Facilitating Social Collaboration in Mobile Cloud-Based Learning: A Teamwork as a Service (TaaS) Approach

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Abstract—Mobile learning is an emerging trend that brings many advantages to distributed learners, enabling them to achieve collaborative learning, in which the virtual teams are usually built to engage multiple learners working together towards the same pedagogical goals in online courses. However, the socio-technical mechanisms to enhance teamwork performance are lacking. To meet this gap, we adopt the social computing to affiliate learners' behaviors and offer them computational choices to build a better collaborative learning context. Combining the features of the cloud environment, we have identified a learning flow based on Kolb team learning experience to realize this approach. Such novel learning flow can be executed by our newly designed system, Teamwork as a Service (TaaS), in conjunction with the cloud-hosting learning management systems. Following this learning flow, learners benefit from the functions provided by cloud-based services when cooperating in a mobile environment, being organized into cloud-based teaching strategies namely "Jigsaw Classroom", planning and publishing tasks, as well as rationalizing task allocation and mutual supervision. In particular, we model the social features related to the collaborative learning activities, and introduce a genetic algorithm approach to grouping learners into appropriate teams with two different team formation scenarios. Experimental results prove our approach is able to facilitate teamwork, while learners' capabilities and preferences are taken into consideration. In addition, empirical evaluations have been conducted to show the improvement of collaborative learning brought by TaaS in real university level courses.

Index Terms—Mobile cloud, collaborative learning, learning flow, social computing, learning styles, task allocation

1 Introduction

The ways of delivering education services are changing very quickly. A newly emerged form of e-learning is mobile learning (m-learning), which allows learners to participate in learning scenarios utilizing mobile devices regardless of their location [1]. Education providers are interested in delivering services using learning management systems (LMS) to assemble all needed materials, while enabling easy access and user-friendly interfaces [2]. Most LMSs are web-based and supported by wireless networks. Examples include the well-known Moodle [3], Blackboard [4], Docebo [5], etc. Thus, directly accessing LMSs from mobile devices, either via web browsers or the latest mobile client programs (i.e. the mobile apps on Android or iOS), is becoming more and more common in learning activities. M-learning is thriving by combining with cloud computing. The basis of cloud computing is that computing is arranged in large distributed systems instead of in local computers or remote servers [6]. Benefiting from the combination of mobile and cloud computing, the user is free to access resources and computing capabilities from the cloud on demand through mobile terminals, which could be simply used both as an input and output device [7].

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In order to make mobile cloud-based learning feasible, existing LMSs need to be migrated to the cloud or upgraded versions of the original LMSs need to be developed on the cloud platform. Functions supporting collaborative learning are gradually provided in several popular cloud-hosting LMSs [8]. It has been shown that learners find collaborative learning has a favorable environment to re-occur more and more frequently among learner who have similar learning purpose.

There have been comparatively fewer studies aimed at facilitating collaborative learning in the new environment of mobile cloud-based learning and there has been little research aimed at finding ways to enhance learners' teamwork performance in virtual teams.

This paper is oriented towards, but not limited to, the delivery of university level online courses. The contribution of our research, is a service-oriented system, 'Teamwork as a Service' (TaaS). TaaS is designed to work in conjunction with current cloud-hosting LMSs. It follows the Kolb team learning experience (KTLE), which is an educational approach, to orchestrate a learning flow in order to refine the process of team learning sequentially [9]. During the execution of the learning flow, a computational optimization process is realized by a genetic algorithm (GA) in order to form appropriate teams and stimulate better teamwork performance.

The rest of the paper is organized as follows: Section 2 introduces the identified issues and Section 3 describes our methodology, Section 4 presents our system framework, Section 5 gives the core algorithm used in TaaS, Section 6 demonstrates our experiments and implementation, Section 7 evaluates TaaS by demonstrating three case studies and gives relevant analyses, Section 8 compares our work with related work. Finally Section 9 concludes the paper and suggests the future work.

2 Problem Statement

2.1 Background

Some researchers have introduced the concept of social computing in order to make collaborative learning easier by organizing human behaviors and simplifying human-machine interactions [10]. One of the typical phenomena is the extensive use of web 2.0 technologies, which bring new ideas for sharing information and offer tools to allow a single task to be controlled by multi-party operations [10]. Current cloud-hosting LMSs have provided or integrated certain built-in or compatible tools, for example, forums, chatting threads, instant messages, Wikis, blogs. Most of these are mobile device accessible. In [11], LMSs with web 2.0 functions are also claimed as social software. Hence, it is clear that the physical conditions for achieving collaborative learning in mobile cloud-based learning already exist. Learners now have more opportunities to access numerous tools for making collaborative learning activities possible and easier.

While cooperating with the new social computing tools in cloud-hosting LMSs, learners are both the authors of and the audience of the online content relevant to their learning purposes. They now feel free to exchange their ideas, discuss their viewpoints, share their experiences and learn from others' strengths to find and improve their own weaknesses. In this way, the constraints of location, nation, or cultural background are overcome, and the influence scopes of education are expanded [12]. With the explosive distribution of knowledge, learners are naturally drawn into intangible social associations [13]. Linked by the internet, a social network emerges among learners where learners are clustered in different granularities due to different demands and individual benefits [14]. The two lowest forms of social granularity are the virtual community and the virtual team [11], [15]. Unlike the virtual community, which is more related to learners' interests and with no entry or exit restrictions, the learners who participate in virtual teams are more focused on task-related outcomes and time constraints, often in the form of deadlines [16]. The structure of the virtual team is cohesive as the task requirements and recognitions hold the teams together, and these teams are not disbanded until the tasks are completed. Also, the virtual team has formal lines of authority and roles [11]. After the collaboration, the outcome of a team are usually assessed by specific criteria in order to judge how well the team members have worked together [17]. To make the full use of mobile cloud-based learning, teachers involved in school-based learning have shown great interest in the delivery of online courses which build a virtual team and adopt collaborative learning. It is also helpful in business areas where companies make use of it to train employees or arrange them into teamwork if a task needs multiple employees working towards a common goal.

Building virtual teams and enhancing their teamwork performance is important. Because the virtual team is usually formed in online courses, we concentrate on this learning scenario in particular as our research background. At present, the 'massive open online course' (MOOC), a new way to deliver university level courses, is open to learners world-wide. This means that it will be useful for TaaS to also be able to facilitate distributed learners' teamwork while they are participating in MOOC.

2.2 Challenges in Collaborative Learning

Some typical problems, which occur in traditional team-based learning, can also have a negative effect on the virtual team in mobile cloud-based learning [18], [19], [20], [21]. Learners belonging to the same team often have different learning styles. Therefore they require diverse learning approaches, tend to learn in different ways and prefer different learning resources [22]. For instance, some students learn best through observation while some others learn best by practice. Each learner's expectations and preferences also influence their motivation to work to the limit of their abilities. Current criteria used for assessing a student's performance are commonly based on final results of the whole group, though some group-based marking schemes are widely used. Properly marking each learner based on their individual contributions is still a big challenge, which would take a fairly amount of time and effort to go deeply by teachers. There are few online tools to deal with this problem either. The whole team's achievements may be negatively affected by some under-performing learners. Specifically, in some kinds of collaboration, one learner's task depends on the completion of another's and delay or poor performance by one may affect the work of all.

In addition, as the context of mobile cloud-based learning is quite different from traditional learning, learners normally lack the guidance to introduce them into effective direction of the learning path. Thus, once a teamwork assignment is given in an online course, because of geographical separation and in some cases, even time zone differences, learners will face many unpredictable difficulties for which may not be sufficiently prepared.

- Without appropriate face-to-face meetings, communication in mobile cloud-based learning may be insufficient and not as convenient as that in traditional learning. Time zone diversity within a team is not rare [23]. This means that deep discussion is not easy to organize and the delay may cause confusion or misunderstandings to occur. [24].
- Due to team members' diversity and the asynchronicity of online activities, the team leaders are unable to monitor the team members as efficiently as in traditional settings. Also, traditional strategy and direction are sometimes ineffective to run the daily process of the team. Whether a team's task is likely to succeed or fail depends both on its nature and on external factors. In addition, the availability of proper resources and support, as well as information about the difficulty and feasibility of the team's task are often not evaluated suitably in such a context [24].
- It is not easy for the team members to have enough information about each other to a satisfactory extent, Team members may be unfamiliar with one another's strengths and skills [25] and this can also affect the quality of team work.

- It is difficult to decide how to get the right set of dedicated and competent team members, which is a major factor in making or breaking the good achievement of a team's tasks. The team members are also uncertain about their common teamwork assignment, including what it is about, how it fits with their roles and expectations, and how it is connected to organizational goals [26].
- Currently, for mobile cloud-based learning, there are neither mature methods to assure that the team members' effort and knowledge are totally translated into performance, nor approaches to help learners maintain motivation and attention to their common tasks. There are also deficiencies in tracking the entire teamwork experience, where problems can be hard to diagnose and solve in a timely manner, while the team learning is actually in progress [27].

3 METHODOLOGY

3.1 Social Computing for Mobile Learning

As mentioned above, it is essential to provide a shared social context for learners to socialize, learn and construct knowledge [28], [29]. To achieve coordinated collaboration, learners should be aware of three kinds of awareness: social awareness (who is around?), action awareness (what's going on?), and activity awareness (how are things going?).

Mobile learning, especially mobile team learning, is not only the process of knowledge being passed on, but also the process of creating knowledge as a result of interactions between social knowledge and personal knowledge [30]. Mobile learning activities normally consist of two sections: online learning and offline learning [31]. Because mobile learners are free to download materials into their mobile devices for viewing offline and being introduced and guided in their practices, they do not always stay online to access LMSs and attend tutorials [32]. For mobile collaborative learning, when some work needs equipment and materials other than mobile devices, even more procedures must be completed offline. A new concept, 'online to offline' (O2O), can help organize mobile cloud-based learning [33]. Using this concept, the process logic of mobile team learning can be clearly defined by online systems, including the transaction details and deliverable resources. Hence, while learners are able to accomplish many of their teamwork tasks offline, for some necessary procedures, such as data entry and work submission, they need to go back online to finish. Using online systems to command and restrain offline behaviors also helps to avoid confusion and misunderstanding, while still offering more offline opportunities.

In the broad sense, social computing has to deal with supporting any sort of social behavior in or through computer systems. It is based on creating or recreating social conventions and social context through the use of software and technology [34]. The tools mentioned earlier in this paper, such as Wiki and blog, are offering these functions and have been available for a while. This goes without saying, but we need to improve existing tools or design new tools that offer a collaborative environment to learners for attaining effective communication, workarounds to supplement the insufficient communication and a mechanism to monitor each member [35].

In the narrow sense, social computing has to deal with computations that are carried out by groups of people and guide them to work in the best way possible [36]. Collaborative learning is closely associated with interpersonal behaviors. We can use the formal methods to denote several social features, and combine them to model valuable features of those social behaviors, in order to offer learners the computational social choices. For example, it is worthwhile to identify the individual learner's strengths and weaknesses with regard to his/her learning styles [37]. Based on the results, we can place students into the most effective groupings [35].

3.2 Teamwork Enhanced Learning Flow

From the top-down view of the whole collaborative learning process, we need to attempt to refine each individual learning activity before joining them together. Combining the features of the mobile cloud environment, where applications are normally service-oriented, practitioners and developers are free to choose useful services on demand and compose them together to establish a virtual environment which provides more comprehensive functions than just one application [38]. In such a new environment, a feasible way to realize the whole teamwork-enhanced learning process is to orchestrate a learning flow. Learning flow, a specification of workflow, refers to the formal description of a set of rules and the process during which the learning activities happen and change [39]. A completed learning flow includes time sequences, logical relationships, connected patterns and trigger conditions of various learning activities, blending them together in the formation of a suitable process. Each learning activity, including conditions of its beginning and its end, as well as related resources and required support, is one logical step or segment in the learning flow.

Generally, the traditional collaborative learning flow in an online course of mobile cloud-based learning can be abstracted as 'receiving team assignments', 'accessing team learning resources', 'proceeding team learning', 'submitting team outcomes' and 'getting evaluations'.

3.3 Design of TaaS

The basic principle of this innovative learning flow execution in TaaS is that learners and teachers are still using cloud-hosting LMSs to process their daily learning activity. Teachers can assign the team learning assignment with the undergoing online course through cloud-hosting LMSs. If there is a team learning activity happening, both learners and teachers are free to switch to TaaS, to access functions to facilitate their teamwork or to supervise the whole progress of the learners.

By utilizing the cloud, TaaS enables different levels of access by different education providers with only once large-scale deployment, and preserve TaaS by load balancers in the cloud to ensure robustness, even when there are sudden increases in network traffic. The need for data and computation during the team learning process can be controlled by the cloud, thus the complexity of the system will not be increased by the limitations of the mobile devices. For ease of use and seamless switching between the two

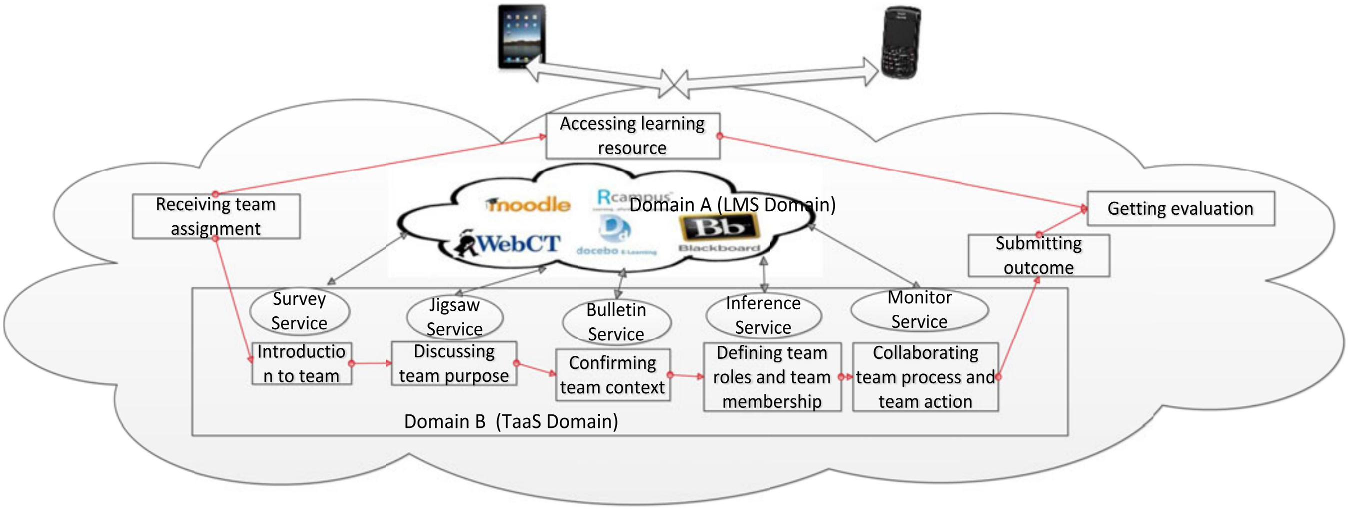

Fig. 1. Teamwork-enhanced learning flow for mobile cloud-based learning.

systems, once the topics of team learning assignments are released, the first synchronization between TaaS and cloud-hosting LMSs is triggered. Both of them will share the same user information over the whole team learning process.

TaaS aims to build a better social context for collaborative learning. In the learning flow, which is shown as Fig. 1, the 'proceeding learning content activities' is subdivided into the seven modules of KTLE, one or more of which is taken by each of the five web services of TaaS to organize a certain type of learning activity. These services work sequentially as a whole in parallel with the activity of 'accessing learning resource'.

To bring the social computing into the learning flow, as a preparation, it is necessary to collect data describing learners' social features as the raw material. In other words, modeling pedagogical variables is a necessary step for which we need to set up parameters relevant to real learning experiences. Individual learning style is an important index that reflects learners' cognition-behavior performance during the gaining of knowledge [22]. Coffield et al. [40] have studied 16 types of learning style and compared them. They illustrate that Kolb has demonstrated four learning styles: accommodating, assimilating, converging and diverging [41], [42]. Basically, 'Accommodating' is learning from hands-on practice and intuition rather than logical analysis. 'Assimilating' refers to discovering and understanding a wide range of information and then categorizing and conforming it into concise and logical forms. 'Converging' is seeing problems in practical terms and find solutions using learning experience. 'Diverging' is more relevant to observation of concrete situations from many different viewpoints. The theory of Kolb's learning style (KLS) has been well studied in order to explore the reaction of learners with different learning styles in real courses [43], and extensively adopted by many educators to seek the best teaching strategy to guide effective teamwork [44].

In addition, Belbin and Loo mapped these four learning styles to four roles (accommodator, assimilator, converger, and diverger), which are equally important and are usually to be found in an experienced team [45], [46]. In [40], it is suggested that KLS is especially useful for experiential learning in higher education (university level), and for this reason, we use KLS in our design of TaaS.

In [47], comprehensive teamwork (CT) skills are identified as the factors central to whether the learner can play a valuable role in a team and achieve sufficient collaborative learning outcomes. This set of skills is normally reflected by learners' actions and behaviors while they are engaging with other learners sharing the same learning targets. Typical comprehensive teamwork skills include, how attentive they listen to views and opinions of others, to what extent they provide help to others and introduce new ideas, and whether they accomplish a fair share of the teamwork, etc. [47].

Here, we briefly introduce the idea of how to import social computing into TaaS, while the detailed work patterns of each service will be addressed in the next section. There are five web services in TaaS.

- The Survey Service works for the 'introduction to teams' module. It supports a platform for learners to know one another at the beginning of the collaborative learning, usually concurring with the release of the team assignment. Data about each learner's social features are collected, in terms of their learning styles and comprehensive teamwork skills.
- The Jigsaw method introduced in [48] is commonly used to organize effective personnel structures for deepening learners' understanding of 'team purpose', the three stages of which can be imitated by the Jigsaw Service.
- The Bulletin Service allows learners to collaboratively define their 'team context' and 'team purpose', by writing down their thoughts about how to accomplish the team assignment. It is also utilized to evaluate each pre-planned task's difficulty and learners' preference regarding it.
- Pinola [23] suggests that a solution to facilitate collaboration and reduce conflict is that the leadership of mobile virtual teams can be shared. We favor the idea and amend it by abolishing the concentrated leadership and share leadership over the both sides of the O2O. The duty to assign the suited 'team

membership' for each capable team and allocate the clear-cut 'team role' for each team member is done by the Inference Service. Because effective grouping is important for each team of learners to perform better [18], [35], [37], this service takes the responsibility of 'computation', in the narrow sense of social computing, to find out how to group learners into competitive teams. The reasoning process of team formation is supported using a GA method [50], [51].

- The other duty of the concentrated leadership that monitors team members' work is replaced by mutual supervision among learners, which is conducted by the Monitor Service. It works to regularize learners' behaviors during the 'team action' and 'team process'. Borrowing the idea of 'within team Jigsaw' [48], in each team, each learner is assigned as the coordinator for another.

4 System Framework

4.1 The Survey Service

The Survey Service offers interfaces to learners for answering questionnaires to investigate their capabilities. Considering the limitations of screen size and input method of mobile devices, the surveys are single-choice based. It can be operated as self-assessment or peer-assessment, which means the respondents of the surveys can evaluate themselves or the other teammates working with them, by giving appropriate grades.

There are five sets of questionnaires pre-installed in the Survey Service, four of which are for the four KLS [41], [42] categories (accommodating, assimilating, converging, and diverging) of KLS [41], [42], and the last is for comprehensive teamwork skills. Questions in these questionnaires come from [42], [52], [53], and can be extended or reduced by teachers manually. Learners can choose one of the ten options to answer each question, which is an integer between 1 and 10, the higher the better.

Let L^k denote the kth learner. In the Survey Service, L^k's capability will be compiled from questionnaires, from both self-assessment and peer-assessment. The results of each question for evaluating L^k will be recorded in a matrix in which each column stands for a question, while each row corresponds to a learner who gives the marks. So five matrices are obtained, they are $\{AC^k\}$, $\{AS^k\}$, $\{C^k\}$, $\{D^k\}$ and $\{CT^k\}$. For example, the capability of accommodating (AC) of L^k can be stated as:

$$\{AC^k\} = \begin{pmatrix} M_1^1 & M_1^2 & ... & M_1^n \\ M_2^1 & M_2^2 & ... & M_2^n \\ ... & ... & ... & ... \\ M_m^1 & M_m^2 & ... & M_m^n \end{pmatrix}, \tag{1}$$

where: M_m^n means the mark for the nth question of the accommodating aspect, which is given in the mth assessment, and M_m^n is an integer between 1 and 10. n depends on the question title's order and m is in accordance with the sequence of questionnaire submission times.

In matrix $\{AC^k\}$, the mean of each column describes the strengths of different types of accommodating, and we use the next equation to calculate the value of accommodating capability of L^k:

$$AC^k = \frac{\sum_{j=1}^{m}\sum_{i=1}^{n} M_j^i}{nm}. \tag{2}$$

In the same way, the Survey Service calculates the values for the other four matrices. Hence, we get these values: AS^k, C^k, D^k and CT^k. They represent the capability values of assimilating, converging, diverging and comprehensive teamwork skills, respectively. We let a four-tuple $KLS^k = \{AC^k, AS^k, C^k, D^k\}$ denote the KLS capability values of L^k as they are closely related.

For self-assessment in a course, which must usually be completed first, learners are not allowed to repeat it. In other words, during the period of one course, if a learner has already answered the questionnaires for evaluating himself/herself, the Survey Service will switch off the entry of self-assessment for him/her. The historical data of his/her survey results collected from other courses are used continually in this course. That is to say, if a learner is a newly registered user of TaaS, the Survey Service will create five new capability matrixes for him/her to record survey results, and these matrixes will be yielded and updated during his/her whole period of learning in different courses using TaaS. If a learner is not a newly registered user of TaaS, the Survey Service has recorded his/her non-null capability values already. The newly collected survey results will be added into his/her capability matrixes rather than replace the historical results.

For peer-assessment in one course, if learners have, at one time, been teammates at any stage of Jigsaw Classroom (Section 4.2) or in the ultimate team working towards accomplishing an assignment, they are able to evaluate each other only once. After any change of team structure, the Survey Service releases the surveys to learners for evaluating former teammates mutually. In this way, one learner may evaluate another more than once during the whole process of an online course. Subsequent survey results will not replace those ones given previously, but will appear as new rows at the bottom of their capability matrixes.

The structure of surveys can be manually changed by teachers, by adding or reducing questions, resulting in the number of columns in the corresponding matrix changing. Accordingly, the types of matrix vary with the change of survey structure.

4.2 The Jigsaw Service

The Jigsaw Classroom [48] has three stages, and the personnel structure of the first one and the third one is the same. Two key points must be considered: the formation of original teams and expert teams.

For 'initial discussion in original team', the Jigsaw Service groups learners into original four-person teams. First, it extracts all learner information from the Survey Service and triggers a computing process about grouping learners into four-person-sized original teams with nearly equal comprehensive teamwork skills in each group. Second, each learner in one original group is assigned one of the four KLS roles as described in [42], [45]. The method of role assignment is to choose the best player according to each aspect, and if there is anyone leading two aspects in the team, choosing his/her best quality. For example, in an original team, learner A has the highest value of accommodating (*AC*), s/he is assigned as the 'accommodator' while another learner, B, leads converging (*C*) and diverging (*D*) in the team with the addition that s/he is better at converging, the Jigsaw Service assigns the 'converger' role to him/her.

For 'joining expert team to refine cognition', the Jigsaw Service arranges learners who played the same role in the original team to join as an expert team. Consequently, there are four expert teams: accommodators, assimilators, convergers and divergers. For 'backing to original group to teach others what was gained in expert group', the Jigsaw Service redirects learners into the original teams from which they have come.

In the cloud Jigsaw Classroom, whenever during the original team learning period or during the expert team learning period, the Jigsaw Service provides a common interface for the whole team where they can interact with each other, it shields the information of other groups. Each modification of team structure in TaaS will be updated to cloud-hosting LMSs. Therefore, learners are also organized into groups in those systems as the same formations in TaaS. Given that most cloud-hosting LMSs provide the 'Group' functions as well as abundant tools for supporting collaborative learning, learners benefit from utilizing such conveniences for assisting their discussions in the three stages of the Jigsaw Classroom.

4.3 The Bulletin Service

The Bulletin Service borrows the idea from the famous Wiki system [54] to establish a collaborative editing environment for learners to plan the detailed task schedule for completing the team assignment. In the traditional Wiki systems, however, users are required to know some kinds of specific markup language in order to publish contents, whereas some typical Wiki systems, such as the most famous Wikipedia, have their particular editing language [55]. As being applied in text management, the Bulletin Service improves the inconvenience by offering the WYSIWYG mode. Hence, learners can type their text content directly to access and edit published task schedules through the user interfaces on mobile devices.

A published task schedule is prepared for the workload of an imaginary team. This consists of: the task topic, the task introduction, several subtasks, stages of each subtask, detailed content and period of each stage, and sequential relationship between subtasks (if a subtask is the premise for another). The content is in text form and the period is counted in days.

The number of subtasks of each task can be pre-set by teachers. Taking an example from real team learning scenarios, we suppose the number is between 3 and 6 and learners are required to consider this task size while they are pre-planning [18]. Before inserting the content of a task, the learner can adjust its structure by adding/reducing the number of subtasks to not more than 6 and not less than 3. S/he can also adjust the structure of each of these by adding/reducing the number of stages.

The subtask's difficulty is marked by expected-achievable values, depending on the publisher and his/her teammates from the same original team of the Jigsaw Classroom. Let a published $S^{i,j}$ represent the jth subtask of the ith task. For $S^{i,j}$, the Bulletin Service allows authorized learners to type in a real number between 1 and 10 for each aspect of the KLS, in order to indicate that is to be better completed by a learner who has similar capabilities. The results are recorded in a matrix $\{S^{i,j}\}$:

$$\{S^{i,j}\} = \begin{pmatrix} V_1^1 & V_1^2 & V_1^3 & V_1^4 \\ V_2^1 & V_2^2 & \dots & V_2^4 \\ \dots & \dots & \dots & \dots \\ V_m^1 & V_m^2 & V_m^3 & V_m^4 \end{pmatrix} \tag{3}$$

where V is the value for one aspect of KLS given by one learner, the four columns denote the aspect of accommodating, assimilating, converging and diverging, sequentially, and each row represents the results given by one learner in accordance with time sequence. We use the next equation to calculate the final expected-achievable value, namely ST^{ij}, of $S^{i,j}$:

$$ST^{ij} = \{AC^{ij}, AS^{ij}, C^{ij}, D^{ij}\} = \{\overline{V^1}, \overline{V^2}, \overline{V^3}, \overline{V^4}\}. \tag{4}$$

Hence a four-tuple $ST^{ij} = \{AC^{ij}, AS^{ij}, C^{ij}, D^{ij}\}$ is obtained, where each element is a real number between 1 and 10.

When examining a task, learners are free to show their preferences for each subtask by choosing one of the five grades. The variableP_k^{ij} denotes the preference grade of the $S^{i,j}$, given by the kth learner. The P_k^{ij} is an integer between 1 and 5, the higher the grade, the higher the learner's preference for doing the subtask. There are five preference categories of subtasks: 'very interesting', 'interesting', 'ordinary', 'uninteresting' and 'very uninteresting' corresponding to the preference grades 5, 4, 3, 2, 1, respectively.

The number of task schedules that can be published by one learner is not limited, while learners are encouraged to use their imagination to supply further ideas.

4.4 The Inference Service

The Inference Service is the core of our solution and it is this service which attempts to tackle the problems caused by the specialization of mobile cloud-based learning.

Referring the capabilities and the preferences of learners, and the expected-achievable values of subtasks, the operation principle of this service is trying to match each learner to the most appropriate subtask. On the other hand, in the inference process, learners who are assigned subtasks belonging to the same task will be grouped into the same team, so that the combined strengths of a team are taken into consideration.

Let us imagine two team formation scenarios:

- 'Keeping the balance between each team', which means the upcoming teams will have similar comprehensive teamwork skills. In addition, the learners' preferences level and capability levels (the level of *P* and the level of *KLS* and *CT*) are diverse in confined shapes, meaning that if we regard each team as an independent unit, its integrated preferences and capability values are very close to those of other units. Therefore, we assume that the inter-team competition between the upcoming teams starts from the same point and is inherently fair.

- 'Letting the learners show their capabilities in the best possible way', which means each learner is able to put their strengths to use as much as possible, so that whether the team members are 'good at' and 'happy in' doing their upcoming subtasks will be the main indices that direct the reasoning process of the task allocation.

The detailed inference process based on the GA will be discussed in Section 5.

4.5 The Monitor Service

Given that each learner is allocated a subtask and grouped into a team using the Inference Service, the Monitor Service takes part in two preparatory steps before learners start their work. First, for each allocated subtask, it checks the period of each stage, and sets a time milestone at the break between two stages as the trigger for message notification. For example, if a subtask has three stages, the periods of each are three days, five days, and five days. Once the team learning starts, the Monitor Service sends a message after three days to the performer of the subtask to notify him/her that the first stage is over, and then sends the second message five days later and the third message after another five days. Second, in each team, it appoints a learner as the coordinator for each subtask who is not the performer responsible for accomplishing the subtask.

For each subtask, once the performer responsible gets a message that a stage is over, s/he is asked to submit his/her periodical achievement. A file transmission channel links him/her with the coordinator for each subtask, and s/he can use it to automatically transfer the periodical achievement to his/her coordinator. Downloading and reviewing the file, the coordinator takes responsibility for judging whether the rate of progress is satisfactory and whether the performer would be capable of continuing or not, by grading the progress as 'satisfactory' or 'unsatisfactory'. If an 'unsatisfactory' grade is given, the coordinator is required to decide how much 'extra time' should be given for work revision. A new message is sent to the performer when the 'extra time' ends, at which time the revised work must be resubmitted. Then the coordinator judges it again.

If a performer receives an 'unsatisfactory' multiple times, the Monitor Service holds a vote among his/her team. Each team member is shown his/her latest outcome and, after reviewing it, chooses one of the two options, 'continue' or 'warning'. All vote results are collected to reach a consensus, while the performer is allowed to start the next stage of his/her work. Then the coordinator gives a mark to the performer for this stage. A penalty mechanism is embedded in this service which automatically reduces the performer's marks if s/he gets any 'unsatisfactory' or 'warning' grade on a stage of his in-progress work. All lost marks are accumulated and fed back to teachers at the end of team learning.

5 Genetic Algorithm for the Inference Service

The solution space of the task allocation problem is very large, being up to $k!$, where k is the number of learners. Hence, we attempt to use the heuristic algorithm to find feasible solutions without huge time consumption. In this Section, we will introduce the GA-based method, one of the widely adopted heuristic algorithms, which will be executed by the Inference Service.

5.1 Problem Modeling

For initialization, the Inference Service checks whether learner L^k is appropriate to accomplish an $S^{i,j}$ by specific calculations. We introduce two variables to describe the deviations of social features between the learner and the subtask. The first variable *DeP* denotes the preference gap between the learner's ideal and reality, where:

$$DeP_k^{ij} = 5 - P_k^{ij}. \tag{5}$$

As the highest grade of preference is 5, the Equation (5) is derived from the single-dimensional euclidean distance, which is the arithmetical difference between the highest grade and the specific chosen grade.

And the second variable *DeK* denotes the deviation of the learner's KLS capability values versus a subtask's expected-achievable values, where:

$$DeK_k^{ij} = -\left\{sign\left[\sum\left(KLS^k - ST^{ij}\right)\right]\right\} \cdot ||KLS^k - ST^{ij}||. \tag{6}$$

Subject to:

$$KLS^k - ST^{ij} = \{AC^k - AC^{ij}, AS^k - AS^{ij}, C^k - C^{ij}, D^k - D^{ij}\} \tag{7}$$

$$||KLS^k - ST^{ij}|| = \sqrt{\begin{matrix}(AC^k - AC^{ij})^2 + (AS^k - AS^{ij})^2 \\ +(C^k - C^{ij})^2 + (D^k - D^{ij})^2\end{matrix}}. \tag{8}$$

In the case of both of these deviations, the lower the better. An ideal DeK_k^{ij} is below 0. Equation (7) is a computation to judge whether the value of Equation (6) is positive or negative. Equation (8) is the four-dimensional euclidean distance between the expected-achievable value of a specific subtask and an individual learner's KLS capability values.

If potential team x is allocated with task i, we use ${}^xDeP^i$, ${}^xDeK^i$, ${}^xCT^i$ to represent its sum of *DeP*, *DeK*, *CT*, respectively.

5.2 Genetic Algorithm-Based Method

To start the GA operation, arrays of k learner/subtask pairs are randomly generated, where k is the number of learners. In each array, the integrities of tasks should be checked. If there is any overflowing subtask within, that array will not be adopted as the initial solution. Taking these initial solutions as individuals (chromosomes), we need to encode them into populations (genomes) for creating the first generation.

A fitness function transfers the task allocation from multi-objective optimization to single-objective optimization. For the first scenario mentioned in Section 4.4, to obtain the proximate ${}^xCT$, ${}^xDeP^i$ and ${}^xDeK^i$ between teams, total teams' variances of these parameters should be respectively minimized. However, for each attribute, several solutions may have different means but with the similar variances. A special situation is that the original difference of potential teams is little. To avoid the evaluation to blindly terminate

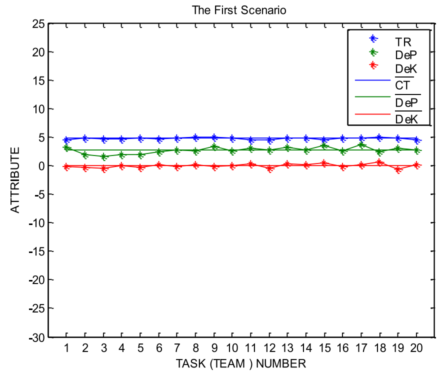

Fig. 2. Task allocation for the first scenarios by GA.

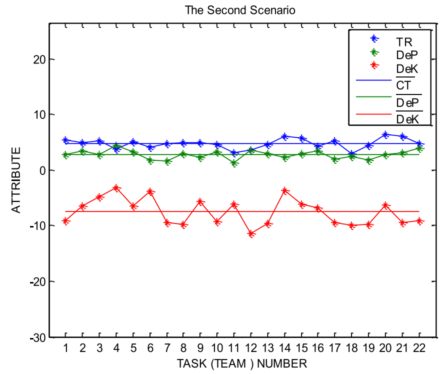

Fig. 3. Task allocation for the second scenarios by GA.

in a partial balance, we take minimizing the means of the *DeP* and the *DeK* of all teams into consideration. So we use the next equation as the fitness function:

$$R_m = \alpha\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{{}^{x}CT^{i}}{N^{i}} - \overline{CT}\right)^{2}} + \beta\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{{}^{x}DeP^{i}}{N^{i}} - \overline{DeP}\right)^{2}} + \gamma\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{{}^{x}DeK^{i}}{N^{i}} - \overline{DeK}\right)^{2}} + \varepsilon\overline{DeP} + \eta\overline{DeK}. \tag{9}$$

For the second scenario, in a candidate solution, minimizing the total *DeP* and *DeK* is more important than minimizing the variance of *CT*, so we take the following fitness function:

$$R_m=\alpha\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{{}^{x}\mathrm{CT}^{i}}{N^{i}}-\overline{\mathrm{CT}}\right)^{2}}+\sum_{i=1}^{n}\left(\beta^{x}DeP^{i}+\gamma^{x}DeK^{i}\right), \tag{10}$$

where each Greek letter in (9) and (10) represents the weight for that attribute, hence, the controlling parameter in our algorithms.

The aim of selection operator is to remove the poor solution with higher fitness. Then the selected individuals evolve to the next generation through the effect of crossover operator and mutation operation. We choose the top percent selection as the selection operator, the partially matched crossover as the crossover operator and the uniform mutation as the mutation operator. In particular, it should be noticed that the partially matched crossover has the function to deal with the appearance of the unfeasible solution that, after crossover, in a genome, a learner is repetitively assigned while another learner is left out.

6 Experiments and System Implementation

6.1 Evaluation of Genetic Algorithm

In order to show the performance of the genetic algorithm method for the task allocation inference, we have coded the algorithm using the MATLAB tool. To simulate the learning scenario we described above, the data of learner information and task/subtask is randomly generated by MATLAB, obeying normal distribution. For the experiment, we set the crossover possibility of the GA at 0.9, the mutation possibility at 0.2, and the terminal condition is iteration for 500 times. The population of learners is chosen to be 100 persons and the number of subtasks is 200. While we are considering to synthesize all attributes and initialize the team formation, we express each attribute's importance by adjusting its weight. It is needful to control the speed of algorithm convergence. In addition, during our experiments, we try out different weights to look out for the optimal results for team formation for both scenarios, namely having the R_m been as small as possible. Finally, in the first scenario, we set the weights $\alpha = 0.5$, $\beta = 0.15$, $\gamma = 0.25$, $\epsilon = 0.05$, $\eta = 0.05$. In the second scenario, we set the weights $\alpha = 0.2$, $\beta = 0.4$, $\eta = 0.4$.

From Figs. 2 and 3, the most intuitive difference between the first and second scenarios is that, in the first scenario, each team's three attributes distribute in very narrow range around the corresponding means of all teams' and lines linking the value of the same attribute of each team are almost straight, while in the second scenario, such three lines have some swings and the mean of *DeK* of all teams is obviously lower. From Fig. 2 (the first scenario), we can find that learners are divided into 20 teams and the values of total *CT*, *DeP* and *DeK* of each team are separately balanced on the nearly same levels. The three attributes between teams are all in close proximities, which means that the teams have almost equal capabilities and preferences to achieve goals of their responsible tasks. And from Fig. 3 (the second scenario), as the solution grouped learners into 22 teams, the *DeK* attributes of each team are below 0, so that each team is competent to their allocated task. The result shows that the *DeP* level of each team is less than 3. Because the team size is 3 to 6 persons, the average *DeP* value of each learner is less than 1. This means each simulated learner has been allocated with a subtask with a high preference, which is deemed better than 'interesting'.

In addition, the general running time of GA is less than half a minute for both scenarios, which is acceptable as demonstrated in our pilot evaluations. Hence, although the attributes of learners and subtasks are complex, our GA method has the ability to seek the proper team formation not only taking the individual learning style of each learner and comprehensive skills of each team into account, but also ensuring each team to have competitiveness and fulfill different learning demands.

6.2 System Implementation

We employ MOODLE, a well-known open source LMS, as our test LMS, by composing the TaaS and MOODLE to execute a teamwork-enhanced learning flow for mobile cloud-based learning. The working principle is that mobile learners access learning resources and perform their conventional learning activities through MOODLE, whereas they utilize functions supported by TaaS to facilitate collaborative learning. To deploy our TaaS, we have launched a Linux instance, which contains one or a cluster of computers, of the Amazon Elastic Cloud Computing (EC2), running in Virginia, USA. We have configured the server environment as Apache + PHP + Mysql, and hosted our TaaS package on it. We have also uploaded the system package of MOODLE into the Amazon EC2, hosted on the same instance.

From the main page of teachers' UI, teachers can click buttons to launch several events, such as starting each stage of the Jigsaw Classroom and activating grouping by triggering the Inference Service. They also have authorities to change the structure of surveys, pre-set the penalty mechanisms embedded in the Monitor Service (set the maximum times allowed for a learner to get 'unsatisfactory' grade, the deduction weight for each 'unsatisfactory' and 'warning'). Learners' capabilities in five areas are summarized in a bar chart in the main page of learners' UI, and can be checked by their teammates. They can click buttons to participate in learning activities by entering new pages. For example, the 'Participate in survey' button works for showing learners the interface of answering the five sets of questionnaires pre-installed in the Survey Service. The status of the message box changes when the new announcement arrives. Their team information and task information are shown on the bottom of the main page. Details of the specific UIs can be found in [56].

7 Empirical Evaluations

To further analyze how learners are benefitting from making use of TaaS, we have conducted several controlled trails to gather empirical feedbacks.

7.1 Case Study 1

The first case study was organized in a postgraduate level course related to web services of the School of Information Systems and Technology, University of Wollongong, Australia, in the mid of 2013. Sixty-four students were enrolled in this course. They were required to accomplish a team assignment and submit it before the final exam. The task of the assignment is to develop a simple prototype of service-oriented system and write a report to describe functions, principles and the development process. Team sizes ranging from three to five students are acceptable. The grade of the team assignment takes 25 percent of the final grade of this course.

Unlike previous years' team assignment, in which students were assigned in random or self-organized teams, we introduced them to use TaaS as the assistant of their collaborative learning. Forty-eight students adopted our suggestion. These students were guided to have surveys about their KLS and CT, either by self-evaluation or peer-evaluations. Then information about their team formation was gathered from their TaaS UIs. As a preparation period, two weeks were given to them to discuss what kinds of service-oriented systems were expected to be developed and how to realize such processes. They were encouraged to publish their thoughts over the Bulletin Service. Based on their published contents, we use the Inference Service to group them into teams according to the second scenario (Section 4.4). During their completion process of team assignment, the Monitor Service helped them keep track on other team members' in-progress work.

After the deadline of the assignment was met, we have interviewed several participated students to gather their opinions about using TaaS. Some typical viewpoints from students' feedbacks are summarized as follows:

- Learners have better knowledge about peers among their teams. They are more familiar with other members' specific features in regards to KLS and comprehensive teamwork skills.
- Learners recognize teams they belong to are formed suitably and they feel more confident to their allocated subtasks as well as having more motivations.
- Compared with team formation in previous courses, TaaS can organize teams more efficiently with less time consuming.
- TaaS enables better interactions among each team. In particular, learners highly impressed by the effective multi-party discussion organized by the Jigsaw Service.
- Mutual supervision supported by the Mornitor Service help learners tackle problems in time during their in-progress work.
- The KTLE learning flow embeded in TaaS refines learners' entire learning process. Their work is settled in a reasonable sequential manner so that they can conduct it systematically.
- Planning task/subtask in advance in the Bulletin Service is central to having a completed and in-depth thoughts about the way to finish their assignments. Detailed task schedules can lead them to work in the right directions.
- Using TaaS is able to detect some rare occasions such as cheating and plagiarizm, and prevent several learners from claiming another's work as their own.

The detailed students' feedback is in Appendix A, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TLT.2014.2340402. In this semester, students using TaaS achieved an average score of 21.33 out of the total assignment mark 25. This score is 2.57 higher than the rest 16 students'. Compared with last years' this course, TaaS help students achieve better scores as well, which increased by 2.29.

We have invited the lecturer and three tutors of this course to evaluate five aspects of TaaS as summarized in Table 1:

For each question, they can feedback on one of the five options: 1) very ineffective; 2) ineffective 3) fair; 4) effective; 5) very effective. (The survey result will be given in Fig. 5 in next section). We have also sought their further opinions. They noticed that, as teachers, initial they have to spend a little time on understanding the operation principle of TaaS, and configuring sorts of measures, from the length of each stage of the Jigsaw classroom to the deduction weights.

TABLE 1
Survey for Evaluations of TaaS by Teachers

Q1	System architecture and entire learning flow
Q2	System integration and switch with Moodle
Q3	Overall user interfaces (UI)
Q4	Organizing discussions by the Jigsaw Service
Q5	Forming teams by the Inference Service
Q6	Setting the penalty mechanism in the Monitor Service

7.2 Case Study 2

We proceeded the second case study in another postgraduate level course related to information management of the same school, in late 2013. Fifty-six students were enrolled in this course. They were given a team assignment which asked them to construct an ontology-based semantic framework and also enclose descriptions of their work product into reports. The grade of the team assignment takes 40 percent of the final grade of this course.

Similarly, we suggested these students involved to adopt TaaS for easing the procedure of their team assignments, and 37 students responded actively of their own free will. We have adopted learners' opinions collected from case study 1 as questions, as shown in Table 2. After they submitted their final assignment works in the 13th week of the semester, we asked these 37 students who drew TaaS's aid to fill the questions in the survey.

For each specific question, surveyed students can opt one in five choices to identify: 1) strongly disagree; 2) disagree; 3) neutral; 4) agree; 5) strongly agree. The results are shown in Fig. 4.

The means for each question of the survey ranging from 3.75 to 4.24. The standard deviations of the overall results are between 0.71 and 0.87. All their returned values have a mean much larger than 3, the neutral response. This indicates that students generally agreed TaaS had facilitated their collaborative learning.

The two lecturers and two tutors of this course were also invited to investigate TaaS using the survey shown in Table 1. The answers from the 8 teachers from the both courses described in case study 1 and 2 are summarized as Fig. 5.

The means of each aspect are higher than 3 and their standard deviations are from 0.60 to 0.99. In particular,

TABLE 2
Survey for Evaluations of Improvement for Collaborative Learning

Q1	Learners have better knowledge of peers, getting familiar with their strengths and shortcomings
Q2	Teams are formed suitably and team members feel more confident to allocated task
Q3	Teams can be organized efficiently with less time consuming
Q4	Have better communication and effective discussions
Q5	Mutual supervision are helpful to tackle problems timely
Q6	The entire team assignment process is refined in a succinct way
Q7	Detailed task schedule is necessary to avoid confusion and the waste of resources
Q8	TaaS is able to detect and prevent rare occasions such as cheating, plagiarism, etc.

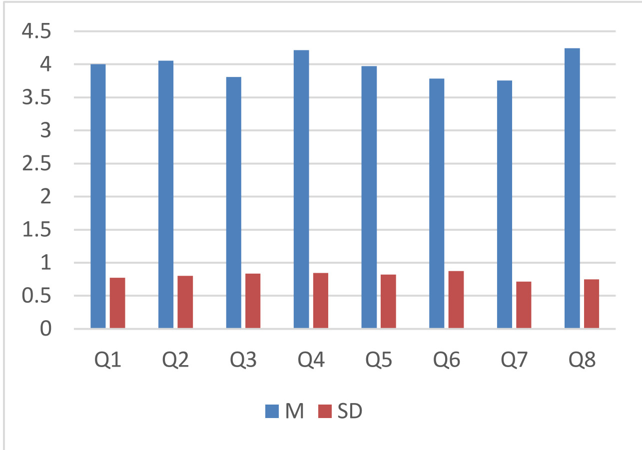

Fig. 4. The means and standard deviations of the responses for evaluations of improvement for collaborative learning.

'Forming teams by the Inference Service' is mostly appreciated, with a mean of 4.25, and 'System integration and switch with Moodle' and 'Setting penalty mechanism' are tied for second with means of 4.125. On the contrary, teachers have relatively lower opinions on the 'Overall user interfaces', which is averagely marked as 3.375, just a little better than the neutral value.

Compared with the 19 students in the control group, these TaaS-aided 37 students obtained a 4.69 higher average score, 34.93 of 40. Another surprising result is that, they also averagely scored 36.41 of 50 in the final exam, which is 3.42 higher than the control group's. This implies, with TaaS, students not only improve their performance in collaborative learning, but also likely deepen their understanding and master the knowledge of this subject to some extent. However, as the current scale of investigation is relatively small, we will engage more students in our further controlled studies.

7.3 Case Study 3

In early 2014, the third case study was conducted in the College of Textiles and Garments, Southwest University, China. Sixty-seven senior students were engaged in an undergraduate level course named 'Careers Guidance'. This course is a compulsory subject, the credit obtained is one condition of

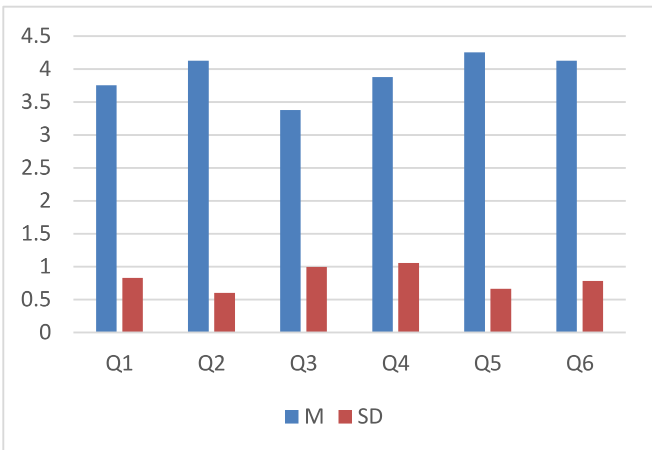

Fig. 5. The means and standard deviations of the teachers' responses for evaluations of TaaS.

TABLE 3
Survey for Evaluations of TaaS by Students

Q1	Self-evaluations by the Survey Service
Q2	Peer-evaluations by the Survey Service
Q3	Discussions in the original teams by the Jigsaw Service
Q4	Discussions in the expert teams by the Jigsaw Service
Q5	Publishing task schedule in the Bulletin Service
Q6	Browsing and modifying published task schedules in the Bulletin Service
Q7	Marking expected-achievable values and preference in the Bulletin Service
Q8	Mutual supervision by the Monitor Service
Q9	Overall User Interfaces
Q10	Integration and switch with Moodle

their successful graduation. Given it was set in their fourth year of bachelor studies, student were normally in their internships which meant they might not be on campus because they were taking duties in companies or institutions all around China. Hence, this course was taught in a distanced manner. They were required to read course-related materials rather than participating in face-to-face lectures. Their team assignment was to write a co-authored essay to express their ideas and cognitions about joining in workforce, along with a detailed job plan.

We asked them to fill an optional questionnaire to measure the usefulness and ease of use of several typical functions of TaaS. These functions are summarized as Table 3 below. For either usefulness or ease of use, the questionnaire was five-choice based: 1) very low; 2) low; 3) neither low nor high; 4) high; 5) very high.

As shown in Fig. 6, the standard deviations of the overall usefulness are between 0.67 and 0.89. Except of the Q9 (Overall user interfaces), all questions' reported means are larger than 3.8. The standard deviations of the overall ease of use are between 0.73 and 0.92. Q9 gets the lowest mean of reported values again, while means for the rest nine questions are very close to or larger than 3.8.

The students have further mentioned that TaaS was very helpful for those who should take off-campus courses like them. They enjoyed the entire process of co-authoring the team report, from the initial work construction, writing in parallel, to revisions and finalization. They admitted that using TaaS put away their worries about the situation that they could not break away from internships in order to fulfill the requirement of this subject, or to participate or even launch the teamwork in such a distributed circumstance.

7.4 Discussion

Based on our case studies, we find that generally learners and teachers recognize that functions of TaaS are of significant assistance to facilitate collaborative learning.

From the eight typical viewpoints in case study 1 and as summarized in Table 2, TaaS is not only able to offer a better learning experience for learners in eight aspects, but also help them to enhance their performance to some extent, which is directly demonstrated by their grades. Based on students' feedbacks, we also conclude following aspects:

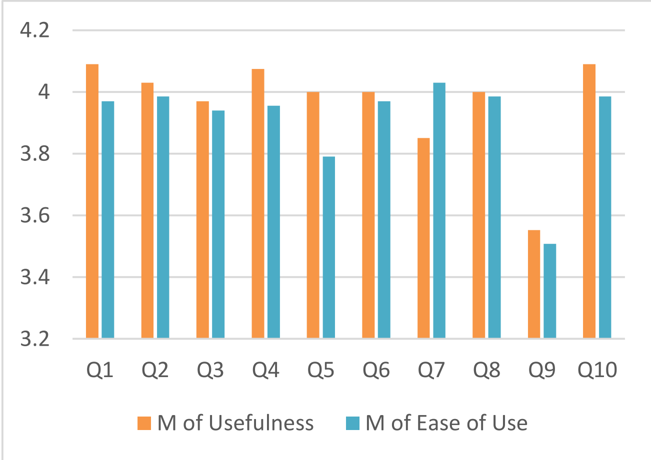

Fig. 6. The means of the responses for the usefulness and ease of use of TaaS.

- TaaS directly introduces learners by showing their KLS and comprehensive teamwork skills in a visual bar chart tool, thereby establishing a culture of trust within the team;
- Learners who see their work as habits rather than choices are more likely to perform better, and have more motivation when faced with difficulties;
- The one-sidedness of team formation is minimized, and some negative interpersonal factors present in traditional team learning are avoided;
- The cloud-based Jigsaw Classroom gives learners 'a better way to learn something' which is 'to teach it to someone else'. Similarly, they are encouraged to assimilate others' viewpoints;
- It promotes positive competition within the team, and decreases the probability that the whole team's outcome is going to be delayed because of a few under-performing members;
- Learners plan for themselves based on their actual situations and skills, thus their tasks are more achievable;
- The mature KTLE theory helps learners structure the essential competencies necessary for team learning, which can be executed smoothly by simple operations through mobile devices.

Among all functions, learners deem that 'self-evaluations', 'discussion in the expert group' and 'integration and switch with Moodle' are very useful in a mobile learning environment. Although they think publishing a task schedule is a useful function, but being limited by the input methods of mobile devices, this function is regarded as comparatively not very easy to use. Conversely, from Fig. 6 the 'marking expected-achievable values and preferences' function is assumed to be easy to use, with a visible difference to its usefulness. This is because it is single-choice based. On the other hand, as the running time of GA is generally satisfactory, and the task allocation method can assign team members in place as soon as the essential preparations are completed over the first three stages of KTLE, hence this approach is deemed efficient to form teams.

Teachers agreed TaaS is workable with a cloud-hosting LMS by only increasing teachers' workload with an acceptable scale. Both teachers and learners raise an issue that there is a room to modify, beautify and improve TaaS's UIs.

In this paper, we mainly focus on the back end mechanism and learners' team learning experience, so that the UIs are roughly developed and basically oriented to web browsers. We will improve this in our future work.

8 Related Work

Some researchers have applied identifying learners' KLS to improving teaching outcomes by recognizing the importance in considering individual student's needs [57], [58]. Some other researchers also noted that the concept of KLS could also be utilized to assist in structuring virtual learning environments, through adapting the design of online distance courses to accommodate learners' styles [59], [60]. Compared with them, our work focus more on teamwork of online courses by adapting learners' KLS to tasks which they would be in charge of so that to ensure their competences and motivations throughout the entire collaborative learning process.

In [61], the authors suggested a way to deal with the online team formation with the assumption that people possess different skills and that each task requires a specific set of skills. They employed a social network to model the capability of potential team members. We further embody learners' skills and other social features, and utilize a heuristic algorithm, GA, to guarantee the formation can be appropriate to learner numbers from dozens in single online class to thousands in MOOC.

The problem of task allocation has been studied by many researchers and GA has been widely applied, especially when there are problems with large scale and complex structure [62]. For example, [63] presented a GA-based study of two task allocation models in distributed computing systems. As reported by [64], in globally distributed software projects, individual tasks can be allocated to resources across locations using a GA. Our work innovatively introduced the GA-based task allocation approach from distributed systems to human being activities, and realized it into TaaS for real university level courses.

In [65], the authors presented a framework by which the candidates' knowledge is analyzed. Based on their knowledge and collaboration, a GA was utilized in that framework to select proper personnel and appoint the appropriate team managers and team members. This work is oriented to human resources in business activities of enterprising institution, and features they adopted to measure candidates' knowledge are quite different to learning styles or preferences. Furthermore, their team structure suits to the requirement of workforce, while in our designed teams, learners are equal to each other. In [66], the authors introduced a GA-based method to discover the optimal learning path from among numerous candidate courses for undergraduate students.

To encourage and help learners to easily participate in collaborative learning, some researchers have exploited cloud computing to construct the collaborative learning platform in the e-learning environment [67]. Multi-person academic writing could also be organized by the supporting tools over the cloud [68], and the establishment of a private cloud educational institution was described by Mousannif et al. [69]. These works inspire us to build a collaborative editing environment over the cloud to offer learners a place to construct and mature their ideas. We apply it in the third stage of the teamwork-enhanced learning flow, namely activities supported by the Bulletin Service. Another study combined the cloud with the mobile environment, by providing an application based on the Android OS [70], and it suggested that a mobile collaborative learning cycle was appropriate for both the ubiquitous learning environment and online classes. This work was helpful for lifelong virtual learning, but did not touch deeply in collaboration. For this reason, we proposed a learning flow rather than cycle, and divided it into stages based on KTLE and carefully refined each by organizing meaningful activities, while taking social features involved in collaborative learning into account.

Our own earlier work also tried to address adaptive content delivery, including UI issues, in mobile learning environments [71], [72], [73], by using neuro-fuzzy networks. This work, on the other hand, focus on improving group work performance on top of that, with the support of GA.

9 Conclusion and Future Work

The main contributions of this paper are:

- We have followed the KTLE to orchestrate a mobile cloud-based learning flow, which consists of necessary steps to build a successful team.
- The execution of the new learning flow is realized by running cloud based web services combined with a popular LMS (i.e., MOODLE), where each of the services contribute functions by adding refined learning activities into the original teamwork processes.
- Additionally, considering the limitation of less face-to-face communication in the mobile environment, we introduce a new approach for task allocation. This approach focuses on assigning learners highly suited tasks. As the attributes of candidate learners and tasks are complex, a genetic algorithm method is utilized to computationally determine the task allocation. Experimental results show that the method functions effectively in real mobile cloud-based learning.
- We have conducted three case studies to prove the usability of TaaS and evaluate how much its help and ease of use has been demonstrated in real courses, and to what extent it facilitates team learning in mobile environment.

Our future work will focus on offering a client application for easier use through mobile devices. Because our mathematical model is extensible, other aspects of social features or social knowledge may also need to be considered in order to provide better prediction for the social context. New exciting opportunities are worth investigating how team members adapt to new pedagogical environments in the social network era.

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