to determine the position of hands up in classrooms, to check students' presence, and disseminate exercises. According to the authors, the application reduced academic staff workload and the consumption of paper, and students reported they felt their physical participation could be increased by the tool.

Besides existing tools and applications, one can also find in the literature other proposals and ideas for learning scenarios where micro-location could be applied. This is the case, for instance, of Chan *et al.* [38] who intend to improve

intellectual capabilities of students with intellectual disabilities using sensors inside the school building and offering an application that provides context-aware services to them. Among other functions, the proposed application could display a limited set of symbols that might be relevant to the communication context of the user (e.g. a picture of a glass of water to communicate feeling thirsty when user is inside the cafeteria). Moreover, Wong *et al.* [39] ventures a language learning scenario for elderly by providing a more realistic context and location-aware situation for learners. In their proposed framework, iBeacons are used to invoke not-running applications in learners mobile and provide context-location aware content and learning materials to the learners. Serrano-Iglesias *et al.* [40] presents a learning scenario where students need to find and differentiate specific trees in groups in the school yard. Beacons would be placed near the targeted trees and help to generate reports about students' location and level of noise. The system would also gather data about students' performance and correlate them with their current context.

While some of the works mentioned here are focused on the location-based dissemination of materials, or are quite interesting but still incipient proposals (or ideas) for monitoring students and teachers, our work introduces a real experiment that focuses on the intersection of monitoring groups of students and the physical materials they use to solve problems and the discovering of patterns of these interactions in indoor environments. To the best of our knowledge, this is the first study involving different groups of students and their physical interaction with materials in indoor environments using micro-location devices. The following sections will provide an in-depth description of the problem of exploring micro-location in learning environments, and the developed solution by using beacon devices.

III. PROBLEM DESCRIPTION

Engineering education involves continuous advancement in professional development. Therefore, prospective professionals must be prepared to be able to tackle the challenges that will arise in a changing and demanding work environment. This generates the need to implement new teaching methodologies and models that allow students to face problems and unlock their full potential. In recent years, different initiatives have been carried out to define a conceptual and working framework on the skills necessary to develop in Engineering careers taught around the world [41], [42]: currently, most careers have redesigned their curricula, moving from one based on objectives to a new model based on skills [43]. In a skills-based model, students are evaluated according to the domain acquired in their skills and/or learning outcomes. Therefore, the learning rate is much more personalized and can be greatly accelerated in the development of the required skills.

Despite the pedagogical innovations made in higher education, there is still a gap between the skills developed by graduate students and the demands of the Information,

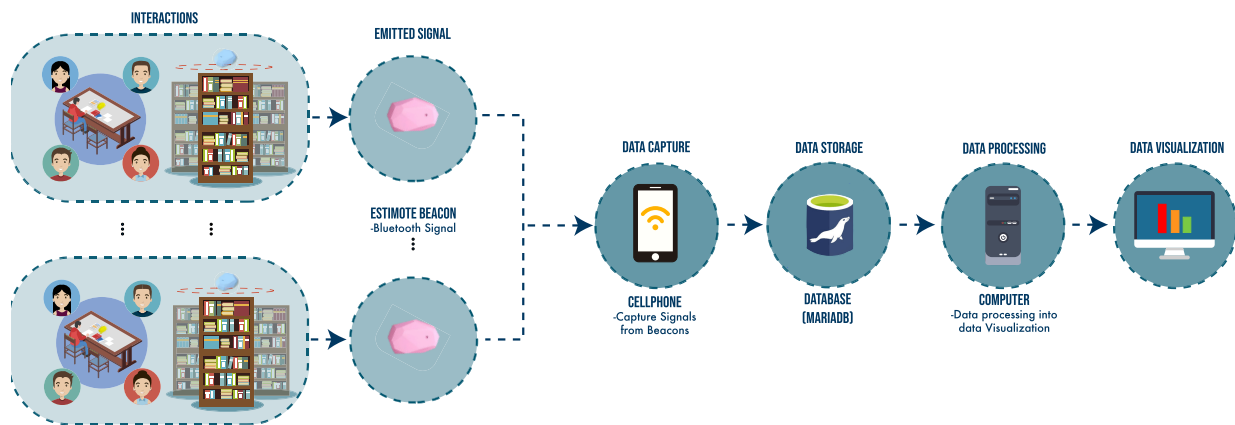


FIGURE 1. Scheme of the developed solution for the collection and analysis of micro-location data using beacon devices.

Communication, and Technology Industry [44]–[46]. Without the right tools, it is impossible for a teacher to fulfill their role as a learning guide as established by the new skills-based model.

The main challenge that currently exists in the development of 21st century skills is having the appropriate technological tools that allow for good measurement and feedback. Accordingly, it is necessary to equip the professor with technological tools capable of helping to have a greater vision in collaborative learning environments. In this context, the micro-location technique appears as a good alternative for the measurement and observation of student behavior and interactions in educational environments. Therefore, the aim of this research is to explore the potential benefits of micro-localization to monitor the behavior of students in a learning environment. In order to fulfill this objective, a case study was carried out in Section V to record the displacements and permanence times of students on work tables and bookshelves, while they carried out a group activity in the library of the Faculty of Engineering of the University of Valparaíso.

IV. DEVELOPED SOLUTION

For the sake of addressing this problem, a framework is proposed for the collection, storage, processing and visualization of geolocation data in closed environments using beacons devices. This framework is related to the one proposed by Riquelme *et al.* [47] for speech measurement using ReSpeaker devices. The system is supported by an application with two main components: a mobile application, that captures the data emitted by Estimote beacons¹ (via Bluetooth), and a web application, where the data captured are processed. Figure 1 illustrates a scheme of the proposed environment.

A. TECHNICAL ENVIRONMENT

The mobile application is used by people who are performing a collaborative learning task (in this case, students).

¹<https://estimote.com/>

The application associates a unique identifier to each user. Through the application, each student's cell phone can capture the data transmitted by nearby beacons via Bluetooth. In this way, the time of entry and exit of the area covered by each beacon can be recorded. The web application processes the data for later viewing. The generated visualizations are shown later in Section VI. The difference in the exit time and the entry time results in the total time spent by one actor in the beacon's vicinity. The data is stored in a database, from where it can be collected in comma separated values (CSV). For data processing, we use Python 2.7, with Plotly libraries for the generation of diagrams and heat maps. This application is based on a three-layer client-server system, on the application developed by Estimote, that allows to notify the entry and exit of the users from the beacon's area. The components of the system are the following:

- Logic Component: Deliver notifications to the user using the Notify Manager Component
- Notify Manager Component: Control of notifications of the signals emitted by beacons, picked up by Bluetooth from the users' mobile devices
- View Component: Architecture presentation; it shows the view for mobile application users
- Retrofit Component: Retrofit makes the HTTP connection of GET, POST, UPDATE type with the express component to send the data to the registry.
- Express Component: Framework that manages HTTP communication from the Retrofit component; it establishes settings for the web application as a connection port
- Controller Component: Responding to user events and invoking requests to the model component on information request
- Model Component: Management of all information access and control of access privileges to the mobile application
- Sequelize Component: Allows the manipulation of the database, converting the tables' data into object-oriented entities, speeding up data access

B. DATA ANALYSIS TECHNIQUES

The following parameters were used for data consolidation:

- User id: identifier of each user involved in the activity
- Beacon id: identifier of each beacon used in the activity
- Entry time: entry time of some user in a beacon
- Exit time: exit time of some user from a beacon
- Interaction: an entrance of some user in a beacon
- time in beacon (tib) per user: total time (sum of all Exit time - Entry time) spent by some user near some beacon
- tib per group: total time spent by all the actors of a group near the beacons

V. CASE STUDY

As a case study, we present an information search activity in a library to carry out a collaborative learning activity in undergraduate students.

Second-year students of the Computer Engineering degree from the University of Valparaíso, Chile, who were taking the Discrete Mathematics course, were invited to participate in the activity. In total, 16 students were enrolled, divided into four groups between three and five members, which were placed in tables deployed in the Library of the Faculty of Engineering. The students were volunteers, grouped by interest or affinity, to examine the collaborative work of study groups that regularly worked together. Note that this is an exploratory study. Therefore, it does not attempt to find causal relationships concerning the learning or training processes, but rather to carry out a proof of concept over a small sample of students, in order to verify the collection, analysis, and data visualization processes.

The primary aim of this case study is to use beacons as a valid type of device for the collection, analysis, and visualization of geolocation data in collaborative learning environments. Considering the library's low usage statistics by the students, we chose this location to foster a free and non-traditional collaborative workflow, away from the classroom. The goal for each group was to find out information related to graph theory and Social Network Analysis. These topics were unknown by the students, which guaranteed that they were in relatively equal conditions in terms of knowledge, and that they should require the search of bibliography to complete the task. The activity was focused on the collaborative work. All groups had the same time limit to prepare an essay about graphs and social networks of maximum two pages. The essay should cover the following requirements:

- 1) Define what a graph and social network is.
- 2) Explain the relationship between social networks and graph theory.
- 3) Provide two examples of social networks together with its corresponding graph representation.

The students were able to use only the books from the library as information resources to prepare the essay. Since Social Network Analysis is an interdisciplinary discipline, with applications in different areas, the third requirement for the essay pursued the need for students to search the different

shelves of the library, and not only those related to computer science.

In addition, students were requested to install a mobile application on their cell phones to allow data collection on their positions around the beacons, and to keep their cell phones in a pocket throughout the activity.

In order to geolocate student movements, seven beacons were considered: three located on the shelves and four on the different work tables. Figure 2 illustrates the library distribution. Shelf beacons are denoted as B-S x , with $x = \{1, 2, 3\}$, and table beacons are denoted as B-T y , with $y = \{1, 2, 3, 4\}$. Red circles represent the range of each beacon.

The time distribution of the activity is presented in Figure 3. The research team prepared the beacons in the first 10 minutes. Subsequently, 15 minutes were spent to organize the groups, and another 15 to deliver the materials, followed by five minutes to give the instructions. The collaborative activity of the students (data collection) lasted 70 minutes in total.

We focus our analysis on the search for characteristic interactions, using the previous beacon configuration. We believe that monitoring the collaborative learning activity would be successful if we could detect the following:

- 1) Students interacting at their respective work tables: it was expected to detect that the students were at their work tables most of the time together with their other groupmates (B-T y in Figure 2).
- 2) Students interacting with the shelves: it was expected to detect that at least one student per group interacted at least once with one of the shelves (B-S x in Figure 2).
- 3) As Computer Science books are placed in B-S2, it was expected to detect at least one interaction of any member of each group with bookshelf B-S2.
- 4) Students interacting with other groups: as inter group interactions are not prohibited, we expected to see students interacting with others from other work tables.

VI. ANALYSIS AND RESULTS

For each student, we measured the tib per user for each work table zone (B-T1 to B-T4) and shelves (B-S1 to B-S3), and recorded the time each interaction tracked. Next, we present our analysis of the four relevant interactions defined in Section V.

Collected data for tib per user is shown in the heat map of Figure 4, summarizing the minutes spent by each subject in each of the detection zones. Based on this information, Figure 5 shows how the total measured time of each detection zone is distributed among the detected subjects: for instance, for B-S1 we measured a total of 21 minutes of interaction, and the subject that spent the most time in that detection zone was the student 7, with a 53% of the total time of interaction. Furthermore, Figure 6 shows the timeline of subject interactions per group. With these results, we analyzed the tracking of each of the relevant interactions.

- *Students interacting at their respective work tables.*
As shown in Figures 6 and 4, we were able to track

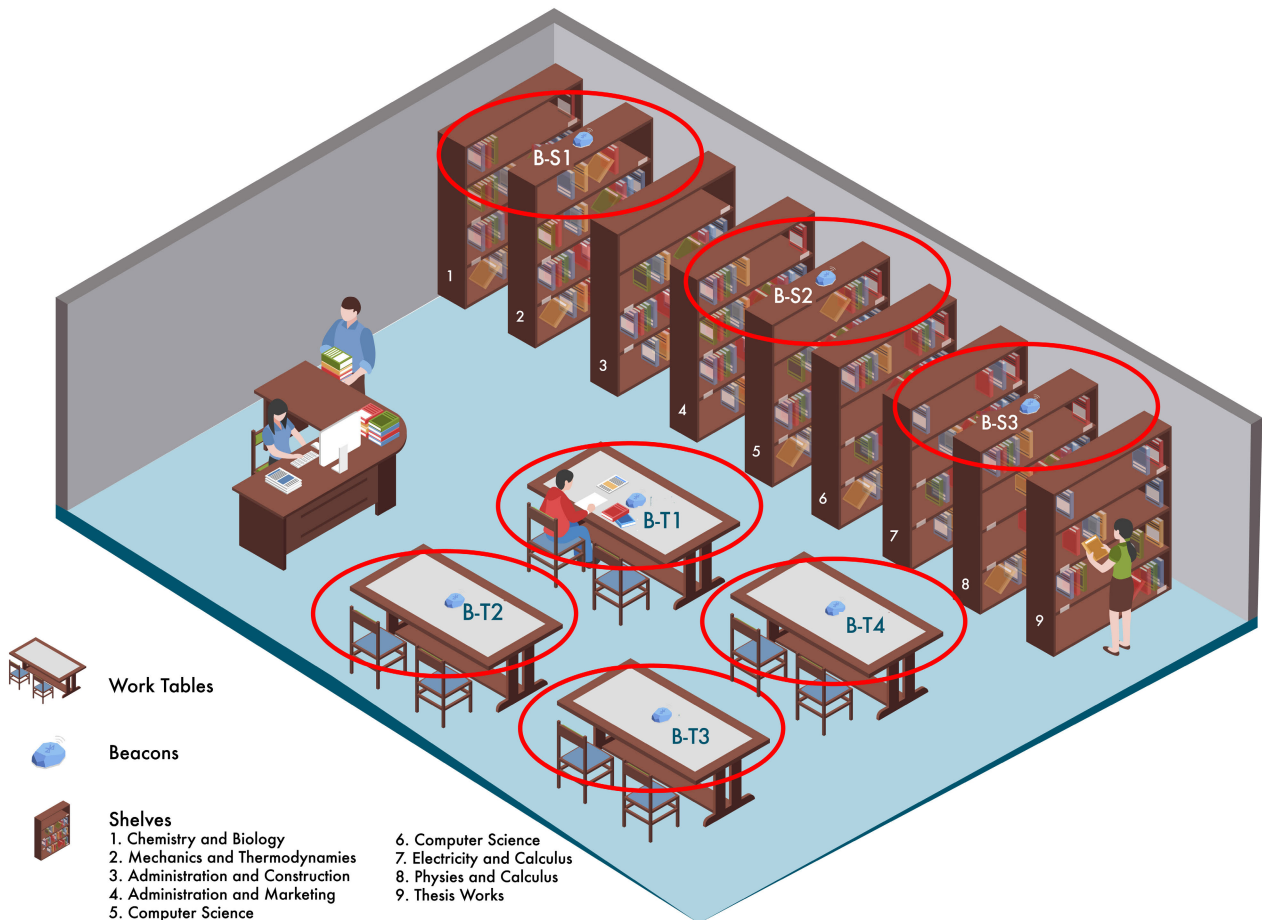


FIGURE 2. Distribution of work tables and shelves in the library, along with the location of the beacons.



FIGURE 3. Activity time distribution.

most of the students in their work space spending most of the time in that zone. Regarding Group 1, we note that all of the five members spent time on their work table B-T1. In Group 2, we see two students working on their table (B-T2) and moving out to the library, and the others (Id8) sharing mostly with Group 3. In Group 3, three of the four subjects were tracked mainly working on their work table (B-T3), although the remaining (Id12) appears to be working mainly with Group 1 (B-T1) and in the shelves as well. Finally, two subjects of Group 4 seemed to work on their corresponding table, while the Id13-subject seemed to collaborate

	Group 1					Group 2			Group 3				Group 4				
Id	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Tot
B-S3	0	0	0	1	0	3	4	0	0	0	0	2	2	0	4	0	16
B-S2	0	0	0	0	0	0	0	0	0	0	0	0	0	40	3	0	43
B-S1	0	0	0	0	0	7	11	0	0	0	0	3	0	0	0	0	21
B-T4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	47	90
B-T3	0	0	0	0	0	0	0	31	8	25	44	0	0	0	10	0	118
B-T2	0	0	0	0	0	27	17	0	0	0	0	0	0	0	2	0	46
B-T1	71	15	70	16	53	0	0	0	0	0	0	60	14	0	0	0	299
Tot	71	15	70	17	53	37	32	31	8	25	44	65	16	40	62	47	

FIGURE 4. Heatmap of tib per user, in minutes. Note: Subject interactions adding less than a minute in a beacon zone are not considered.

with Group 1 (B-T1) and id14-subject mostly in the shelves area. As a conclusion, we were able to track most of the subjects working on their respective workspace. We named as *secretaries* the students that stayed for most of the activity in their own work tables, such as Id1, Id3, Id5, and Id12.

- *Students interacting with the shelves:* Figure 4 shows that at least one student of each group visited the bookshelves, but no group went with all its members to the

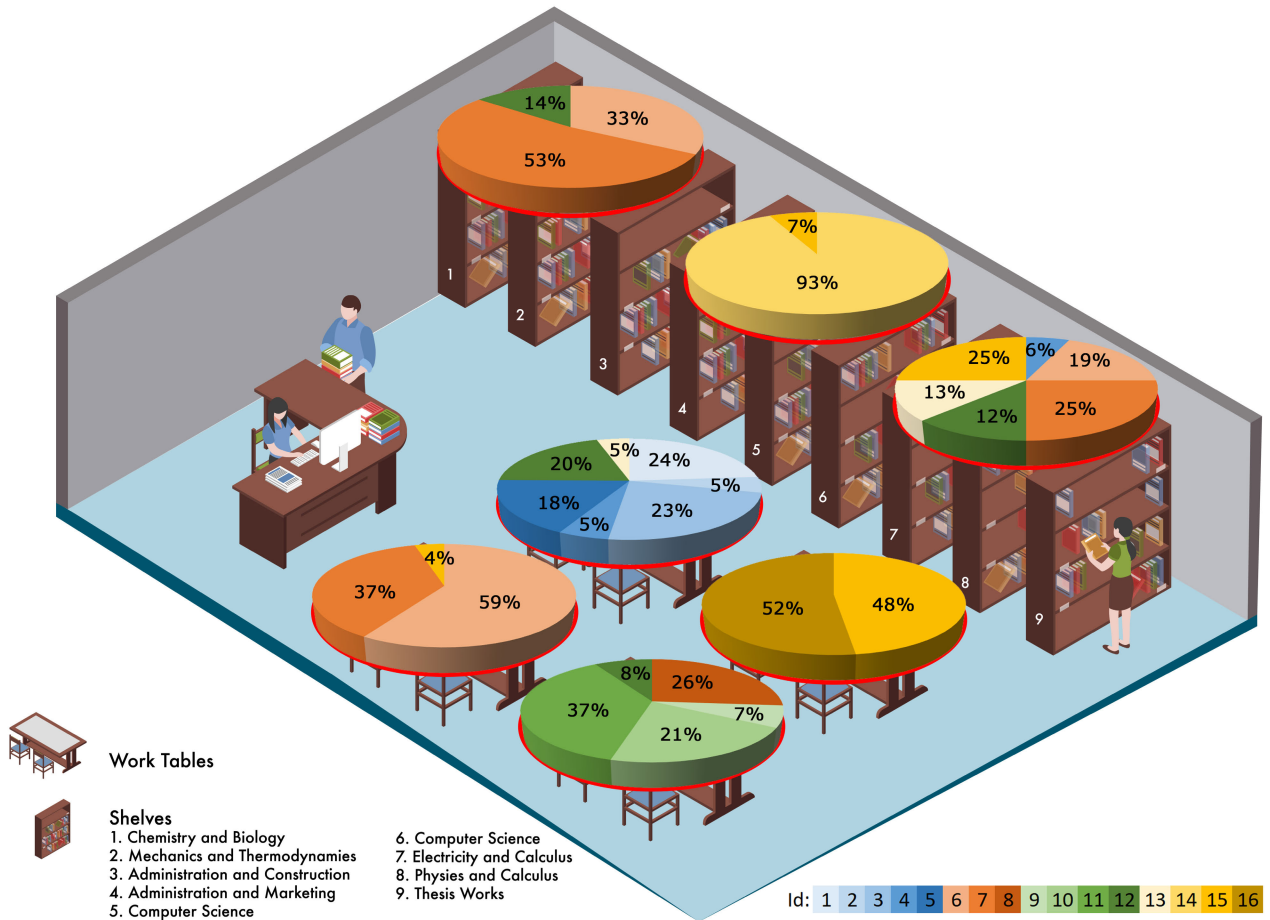


FIGURE 5. Percentage of time contributed by each student to the total time of interaction measured for each detection zone.

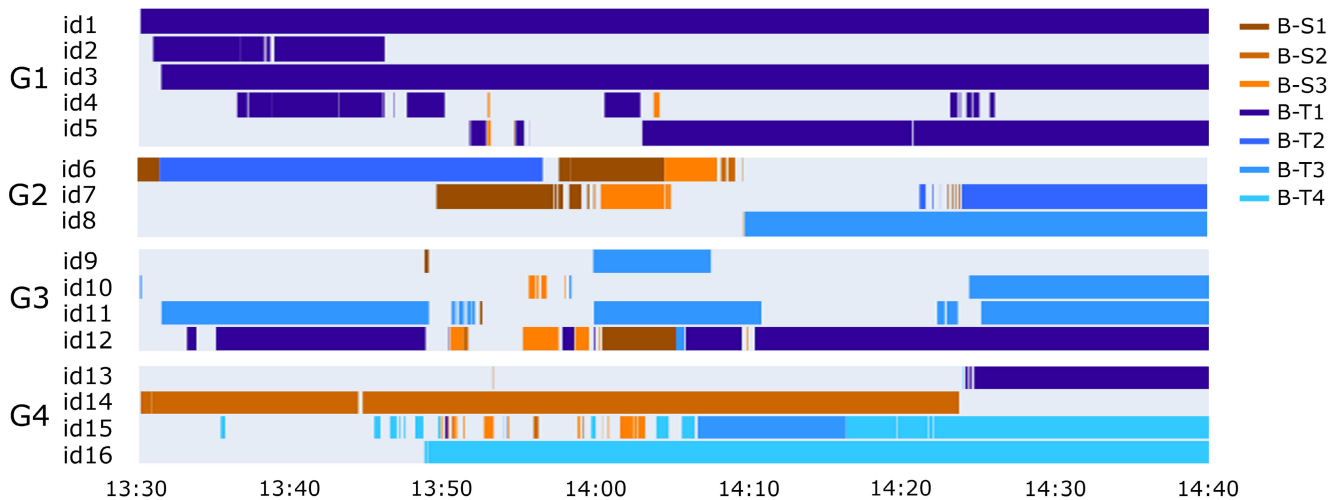


FIGURE 6. Timeline of interactions for each group.

books zone. We named the subjects that collected data from the shelves as *collectors*. Groups 2 and 4 used the shelves the most, while Group 1 was there for a very

short time (note that, since Figure 4 only shows the interactions lasting at least 1 minute, it is only counted one of the Id4-subject interactions registered in Figure 6).

- *Students interacting with the “right” shelf*: we hypothesized that B-S2 could be the most used shelf to support the definitions required in the essay. However, we tracked and observed little interactions with this shelf, with the exception of Group 4. This could be explained by a more intensive use of books in the zones B-S1 and B-S3 to look for examples of social networks in science and management areas. Considering that Id14-subject spent a lot of time in B-S2 zone, we looked for effects in the essays produced by the groups. The evaluation of the essays was conducted by the teacher, in a traditional way, considering coverage of the requirements and compliance to the essay structure. The results did not provide any insight into quality differences between the work products.
- *Students interacting with other groups*: As Figure 4 shows, all of the groups, except by Group 1, interacted with other groups. These interactions were concentrated in one of the subjects of each group, that we named *ambassadors* (Id8-subject for Group 2, Id12-subject for Group 3, and Id13-subject for Group 4).

During the activity, some technical and setup issues yielded to some ambiguity in the tracking. For instance, most of the subjects had timeline periods with no tracked activity. This could be associated to transit spaces between the beacons zones. Therefore, a more fine-grained beacons array could help us to detect these issues. In addition, we observed some intermittences in the detection of students who remained in the same area for several minutes. We associated this behavior to technical issues, such as intermittence in the WiFi connection. Other lessons learned are: protecting and hiding beacons to avoid involuntary movements, checking the setup of the mobile devices to ensure that Bluetooth is enabled and no battery-safe configuration is activated, and ensuring a stable WiFi connection.

Regarding the educational aspects, the roles that naturally emerged in the teams during the activity were explicitly shown by the sensors. This is a central contribution of MMLA to the improvement of teaching methods: the teacher could improve the design of the learning activity by introducing roles with specific responsibilities and tasks that could be facilitated and evaluated during the execution of the activity. In this improved design, the teacher could use the sensors to support each student’s compliance with the defined role.

VII. CONCLUSION AND FUTURE WORK

Multimodal data seeks a comprehensive view on how students are developing their learning process [48]. We believe that the incorporation of micro-location as an MMLA technique for the analysis of student behavior in learning environments will deliver promising results in the short term. As there is little scientific evidence in this area, our work is considered as a good starting point to recognize the limitations and difficulties to take into account in the use of this type of technology.

This research allowed us to explore the potential benefits of integrating new technologies with MMLA to monitor and evaluate soft skills. Through the application of the proposed framework, it was possible to record the individual and group movements of students during an academic activity. For the development of this research, it was necessary to implement two applications: a mobile application that captured the data issued by Estimote beacons and a web application that allowed to process the captured data and visualize it from a well-defined tip metric and the timestamped tracking of interactions. The performance of both applications during the experience was satisfactory.

One of the main difficulties encountered is the configuration of the capture range of the beacons and their location in space. On the one hand, students should be detected when they are within the required space (shelves or work tables, in this case), even if this means not being very close to the beacon. On the other hand, the signals of the beacons should not intersect, so that the same student appears registered as in two places at the same time. Additionally, the best way to transport the cell phone throughout the experiment must still be explored. The most natural thing would be to assume that the cell phone will always be at pocket level. In addition, it should be ensured that the application is not affected by incoming calls or other events of a cell phone connected to the Internet.

In our research, the beacons allowed us to perform an analysis of student collaborative behavior in a learning environment based on the recorded displacements. For the analysis and interpretation of the results, different strategies used by the work teams were identified. Moreover, it was possible to recognize three student roles: the *collectors*, in charge of collecting data; the *secretaries*, who shaped and wrote the essay on their work tables; and the *ambassadors*, who interacted with other work tables. This finding is a valuable feedback for enhancing the learning activity.

After this first exploratory study, we are aware of the need to continue deepening our approach, both in technology issues and in the assembly of quantitative feedback along with the improvement of the learning process. Regarding technology issues, future work will be centered in solving detection issues and enhancing data analysis applications to get a real time overview of the dynamics of the activity. For the learning process feedback, we aim for an empirical comparison of the presented learning activity and a role-guided improvement, based on the three roles that the study revealed, as a first step towards a MMLA-driven Teaching Process Improvement method.

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