Multilevel analysis of collaborative activities based on a Mobile Learning Scenario for real classrooms

Irene-Angelica Chounta[1], Adam Giemza[2], H. Ulrich Hoppe[2]

[1] HCI Group, University of Patras, Greece
houren@upatras.gr
[2] Collide, University of Duisburg-Essen, Germany
{giemza, hoppe}@collide.info

Abstract. This paper describes the analysis of collaborative mobile learning activities. We explore the use of learning analytics for the evaluation of the performance of students as individuals and the performance of teams. We argue that traditional metrics used for learning analytics can provide insight with respect to the quality of the activity and the learning outcome. We propose a way to integrate innovative mobile learning scenarios into traditional classrooms and to analyze collaborative learning activities on both the group and the individual level.

Keywords: learning analytics•group activity•mobile learning•collaboration

1 Introduction

During the past years, the idea of mobile phones as small computers empowering students to learn at any time and any place has been implemented in many educational scenarios. The variety of mobile learning scenarios ranges from applications inside the classroom, e.g., collaborative problem solving [1] and discussion tools [2], applications for field trips, e.g., language learning applications in the field [3] and data collecting applications [4, 5], or workplace learning scenarios [6] and educational (serious) games [7]. Mobile devices have a central role in these mobile learning activities.

Even though the use of mobile scenarios for learning activities is widely studied, the analysis of such activities is usually carried out through qualitative methods making it a tiresome and time consuming task [8, 9]. The analysis becomes more complicated when the mobile scenario aims to support collaborative activities. In order to support the task of analysis, researchers propose the use of learning analytics into a mobile learning context [10]. The advantage of mobile devices for learning analytics in comparison to classical desktop systems is that can they provide more information about the context of the user and his learning situation through the device's sensors.

It is argued that "*the term learning analytics is currently mobilized within a multidisciplinary community of researchers*" [11], thus offering new possibilities and setting new research goals and questions. In this paper we explore the use of a mobile learning scenario for assembling computers in a traditional school classroom. The

adfa, p. 1, 2011.

scenario is designed for computer science classes and teaches the functionality of a computer by relating the theoretical concepts to real-world technology with hands-on experience. The students are guided through a scenario using the Mobilogue app on a smartphone. The scenario involves scanning QR codes attached to computer parts, reading background information, watching instructional videos and assembling the computer step by step. For the analysis of the activity we use learning analytics that derive from the activity logfiles and transcripts of the activity recorded by experts. The learning outcome was evaluated by knowledge tests and questionnaires were used to evaluate students' experience.

2 Related Work

User data is a valuable source of information for the analysis of collaborative activities in the fields of CSCL and CSCW. Researchers use data-driven, bottom up approaches to define metrics of user activity. These metrics are usually studied for potential correlations to the quality of collaboration or to the quality of the outcome. The number of messages exchanged in a dialogue or the average number of words per message are typical metrics for the assessment of collaborative practice [12, 13]. For the case of shared workspaces, the use of metrics that represent the symmetry of user activity is common to evaluate coordination [14, 15]. Depending on the learning context, activity metrics may vary. Metrics deriving from graph theory, such as density, have been proposed to assess collaboration quality [16] while metrics of spatial proximity have been proposed for scenarios such like jigsaw puzzles or algorithmic flowcharts [18]. Significant part of the literature is dedicated to the use of time-related metrics such as total duration of an activity, time gaps or time proximity [17, 18, 19]. Apart from the evaluation of typical collaborative learning scenarios, activity metrics have been proposed to support communities of practice [20] or to analyze the activity of users involved in location-based games [21, 22]. Mobile learning, in particular, constitutes a suitable field for the adaptation of data analysis methods deriving from multidisciplinary fields such as CSCL and EDM [10].

A combination of assembling a computer with mobile support has been presented in [23]. The focus of this work was to link user created (tutorial) videos with environmental objects and to provide the combined information for others as video support upon scanning tagged objects. This system was evaluated with students who were assigned four different computer assembly tasks. The tasks involved the creation of videos linked with the RFID marked objects. The result provided content to a second group of learners that had to fulfill the same tasks with support through the LORAMS system, which served the user created videos. In contrast to that, our scenario focuses on the guided support of the assembly task and the consumption of learning content. The guidance follows a strict path through the task and instructs the learner part by part. The relevant information and video instructions are provided based on the QR-code attached to the computer part. Additionally, students can capture videos and images of their activities using the Mobilogue app. However, these artifacts are not incorporated into the scenario directly, but can be later reused for reporting on the field trip and follow-up activities with the teacher. Hsu et al. [24] propose a situated multimedia ubiquitous learning (SMUL) system that applies mobile devices in a computer assembly learning activity. The system supports learners by providing information for the assembly task by scanning RFID (radio frequency identification) tags on the computer hardware components. The study shows that the context-aware ubiquitous learning approach achieved better learning effects compared to conventional approaches. Our study also aims to demonstrate the flexibility of the Mobilogue framework as a general tool to design, set up and orchestrate station-based learning scenarios with mobile support used for the Computer Kit scenario. Instead of RFID tags, Mobilogue produces QR codes for identifying learning stations, in this case computer parts that are cheap and easy to create for schools and learners. Furthermore the application does not demand specialized hardware (like NFC or RFID readers in smartphones) but only relies on a camera, which allows students to user their own devices.

3 Mobilogue Computer Kit

3.1 The scenario “Computer Kit”

Technology is more and more in the focus of everyday life with the rapidly increasing use of digital devices like smartphones, tablets, computers and gaming consoles. While their usage becomes very natural, resulting in an implicit awareness of technology, the knowledge about its basic functionality often does not matter. However, the knowledge of computer architecture and the curiosity about technology are very important as STEM education becomes a crucial issue [25] all over the world. Especially computer science is very important for future generations with the high impact of technology in all areas nowadays.

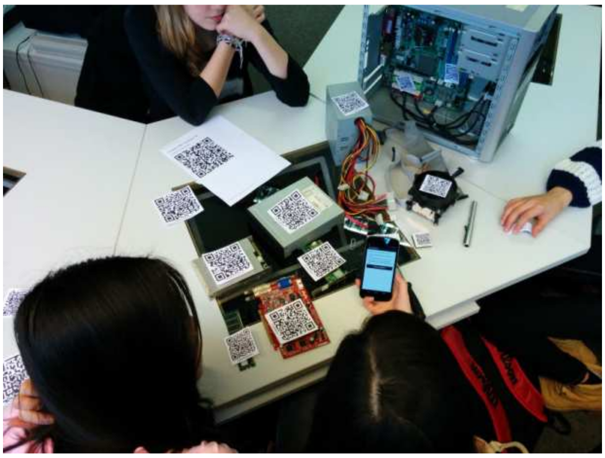

Fig. 1. Initial setting of the Computer Kit scenario

The curriculum for high school level students in Germany includes teaching the structure and functioning of a computer (i.e., Von Neumann architecture). In order to support teachers to communicate this fundamental topic, we designed a scenario using our Mobilogue framework [26]. The scenario teaches hands-on the theoretical concepts in combination with real-world technology. Students use a smartphone as a guide for assembling a computer while they receive background information about the computer parts, their functionality and video-based support on how to install them. Fig.1 shows the initial setting of the Computer Kit scenario. The students are equipped with a smartphone running the Mobilogue app and all computer hardware components with accompanied by QR codes. Fig. 4a shows the Mobilogue Android app with an information page about the computer mainboard. Students walk through the scenario step by step until they have fully assembled the computer and start it up to check their success.

3.2 The Mobilogue Framework

Mobilogue [26] is a flexible tool for authoring and conducting mobile learning field trip scenarios. It maps the concept of field trips onto guided tours across multiple (physical) locations supported by a mobile device. Its basic pedagogical underpinning is learning at stations (or learning circles). The learning takes place at stations, i.e. specific locations, by providing content related to the place or an object at that place and additional stimuli to foster interaction and curiosity by challenging the learner with a quiz. Locations can be spatially distributed around an area or – like in the Computer Kit case – simply represented by physical objects. These locations can also be interpreted as stations of a tour in a certain order. Mobilogue guides the learner across the different stations of the tour, i.e., the learning scenario.

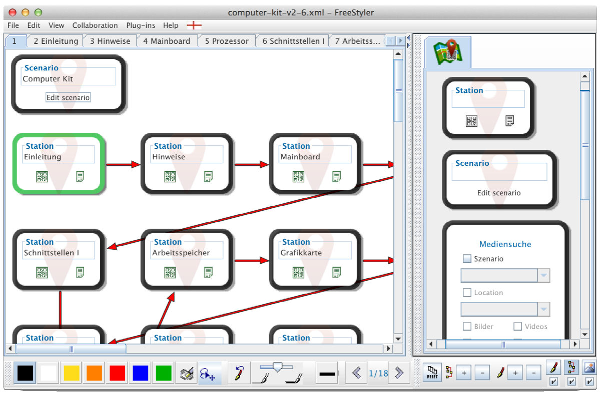

Fig. 2. Graph-based Mobilogue authoring environment with Computer Kit scenario

Mobilogue consists of four elements: the authoring environment to create mobile guidance scenarios, the backend containing the repository for storage and exchange as well as the action logging service to store user activity logs, the mobile application for running the authored scenarios and finally the Mobilogue portal for management and supervision (Fig. 3). The authoring environment enables teachers as well as students to create field trip scenarios without the need to learn a complex authoring tool or to care about the technological background. The basic concept of the authoring environment is related to consuming (multimedia) content in different locations in a certain (guided) order. The authoring tool (Fig. 2) allows to create such locations and to organize them in a certain sequence as the guided field trip for the learner through different locations. The authoring workflow is implemented as a plug-in of the graph-based modeling environment FreeStyler [27]. The modeled workflow graph is later interpreted as the route along the scenario on the mobile devices.

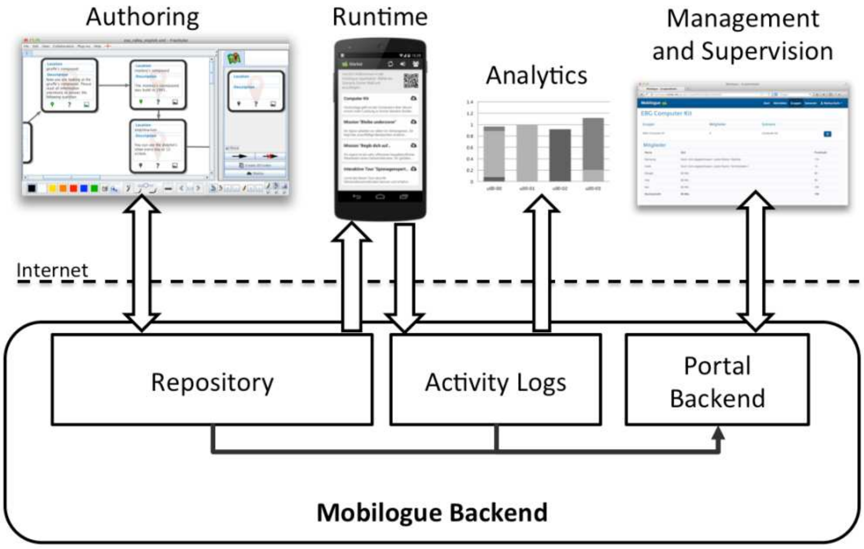

Fig. 3. Mobilogue architecture overview

The Mobilogue backend includes the repository as the mediator between the authoring environment and the Mobilogue app. The authoring environment publishes scenarios to the repository and makes them thereby available to the mobile application. The Android application on the other hand retrieves scenarios via a web service from the repository and stores them in the local database on the phone for offline access. All user activities are logged on the mobile devices and locally persisted in case of no Internet access. In the case of connectivity to the Mobilogue backend, it sends all user logs to the activity log service. The log service provides web services for storing and retrieving action logs in JSON Activity Streams format[1]. We will present later how we use this web service for extracting the relevant log data. The last part of the backend is the portal backend component. It servers the Mobilogue portal

[1] JSON Activity Streams format specification 1.0 - http://activitystrea.ms/ (last visited: April 2014)

where scenario authors can manage their uploaded scenarios, teachers or tutors can create and organize groups for classroom runs and finally users can review their Mobilogue runs. We will not further describe this component as it is not subject to this study.

The Mobilogue app acts as the runtime for Mobilogue scenarios. Scenarios are retrieved from the repository and run by the native Android application. The app renders the scenario as information pages with images and text (Fig. 4a), as multiple choice or free text quiz, provides awareness about the performance and progress of the user (Fig. 4c) and also plays multimedia data like video (Fig. 4b), sound and HTML-based content packages.

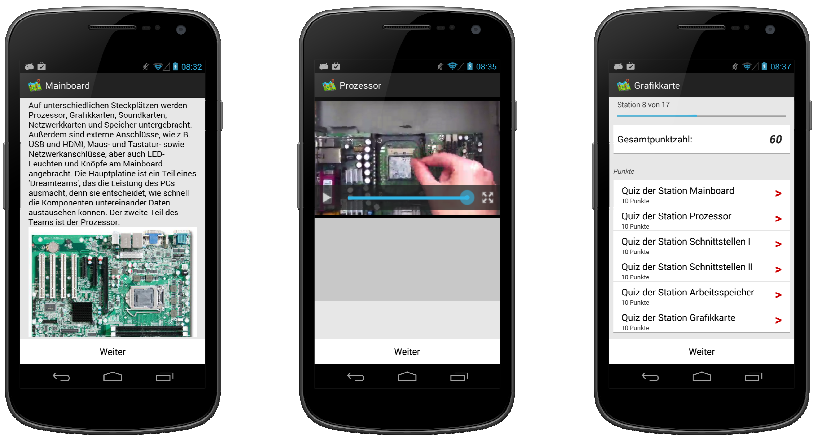

Fig. 4. Mobilogue app with (a) information screen about mainboards (b) instructional video how to install a CPU (c) progress review screen

The app uses the built-in camera to scan QR codes and to decode the identifier of the learning station. The scanned station is queried from the locally cached scenario and the appropriate information is presented. During a scenario run, the user performs multiple activities: starting a scenario run, scanning a (valid) code, visiting an information page, answering a quiz, watching a video, etc. When the user finishes the scenario, he/she also finishes the run. All the user actions are logged to the activity logs service in JSON Activity Streams format.

The following extract exemplifies the format: It contains the date of occurrence (*published*), the *actor* of the activity (in Mobilogue an anonymized run id), the *verb* describing the activity (in this case a visit of the *object*, i.e., a location identified through the id). Based on this information, we can identify all actions of a user through the persistent run id (throughout one scenario run). The detailed information of the location can be queried from the scenario document based on the logged location id.

```
{
  "published" : ISODate("2014-02-27T07:22:38.373Z"),
  "actor" : {
    "id" : "ac86989c-2ca6-408a-b86a-694873f1c79b",
    "objectType" : "run"
  },
  "verb" : "visit",
  "object" : {
    "id" : "05ae5db61e83b761:7aa20533:13f38bfb685:-7fbb",
    "objectType" : "location"
  }
}
```

A complete scenario run produces a sequence of activity objects, the activity stream. The action logs service allows querying such a stream for single runs, for a certain scenario, for a certain timeframe, etc. Consequently, we are able to use these data for the analysis of the activity.

4 Method of the Study

In this paper we analyze the activity of groups of students who work together in order to assemble a PC. The study was carried out in two phases. In the first phase we conducted a preliminary study (Case A). The results were used to improve the study set up and a second study (Case B) followed shortly after.

In both studies each group was supported by one mobile device that walked them through the process according to the Mobilogue scenario “Computer Kit”. We provided each team with one mobile device in order to ensure that the students who formed a team would collaborate and work together towards the common goal. Moreover our aim was to record the strategy of each team with respect to roles’ adaptation and whether this strategy would affect its practice. We argue that members of homogeneous teams (teams that consist of students of similar knowledge background) will get involved in all the stages and roles of the activity. On the other hand, members of heterogeneous teams (i.e. students of different knowledge background who co-exist in the same team) will follow a certain plan with discrete roles and they will stick to that plan throughout the activity.

To that end, each group was given the freedom to plan its practice and make important decisions (e.g. which group member would operate the device, whether they would switch roles in turns, etc). The practice of teams was further studied with respect to the teams’ homogeneity. To analyze the activity, we used the logfiles of the Mobilogue application to extract activity metrics. We argue that these metrics reflect the activity on a group level since the operator of the device does not act on his own, but follows the instructions of the group. Due to the strictly controlled scenario, activity metrics such as total number of QR-code scans or total number of actions cannot be used. Therefore we explore the use of time-related metrics such average time gap among consequent actions (avg_timegap) and average response time to quizzes (avg_resp). The time gap is measured as the time between two “page visits”, i.e., the time between opening an information page and opening the succeeding page in the mobile app. The time gaps differ regarding the content. Some short information texts can be grasped quickly, whereas the tutorial videos take up to 50 seconds. Time is a key factor for collaborative activities [28] and time related metrics have been used to assess collaboration quality. For example, average response time in chat has been found to correlate negatively with collaboration quality [14]. This indicates that groups who collaborate efficiently are faster in their responses. The average time gap among consequent actions is an indication of the rhythm (or speed) of group activity. Groups that coordinate efficiently are expected to work on a faster pace and therefore demonstrate smaller time gaps between consequent actions. The score, as computed from the quizzes of the Mobilogue scenario, was also introduced as a metric of group activity. In Case B, two evaluators were asked to monitor the activity and take notes with respect to students practice (activity transcripts). The transcripts were further used to provide insight into the group dynamics.

In order to measure the learning impact of the application of the Mobilogue scenario, the students were asked to take pre and post knowledge tests. Each test consisted of ten questions relevant to the learning activity. In addition, the students filled in questionnaires regarding their experience. In Case A the questionnaires were used for the evaluation of the Mobilogue application while in Case B we used questionnaires for the evaluation of the collaborative aspect of the activity itself and the students' experience.

5 Results

In the following paragraphs we present the results of the two case studies, Case A and Case B. Overall, the purpose of the study was to explore the use of learning analytics in a mobile learning scenario. Therefore, we analyze the practice of teams with respect to the logfiles of the application that mediated the activity and in combination with the learning outcome, as evaluated by knowledge tests and observations made by experts during the realization of the activity.

5.1 Case study A

The first case study took place during a school computer course. Seventeen (17) students, aged from 13 to 15, participated in total. The students were randomly grouped in five teams. The whole duration of the activity was about one hour and a half. One mobile device was given to each team (Fig. 1). There was no instruction on how to use it (in turns, randomly etc) other than to follow the Mobilogue scenario. The students were advised by the teacher to document their activities for later reflections (Fig. 5a). Fig. 5a gives an impression on how the students followed the tutorial videos in order to assembly the computer part.

The results of the case study are portrayed in Table 1. Regarding the profiles of the teams as assessed by the pretest, the results portray a team with good knowledge of the learning field (team A), both on a group and on an individual level (average group score = 6.25, maximum individual score = 8), a weak team (team E) on group and individual level scores (average group score = 1, maximum individual score = 1) while the rest three teams were of average performance. After the ending of the activity, the students took a posttest. The results show that teams of average performance in the pretest achieved the greatest improvement, both on average as well as on the individual level. The “good” team (team A) maintained the same score on average and scored less on the individual level while the “bad” team (team E) slightly improved but overall its performance was still low. The scores of the knowledge test were also reflected in the quiz score. Team A scored the highest while team E scored the lowest.

The average response time (avg_resp) does not follow a certain pattern with respect to either the score of the quiz or the knowledge tests. On the other hand, the average time gap (avg_timegap) correlates negatively with the quiz score. Teams that have a high quiz score are also faster throughout the activity. This also shows that teams with good pre-knowledge tend to move faster through the activity.

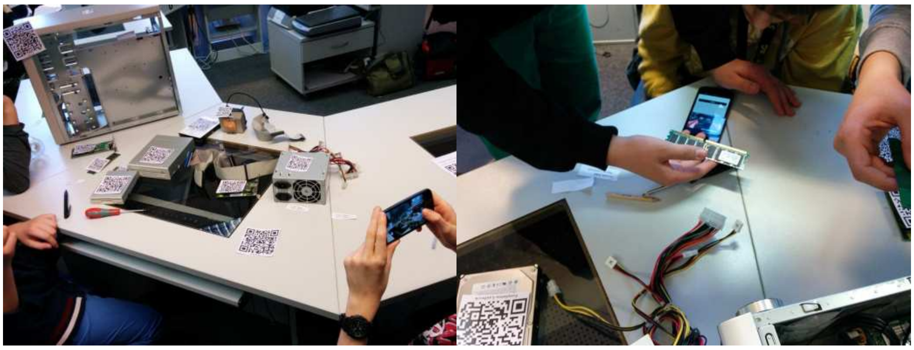

Figure 5: (a) Students taking pictures to document their run (b) students watching video instructions on how to install RAM

Table 1. Case Study A: Results of pre and post knowledge tests and activity metrics as computed from the logfiles of the Mobilogue application

	Pretest Scores		Posttest Scores				
	avg_group	**max_idv**	**avg_group**	**max_idv**	**avg_time gap (sec)**	**avg_resp (sec)**	**Quiz Score**
teamA	6.25	8	6.25	7	27.63	32.02	120
teamB	3.75	5	6.25	8	36.56	56.96	120
teamC	4.33	5	5.67	7	37.14	23.70	100
teamD	2.67	4	6.00	7	37.91	31.55	90
teamE	1.00	1	2.00	3	38.43	57.43	80

In order to measure team homogeneity, we compared the average group score (avg_group) to the maximum individual scores (max_idv) for each team. Team E, for example, scored the lowest score both in the knowledge test on a group and individual level therefore is homogeneous (avg_group – max_idv = 0). Team A, on the other hand, is the most heterogeneous team based on the test results (avg_group – max_idv = 1.75) with the rest of the teams falling in between. We should note that Team A had no knowledge gain according to the tests however, that can be justified since the highest score overall was already achieved by the same team. The comparison of pre and posttest scores shows that strongly heterogeneous teams increase their homogeneity and vice versa, with the exception of the weak team that showed no difference. Heterogeneous teams also portray smaller time gaps i.e. they follow the mobile scenario in a faster pace. This could indicate that in heterogeneous teams, the students who have prior knowledge or experience take the lead. However, in this case study there were no activity records or transcripts and therefore we cannot have a clear picture on group dynamics.

5.2 Case Study B

The original study (case A) was repeated in order to improve the experimental setup and to further validate the results. To that end, we asked from expert evaluators to attend the study and take notes of observations with respect to group dynamics. In particular, the experts were asked to observe the behavior of individuals within teams. In addition, the students were asked to keep notes of the role each individual chose to have within the team, if any, i.e. to operate the device, to take notes, to assemble the device. The learning effect was evaluated by pre and post knowledge tests. The students took those tests individually. Each test consisted of ten questions which were related to the learning objective. Overall, 24 students (13-15 years old) participated in the study. The students attended a computer school course and the teacher of the class gave a lecture prior to the study to ensure that all students would have the necessary background. The students were grouped into six teams of four. The grouping was done by the teacher with respect to the students' skills and general impression. The results for Case B are presented in Table 2.

Table 2. Case Study B: Results of pre and post knowledge tests and activity metrics as computed from the logfiles of the application

	Pretest Scores		Posttest Scores				
	avg_group	max_idv	avg_group	max_idv	avg_time gap (sec)	avg_resp (sec)	Quiz Score
team00	2	4	3.5	7	20.89	51.88	120
team 01	5.75	9	7.5	8	23.42	49.02	120
team 02	4.25	5	6	7	24.00	45.73	110
team 03	6.5	8	6.5	7	25.84	61.99	90
team 04	5.5	7	7.25	8	40.44	72.51	70
team 05	1	2	6	9	27.75	82.56	70

The six teams participating in Case B can be grouped into three categories with respect to their performance, as evaluated from the pretest scores: (a) weak (team00 and team05), (b) average (team01, team02, team04) (c) strong (team03). Two teams (team00 and team01) are strongly heterogeneous, regarding the difference among group and maximum individual score. Team02 is the most homogeneous, according to the same criterion. The grouping of the teams regarding homogeneity was also confirmed by the teacher.

The scores of the knowledge posttest indicate that students' performance improved on a group level (47% on average). The "strong" team (team03) was the only team with a zero knowledge gain while the maximum knowledge gain on a group level was scored by a "weak" team (team05). The score also improved for maximum, individual performance (31% on average) although there were two cases of "knowledge loss" (team01 and team 03). The quiz score does not correlate to either the pretest or the posttest score. The best scores were achieved by team00 and team01 which were perceived as "weak" and "medium" teams respectively. On the other hand, the "strong" team (team03) achieved a medium score in the quiz. That shows that the quiz score is not a good indicator of either pre-knowledge or learning outcome.

In order to measure group homogeneity, we compared the group and individual scores of the knowledge tests for each team, as in Case A. The comparison showed that weak learners forming heterogeneous teams or medium ability learners forming homogeneous teams do not necessarily achieve the maximum knowledge gain in the current learning setting, as expected [29]. For example, a homogeneous weak team that does not follow a strict role distribution but allows its members to get involved freely (team05) achieves a higher knowledge gain than a heterogeneous weak team where one, or more, experienced members take the lead and assign a strict role policy (team00). Even though the heterogeneous team scored higher in the activity quizzes, the performance of the individual members was not satisfactory on average and they were disappointed with respect to the activity, as the post-questionnaires reveal. This also led to the increase of the heterogeneity of the weak teams since there were students who took the lead and were more benefited than the group average. On the contrary, the average and strong groups became more homogeneous because the "good" students either appeared to have "knowledge loss" in the posttests or there was no room for big improvement in comparison to the group average.

The time-related activity metrics were also studied with respect to the learning outcome and quiz performance. The average time gap (avg_timegap) correlates negatively to the quiz score. This was also observed in Case A. Teams that moved faster in the scenario achieved higher quiz scores. Taking into consideration that the heterogeneous teams achieved higher scores (team00 and team01), this finding confirms the existence of a student (or more) who takes the leading role. This however does not ensure or presuppose the increase of knowledge gain on a group level.

The students were allowed to organize their practice freely and decide which member will undertake what role, to what extent, etc. In case B, the activity was monitored by the students who kept transcripts of their own work, as well as by experts who recorded the practice of the teams. We identified three roles that the students undertook throughout the scenario: a. the operator of the mobile device (operator), b. the one who was keeping notes (scriber) and c. the one who assembles the computer (assembler). Four out of six teams did not follow a strict policy in roles' distribution. All students undertook different roles as the activity progressed. Fig. 6 gives an overview of the roles' distribution per team member for all teams. Some teams adopted turn taking in their practice (team01) while others followed a seemingly unstructured way (team04). Two out of six teams (team00 and team03) followed a certain plan throughout the whole duration of the activity and their members maintained the same roles. This strategy was not effective for their overall performance and these teams portrayed the lowest knowledge gain on a group level. They claimed it was not easy to assemble the computer and learn about hardware while working in a group. There were also some negative comments regarding the practice of their fellow team members.

Table 3. Average ratings per team on the questionnaire used to evaluate the experience of students

	Q1	Q2	Q3	Q4
team00	3.5	4	3	0
team01	4	4	3.75	1
team02	3.25	3.5	3.75	0.75
team03	3.25	3	2.25	1.5
team04	3	4	3.25	0.75
team05	3.75	4	3.5	0

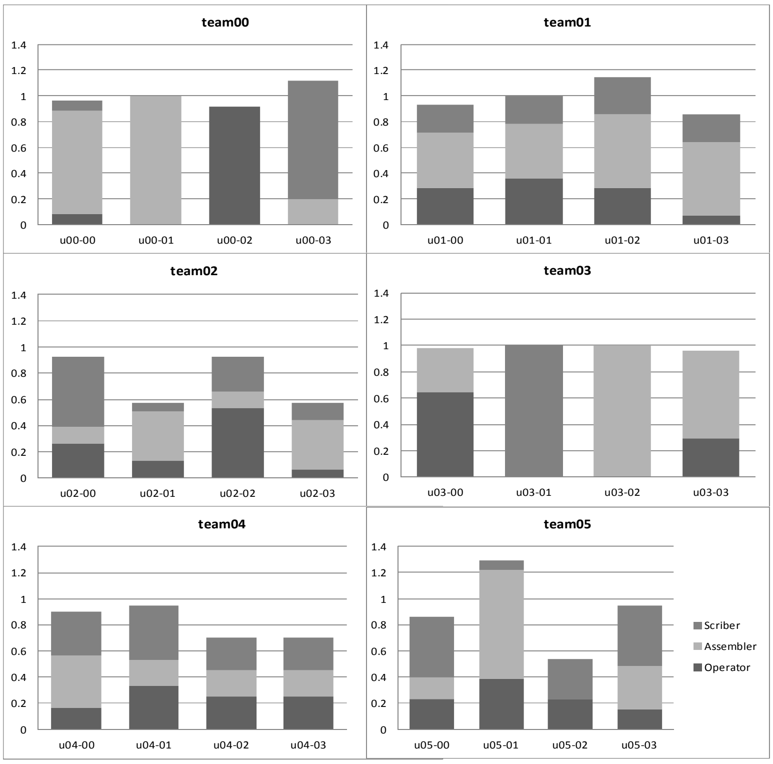

Fig. 6. Roles' distribution per team and among team members. Three discrete roles, with respect to users activity, were recorded: the scriber, the assembler and the operator. The figure presents the involvement of each student per role for the whole duration of the activity.

The students were also asked whether they would have been more efficient if they worked on their own. The good and average teams perceive that they would have done better on their own, while the weak teams (team00, team05) replied negatively. Overall the questionnaire regarding the students experience consisted of four questions. These questions were:

Q1: "*After the end of the activity I knew more about the structure of a computer*".
Q2: "*The activity was fun*"
Q3: "*It was easier to assemble the computer and learn about the hardware while working in a team*"
Q4: "*I could have done it better if I were working on my own*"

The results of the post-questionnaire are portrayed in Table 3.Each question was rated on a five-point Likert scale by all the team members, where zero (0) stands for "I do not agree" and four (4) stands for "I fully agree". The overall rating per team (team00 – team05) on each one of the four questions (Q1 – Q4) as presented in **Table 3**, was computed as the average of the ratings of the team members.

6 Conclusion

This paper presents the application of a mobile learning scenario in a traditional, collaborative classroom setting and the analysis of the activity. To that end, we carried out two case studies where students had to work together in groups with the support of a mobile device (smartphone) in order to assemble a computer. Our goal was to study the application of learning analytics for mobile learning activities on the group as well as on the individual level. The activity of each group was analyzed with the combined use of logfile analysis, activity transcripts, questionnaires and knowledge tests. We argue that the multilevel analysis can provide valuable information and enhance mobile learning.

The activities were analyzed with respect to the learning outcome as well as the practice of users. The analysis of the results revealed that the scenario application was more effective for students of weak and medium knowledge background. The knowledge gain in the case of teams of weak and medium performance was bigger and the students of such teams also perceived it as a helpful experience. On the contrary, strong teams showed little or no knowledge gain at all on a group level. On the individual level, students with high performance in the pretest, scored lower in the post knowledge tests while they noted they could have performed better if working on their own. The teams were also categorized as heterogeneous or homogeneous with respect to their members' individual performance. It was shown that heterogeneous teams achieved a higher score in the quizzes set by the scenario, although there was no correlation to the overall knowledge gain or overall score of the knowledge tests. The heterogeneous teams also moved faster through the stages of the scenario which points that the "stronger" members pushed forward the rest of the team. Overall, it was found that homogeneous teams tend to increase their heterogeneity and vice versa. This was expected since in heterogeneous teams the weakest members have more room for improvement that the strong ones. In homogeneous teams, some of the team members inevitably will benefit more than the rest, increasing the team's heterogeneity. Each team was allowed to choose its action plan (i.e. who would undertake what role etc.) as long as they would follow the instructions of the Mobilogue scenario. The majority of the teams did not follow a plan but they all participated in the activities imposed by the scenario and switched roles in no certain order. In few cases, the students split tasks and followed the same pattern throughout the whole activity. These teams achieved the minimum knowledge gain on a group level while some members made negative comments for the practice of their fellow students.

The strict structure imposed by the scenario guided the students through the activity. On one hand, the tight planning was necessary due to the nature of the learning objective but on the other hand it did not give students the opportunity to take the initiative, argument and build common knowledge by trial and error. These fundamental characteristics not only allow team members to bond and perform better on a group level. They would also lead to more complicated practices, enriching the user data and thus allowing the application of a bigger set of activity metrics and data analysis methods. In future work, we plan to test different kinds of scenarios with varying degrees of freedom to classroom activities. The concurrent use of multiple devices within a team, the nature of learning activities that could be supported effectively by the use of mobile devices and additional parameters should be further studied in order to fully explore the application of learning analytics for mobile learning collaborative activities.

References

1. Zurita, G., Baloian, N., Baytelman, F.: Using mobile devices to foster social interactions in the classroom. In: 12th International Conference on Computer Supported Cooperative Work in Design, CSCWD 2008, pp. 1041-1046. IEEE (2008)
2. Bollen, L., Giemza, A., Hoppe, H. U.: Flexible analysis of user actions in heterogeneous distributed learning environments. In: Proceedings of the European Conference on Technology Enhanced Learning (EC-TEL), Maastrich, NL, pp. 62-73 (2008)
3. Ogata, H., Hui, G. L., Yin, C., Ueda, T., Oishi, Y., Yano, Y.: LOCH: supporting mobile language learning outside classrooms. International Journal of Mobile Learning and Organisation (IJMLO), 2 (3), 271-282 (2008)
4. Spikol, D., Milrad, M., Maldonado, H., Pea, R.: Integrating co-design practices into the development of mobile science collaboratories. In: Proceedings of the 9th IEEE International Conference on Advanced Learning Technologies (ICALT). Riga, Latvia, pp. 393-397 (2009)
5. Giemza, A., Bollen, L., Hoppe, H. U.:LEMONADE: A flexible authoring tool with support for integrated mobile learning scenarios. International Journal of Mobile Learning and Organisation (IJMLO), 5 (1), pp. 96-114 (2010)
6. Verheyen, P., Ziebarth, S., Novak, J., Hoppe, H. U.: Mobile Werkzeuge zur Erstellung multimedialer Notizen als Basis für medizinische Fallbeispiele. In: Proceedings der Pre-Conference Workshops der 11. e-Learning Fachtagung Informatik-DeLFI 2013. Logos Verlag. (2013)

7. Schmitz, B., Ternier, S., Kalz, M., Klemke, R., Specht, M.: Designing a mobile learning game to investigate the impact of role-playing on helping behaviour. In: Scaling up Learning for Sustained Impact, pp. 357-370. Springer Berlin Heidelberg. (2013)
8. Stenros, J., Waern, A., Montola, M.: Studying the Elusive Experience in Pervasive Games. Simulation & Gaming. (2011)
9. Reid, J., Hull, R., Clayton, B., Melamed, T., Stenton, P.: A research methodology for evaluating location aware experiences. Personal Ubiquitous Comput. 15, 53–60 (2011)
10. Aljohani, N. R., Davis, H. C.: Significance of learning analytics in enhancing the mobile and pervasive learning environments. In: 6th International Conference on Next Generation Mobile Applications, Services and Technologies (NGMAST) 2012, pp. 70-74. IEEE. (2012)
11. Balacheff, N., Lund, K.: Multidisciplinarity vs. Multivocality, the case of learning analytics. In: Proceedings of the Third International Conference on Learning Analytics and Knowledge, ACM, pp. 5-13 (2013)
12. Harasim, L.: Collaborating in cyberspace: Using computer conferences as a group learning environment. Interactive Learning Environments 3, 119-130 (1993)
13. Benbunan-Fich, R.,Hiltz, S. R.: Impacts of asynchronous learning networks on individual and group problem solving: A field experiment. Group decision and Negotiation 8, 409-426 (1999)
14. Kahrimanis, G., Chounta, I. A., Avouris, N.: Study of correlations between logfile-based metrics of interaction and the quality of synchronous collaboration. In: 9th International Conference on the Design of Cooperative Systems, Workshop on Analysing the quality of collaboration, International Reports on Socio-Informatics (IRSI), Aix en Provence, pp. 24 (2010)
15. Marshall, P., Hornecker, E., Morris, R., Dalton, S., Rogers, Y.: When the fingers do the talking: A study of group participation for different kinds of shareable surfaces. (2008)
16. Hoppe, H. U., Engler, J., Weinbrenner, S.: The Impact of Structural Characteristics of Concept Maps on Automatic Quality Measurement. In: International Conference of the Learning Sciences (ICLS 2012), Sydney, Australia (2012)
17. Schümmer, T., Strijbos, J. W., Berkel, T.: A new direction for log file analysis in CSCL: Experiences with a spatio-temporal metric. In: 2005 Conference on Computer Supported Collaborative Learning (CSCL'05), International Society of the Learning Sciences, pp. 567-576 (2005)
18. Suthers, D. D., Dwyer, N., Medina, R., Vatrapu, R.: A framework for conceptualizing, representing, and analyzing distributed interaction. International Journal of Computer-Supported Collaborative Learning 5, 5-42 (2010)
19. Persico, D.,Pozzi, F.: Task, Teams and Time: three Ts to structure CSCL processes. Techniques for fostering collaboration in online learning communities: Theoretical and practical perspectives 1-14 (2011)
20. Bratitsis, T., Dimitracopoulou, A., Martínez-Monés, A., Marcos, J. A., Dimitriadis, Y.: Supporting members of a learning community using Interaction Analysis tools: The example of the Kaleidoscope NoE scientific network. In: Advanced Learning Technologies, 2008. ICALT'08. Eighth IEEE International Conference on, IEEE, pp. 809-813 (2008)
21. Sintoris, C., Stoica, A., Papadimitriou, I., Yiannoutsou, N., Komis, V., Avouris, N.: MuseumScrabble: Design of a mobile game for children’s interaction with a digitally augmented cultural space. International Journal of Mobile Human Computer Interaction (IJMHCI) 2, 53-71 (2010)

22. Chounta, I.-A., Sintoris, C., Masoura, M., Yiannoutsou, N., Avouris, N.: The good, the bad and the neutral: an analysis of team-gaming activity. In: ECTEL meets ECSCW 2013: Workshop on Collaborative Technologies for Working and Learning, Cyprus. (2013)
23. Ogata, H., Matsuka, Y., El-Bishouty, M. M., Yano, Y.: LORAMS: linking physical objects and videos for capturing and sharing learning experiences towards ubiquitous learning. International Journal of Mobile Learning and Organisation 3(4), 337-350 (2009)
24. Hsu, C.-K., Hwang, G.-J.: A context-aware ubiquitous learning approach for providing instant learning support in personal computer assembly activities. Interactive Learning Environments (2012)
25. Kuenzi, J.J.: Science, technology, engineering, and mathematics (stem) education: Background, federal policy, and legislative action. (2008)
26. Giemza, A., Malzahn, N., Hoppe, H. U.: Mobilogue: Creating and conducting mobile learning scenarios in informal settings. In: 21st International Conference on Computers in Education (2013)
27. Gassner, K.: Diskussionen als Szenario zur Ko-Konstruktion von Wissen mit visuellen Sprachen. Universität Duisburg-Essen. (2003)
28. Reimann, P.: Time is precious: Variable-and event-centred approaches to process analysis in CSCL research. International Journal of Computer-Supported Collaborative Learning 4, 239-257 (2009)
29. Lou, Y., Abrami, P. C., d'Apollonia, S.: Small group and individual learning with technology: A meta-analysis. Review of educational research 71, 449-521 (2001)