# Intelligent Support for Group Work in Collaborative Learning Environments

by


## Shuangyan Liu


A thesis submitted in partial fulfillment of
the requirements for the degree of

**Doctor of Philosophy in Computer Science**


**Department of Computer Science**


March 2012


THE UNIVERSITY OF
WARWICK

# Contents

# List of Tables

# List of Figures

# Acknowledgments

I would like to express the deepest appreciation to my supervisor, Dr. Mike Joy, who led me to the interesting field of educational technology. He provided great guidance, support and encouragement to my study, and has always been patient to offer advice on my research. I would also like to thank my co-supervisor, Dr. Nathan Griffiths, for his valuable suggestions and feedback made to this thesis.

My thanks must also go to Dr. Sarabjot Singh Anand for his time and constructive feedback at the annual meetings during years of my study.

I am also very appreciative of Dr. Steve Russ, Dr. Jane Sinclair, Dr. Alexandra Cristea, Dr. Christine Leigh, Roger Packwood, and other staff members in the Computer Science Department, for their kind support during this PhD project. I also give sincere gratitude to the past and present colleagues in the Intelligent and Adaptive Systems Group. It was a great pleasure to work with them and they were very supportive and enthusiastic during my study.

In addition I would like to thank the students who participated in the experiments and the survey study for this PhD project, for their contributions and time, and the tutors in my department in coordinating the student groups, the university representatives in delivering the survey.

Thanks to my parents and sister for their unlimited support and encouragement. Without their love, care, and faith this thesis would have remained a dream.

Last but not the least, I would like to thank Xinuo from the deep of my heart, who has accompanied me to spend the most memorable time in my life. Thanks to his unending love and support. Thank you!

# Declaration

This thesis is presented in accordance with the regulations for the degree of Doctor of Philosophy. It has been written by myself and has not been submitted in any previous application for any degree. The work presented in this thesis has been undertaken by myself except where otherwise stated. Parts of this thesis have been published or submitted for publication as below.

The proposed approach in Chapter 3 was published in [114] and extended with much more details and the developed tool in [113]. The evaluation and its results presented in Chapter 4 have been submitted as a paper to a journal publication [111] and it is accepted and under revision. The survey-based study and its results described in Chapter 5 has been published in [115]. An overview of the proposed mechanism and the prototype system in Chapter 6 was published in [109], and the details of the predictive modelling process described in Section 6.2.2 and and 6.2.3 will be published in conference proceedings [110]. Chapter 8's detailed analysis and design processes of the architecture were published in [112].

# Abstract

The delivery of intelligent support for group work is a complex issue in collaborative learning environments. This particularly pertains to the construction of effective groups and assessment of collaboration problems. This is because the composition of groups can be affected by several variables, and various methods are desirable for ascertaining the existence of different collaboration problems. Literature has shown that current collaborative learning environments provide limited or no support for teachers to cope with these tasks. Considering this and the increasing use of online collaboration, this research aims to explore solutions for improving the delivery of support for group work in collaborative learning environments, and thus to simplify how teachers manage collaborative group work.

In this thesis, three aspects were investigated to achieve this goal. The first aspect emphasises on proposing a novel approach for group formation based on students' learning styles. The novelty and importance of this approach is the provision of an automatic grouping method that can tailor to individual students' characteristics and fit well into the existing collaborative learning environments. The evaluation activities comprise the development of an add-on tool and an undergraduate student experiment, which indicate the feasibility and strength of the proposed approach — being capable of forming diverse groups that tend to perform more effectively and efficiently than similar groups for conducting group discussion tasks.

The second focus of this research relates to the identification of major group collaboration problems and their causes. A nationwide survey was conducted that reveals a student perspective on the issue, which current literature fails to adequately address. Based on the findings from the survey, an XML-based representation was created that provides a unique perspective on the linkages between the problems and causes identified.

Finally, the focus was then shifted to the proposal of a novel approach for diagnosing the major collaboration problems identified. The originality and significance of this approach lies in the provision of various methods for

ascertaining the existence of different collaboration problems identified, based on student interaction data that result from the group work examined. The evaluation procedure focused on the development of a supporting tool and several experiments with a test dataset. The results of the evaluation show that the feasibility and effectiveness are sustained, to a great extent, for the diagnostic methods addressed.

Besides these main proposals, this research has explored a multi-agent architecture to unify all the components derived for intelligently managing online collaborative learning, which suggests an overarching framework providing context for other parts of this thesis.

# Abbreviations

| | |
|---|---|
| API | Application Programming Interface |
| BDI | Belief-Desire-Intention |
| CLE | Collaborative Learning Environment |
| CSV | Comma-separated Values |
| DLS | Diverse Learning Style |
| FSLSM | Felder-Silverman Learning Style Model |
| GCPD | Group Collaboration Problems Diagnosis |
| HTML | Hypertext Markup Language |
| IDE | Integrated Development Environment |
| ILS | Index of Learning Styles Questionnaire |
| iGLS | Intelligent Grouping based on Learning Styles |
| JSP | JavaServer Pages |
| OOAD | Object-Oriented Analysis and Design |
| LAMS | Learning Activity Management System |
| LMS | Learning Management System |
| LSQ | Learning Style Questionnaire |
| MLR | Multinomial Logistic Regression |
| Moodle | Modular Object-Oriented Dynamic Learning Environment |
| SLS | Similar Learning Style |
| SPSS | Statistical Package for the Social Sciences |
| SQL | Structured Query Language |
| XML | Extensible Markup Language |

# Chapter 1
# Introduction

This research pursues answers for the following main research questions. What approach can be applied for group formation that tailors to individual students' characteristics and fits well into the existing collaborative learning environments? What problems exist widely in group collaboration and what are the factors that may lead to these problems? What approach can be adopted for automatically diagnosing these identified group collaboration problems in a collaborative learning environment?

## 1.1 Problem Statement and Motivation

Collaborative learning enables individual students to combine their own expertise, experience and ability to accomplish a mutual learning goal. Teachers are key performers in the process of structuring and managing online group work in current collaborative learning environments (CLEs). There is limited or no support for them to cope with tasks relating to organizing effective groups that satisfy individual students' needs and assessing their problems in the collaborative process. As a result of this, the teachers must adopt a direct-manipulation method of interaction to cope with these tasks [141]. However, this direct-manipulation method is very time-consuming and labour-intensive for information gathering, retrieving and filtering. Along with the increasing use of online collaboration, there is a growing need to improve the delivery methods and to simplify how teachers manage collaborative group work.

The composition of groups is one of the factors that determine the effectiveness of collaborative group work, and is affected by several variables, including the demographics of the group members such as age, gender and race, the size of the group, and other differences between participants [54], and the allocation of students to such groups should take those factors into consideration. Furthermore, for a group to function effectively in a given learning environment, teachers should identify specific student characteristics and the group type (homogeneous or heterogeneous) which they understand to be appropriate for the learning activity [168]. However, the approaches adopted by teachers for group formation are usually forming ad-hoc groups in which these two aspects are ignored. Take self-created groups and computational randomly assigned groups as an example, it could be argued that these approaches provide no particular educational benefits. Self-created groups in particular friendship groups usually tend to avoid heterogeneity [148]. Randomly assigned groups do not ensure that students satisfy their individual needs.

Recent work has highlighted how consideration of learning styles in the process of group formation for collaborative learning can have a positive impact

[7,139,165]. However, current research does not suggest an approach that can automatically and efficiently form learning style groups. It motivates this research to propose an approach for group formation based on students' learning styles.

Some recent empirical studies including [8,71,81,93,118,142,143] have revealed that there is still a variety of problems existing in group collaboration, which eventually affects the effectiveness of collaborative group work. Some problems are caused by factors not directly related to the students such as challenges inherent in virtual communication relying solely on written language, insufficient and ambiguous instructions, and problems presented by working in different time zones. These studies also indicate that student-induced problems are the most serious. However, current literature does not systematically address the major student-induced group collaboration problems and the factors that may cause such problems. This issue motivates the research carried out in this thesis to identify student perceptions of the major group collaboration problems and their causes.

Assessing these collaboration problems can assist teachers or moderators to understand and evaluate how individual students perform in a collaborative group as well as help students to reflect on their own learning. However, judging the existence of these problems is a complex task because a variety of such problems exist and distinct methods or techniques are required to support the analysis of these problems. Current applications that support online collaboration (including single tools such as forums and wikis as well as collections of tools such as collaborative learning environments) have limited or no support for monitoring the collaborative process and thus assessing the problems encountered by individual students and groups.

A number of research studies in interaction analysis for collaborative activities including [9,30,31,33,91,164,166] have indicated that quantitative data relating to student interactions with a collaborative learning system can account for the behaviours of individual students and collaborative groups. For example, Talavera and Gaudioso suggested that the number of threads started by an individual student can indicate the degree of involvement to produce a contribution [164]. Therefore, this research also seeks to propose an approach that can automatically diagnose the identified types of group collaboration problems based on student interactions with a collaborative learning environment.

Besides the above main research questions, this research also explores an architecture which can intelligently manage online collaborative learning. This is because the proposed approaches for group formation and collaboration problem diagnosis derive a set of components providing solutions to the detailed issues faced, and an architecture is needed to unify all the components into a single system. This architecture serves as an overarching framework that provides context for other parts of this research.

A number of researchers have used software agents for developing pedagogical systems to support online collaborative learning including MASCE [122], SACA [99], ELMS [116], I-MINDS [159] and CITS [147]. It is indicated from these researches that software agents are a useful tool for constructing intelligent collaborative learning environments because they provide increased flexibility and autonomy for the system to be developed. This aspect motivates this research to explore a multi-agent architecture for supporting online collaborative learning.

## 1.2 Research Aim and Objectives

The aim of this research is to explore solutions for improving the delivery of support for group work in collaborative learning environments, which can provide an enhanced and efficient way for teachers to cope with tasks of constructing collaborative groups and diagnosing group collaboration problems.

To achieve this aim, the following objectives are to be addressed.

- Investigate the state of the art in the fields of collaborative learning environments and group collaboration, and assess the existing approaches for group formation and collaboration problem diagnosis.
- Propose an approach that can automatically and efficiently form groups based on students' learning styles and is generally applicable for contemporary collaborative learning environments.
- Develop an add-on tool for group formation in a representative collaborative learning environment that implements the proposed approach for group formation.
- Evaluate the effectiveness of the grouping algorithm for group formation which is the core component of the proposed approach by conducting a collaborative process-oriented experiment.
- Identify major student-induced group collaboration problems and their causes from the perspectives of students via a nationwide survey in the UK, and provide a machine-readable form of the linkages between the problems and their causes.

- Propose an approach that can automatically diagnose the identified types of group collaboration problems based on student interactions with a collaborative learning environment.

- Develop a tool for diagnosing group collaboration problems that implements the core components established for the diagnosis approach proposed.

- Carry out an evaluation of the diagnostic mechanism developed using a mixture of methods to determine its validity and effectiveness in ascertaining the existence of the collaboration problems identified on a test dataset.

- Unify the components derived from the proposed approaches in a multi-agent architecture for managing online collaborative learning.

- Reflect on the findings from the evaluations and make conclusions about whether the approaches proposed could enhance the ways teachers manage online group work.

The contributions of this thesis are presented as follows.

- This research proposes a novel approach for group formation which can automatically and efficiently form heterogeneous learning style groups in web-based collaborative learning environments, which current research fails to address.

- Based on the results from a survey-based study, this research identifies major student-induced group collaboration problems and their causes from the perspectives of students, and establishes a machine-readable representation of the linkages between the major problems and their causes. This is the first study that systematically addresses this issue, and the representation provides a unique perspective on the linkages between the problems and causes identified.

- This research proposes a novel approach for automatically diagnosing the major group collaboration problems based on student interactions with a collaborative learning environment. This is, to our knowledge, the first approach that addresses various methods for ascertaining the existence of different group collaboration problems.

- A multi-agent architecture is defined which unifies all the derived components of the proposed approaches into a single system. Although this is not a main contribution of this thesis, it suggests an overarching framework providing context for other parts of this thesis, and it can also support the development of intelligent collaborative learning environments.

## 1.3 Thesis Outline

The structure of the remaining chapters is as below.

Chapter 2 presents a literature review of collaborative learning environments, group formation, group collaboration problems and diagnosis of collaboration problems. This review analyses the relevant theories and practice and identifies the gaps in existing literature which motivates this research.

Chapter 3 starts with an overview of the proposed approach for group formation and then discusses the components of the approach in detail. It also describes the add-on tool developed for the Learning Activity Management System (LAMS) and demonstrates how it supports the process of group formation in a real world scenario.

Chapter 4 describes the methodology and results of a student experiment which examines the effectiveness of the grouping algorithm proposed. Both quantitative and qualitative methods were applied for analysing the experiment data and a comprehensive discussion on the findings is presented.

Chapter 5 reports the methodology and results of a nationwide survey in the UK, which reveals student perceptions of group collaboration problems with online group work and the factors that can cause these problems. An XML-based representation of the linkages between the identified major problems and their causes is described followed by a discussion of its potential use.

Chapter 6 moves on to present one of the main contributions of this thesis. It begins with an overview of the approach proposed for diagnosing group collaboration problems, and continues with a description of its components. This chapter finally describes a supporting tool that was implemented and acts as a proof-of-concept of the core mechanism constructed.

Chapter 7 focuses on presenting the methods and results of several experiments carried out for evaluating the performance of the diagnostic mechanism proposed, using a test dataset that was collected from a web-based computer science group project. It also provides an exhaustive discussion of the evaluation findings.

Chapter 8 builds up a multi-agent architecture incorporating the components derived from the main research proposals using an agent-oriented modelling methodology. The focus of this chapter is not on presenting a critically evaluated system but exploring an overarching framework that provides context for other parts of this thesis. The methodology, the analysis and design process and the architecture itself are presented.

Chapter 9 concludes this thesis and summarises the main contributions of this thesis to the research field. This chapter also suggests some possible directions for future work.

# Chapter 2

# Background and Related Work

Having addressed the aims and objectives of this thesis in Chapter 1, this chapter presents a review of relevant literature which provides a theoretical foundation of the thesis. The emphasis of this literature review has been laid on current delivery of support for group work in collaborative learning environments with regard to the formation and diagnosis for groups, and theories and practice relating to the topics of interest. This literature review has identified the gaps in research that motivate this thesis.

## 2.1 Collaborative Learning Environments

A collaborative learning environment (CLE) is a web-based educational system that provides collaborative learning specific functionalities (i.e. structuring and managing the collaboration [149]) as well as other supporting functionalities for online learning (e.g. designing, managing and delivering learning content). Dimensions along which collaboration can be structured include but are not limited to the allocation of members to groups [47], assigning group members to roles such as ‘producer’ and ‘reviewer’, and regulating who can interact with whom over time [10]. Forms through which collaboration can be managed include collecting interaction data, constructing models of interaction, comparing with desired state, moderating [149], etc. The supporting functionalities constitute the basic platform for online collaborative learning as for other e-learning forms, which include administration, content management, the learning workplace and tools for interaction (e.g. chats, forums, bulletin-boards) [126]. This definition of a CLE is also used by prior research in web-based collaborative learning environments including [97,107,153].

Current collaborative learning environments, which are better known as Learning Management Systems (LMSs), are used to distribute courses over the Internet with features for online collaboration. Some common LMSs are Moodle [128], LAMS [49] and Blackboard Learn [26]. The main feature of the existing collaborative learning environments is that they consist of courses that contain activities and resources. Students can take an online course by participating in the activities arranged for the course. Here an activity means the work to be completed by students for the purpose of learning or assessment. There are mainly three common types of activities that are supported by these collaborative learning environments: informative activities (e.g. noticeboards, announcements, and sharing resources), collaborative activities (e.g. chats, forums, and wikis), and assessment activities (e.g. choices, questions and answers, and submitting files).

An activity-based collaborative learning environment is structured mainly for designing, delivering and managing such activities. Such an environment supports various functionalities: content management allows various activities to be defined and arranged for a particular course; tools for supporting activities provide different ways to present the activities; a collaborative workplace allows online students to carry out learning activities together and interact with each other remotely in synchronous or asynchronous ways; administration allows technicians to maintain the collaborative learning system and course managers to manage online courses.

Moodle is a typical activity-based collaborative learning environment, which is suitable both for individual learning and collaborative learning. Moodle offers 13 different types of activities that a student can complete via interacting with other students and/or the teacher. Among these activities, there are five types of activities that are used to support group work: chats, forums, wikis, blogs and glossaries (i.e. lists of definitions that can be created and maintained collaboratively). Moodle also supports a range of resource types such as files, pages (in HTML format) and links (URLs) that a teacher can add to a course to support student learning. It possesses all the supporting functionalities that are needed for a CLE. Regarding the collaborative learning specific functionalities, Moodle provides a basic level of support for structuring and managing collaboration. These include manually created or randomly created groups, logs of student participations ("view", "add", "update" and "delete") in any group activities and reports on the number of the hits on the group activities.

LAMS is an authoring and delivering system for online collaborative learning activities. LAMS is different from Moodle in that it is capable of capturing sequences of learning activities which involve groups of students, rather than a single activity or simply content. This is because LAMS has been developed in accordance with the Learning Design approach [36], which emphasises the capturing of the "process" of education instead of simply content. It is different from the well developed approach for e-learning which is dedicated to the authoring of content-based, self-paced learning objects for individual learning. LAMS provides 22 various types of activities of which six are for the group activities: chats, web conferencing, forums, Google maps (to add students' own place markers and view others' markers), mind maps and wikis. LAMS also allows a teacher to add a number of resource types such as files, URL links and zipped websites into a sequence of learning activities. Similar to Moodle, LAMS incorporates all the required supporting functionalities for a CLE and some simple collaborative learning specific functionalities such as teacher or student selected groups and random-created groups, and logs of user access to the group activities (for example, viewing a forum or a thread).

Blackboard Learn is a commercial application while Moodle and LAMS are open source LMSs. It provides a broad range of activities and resource types that a teacher or student can add to a course for supporting teaching and learning. There are six types of activities that deliver the support for group work including forums, glossaries, chats, web conferencing, blogs and wikis. Blackboard Learn comprises all the supporting functionalities that are needed for a CLE but provides very limited support for structuring and managing collaboration. Forms of support includes student self-enrolled or teacher manually enrolled groups and randomly created groups, and logs of user accesses to the group activities. Although providing simple methods for group formation, Blackboard Learn does not support the association of created groups with any group activities as Moodle and LAMS provide. Blackboard Learn can only create groups for certain activities which include discussion boards, email lists, file exchanges and online chats.

As can be seen from the above discussions, the existing collaborative learning environments provide a variety of supporting functionalities for online collaborative learning. Although they provide support for teachers to create collaborative groups, the methods adopted for constructing groups do not tailor to individual students' characteristics because students are usually assigned to groups manually by teachers or randomly by the systems. Moreover, most contemporary CLEs are capable of tracking the accesses and actions performed by users, which enable student interactions stemming from the collaborative activities examined to be captured. However, they do not provide support for teachers to check the progress of student collaboration and thus to assess the collaboration problems. To investigate these issues, the following sections present a discussion of the methods, tools, theories and practice for group formation, prior research which revealed the problems impeding group collaboration, and the methodologies for establishing the diagnostic methods.

## 2.2 Group Formation for Collaborative Group Work

### 2.2.1 Methods & Tools for Group Formation

Forming effective groups is a critical issue for improving the quality of collaboration for student group work [148]. The formation of collaborative groups, as addressed by Wessner and Pfister, is the process of identifying students who belong to one specific group [170]. In practice, the formation of learning groups is an educational instrument used by teachers to carry out their instructional design. Groups can be formed for different purposes. Student project groups for computer science courses are an example of task groups, which are formed to solve a specific problem. Student reading groups for language learning courses are an example of learning groups, which are formed mainly to enable learners to practice for a particular course assignment with no specific problem to solve (e.g. improving the speaking ability in English in front of other learners).

Group work in face-to-face setting and online setting each have their different features. Face-to-face group work has the advantage of verbal and non-verbal cues that can enrich the collaboration process while online group work is time independent and enables 'many-to-many' interactive communication which can boost the quantity and quality of interaction between students. These different features allow groups to collaborate differently in the two settings. As revealed from Smith *et al.*'s study [158], the most significant difference between face-to-face groups and online groups was that online groups felt less able to resolve their logistical issues including scheduling, time allocation and other related issues compared to face-to-face groups. Another significant difference lied in the communication methods and tools. In online setting, text communication is mainly used whereas in face-to-face setting students can easily conduct visual communication (e.g. draw rough sketches or point to hardcopy images) besides verbal communication. However, in an exploratory study conducted by Warkentin *et al.* [169] it suggested that there were no statistically significant difference in the proportion of unique information items exchanged between the online and face-to-face groups. Smith *et al.* [158] further suggested that there were no significant difference in satisfaction with a participant's group between students worked in face-to-face groups and online groups. From the study conducted by Stein and Wanstreet [161], it was revealed that there were no significant difference in satisfaction with the overall course and course structure between collaborative groups in the two settings.

Groups can either be homogeneous or heterogeneous. Many advocates of collaborative learning strive for heterogeneous groups. One of the main reasons is that heterogeneity naturally produces controversy more frequently [59]. This is consistent with literature on constructive controversy [58] which believed it can bring in multiple perspectives and impact on the collective acquisition of knowledge and skill within teams. Another reason is that heterogeneous groups can demonstrate more creative behaviours than homogeneous groups [154].

In traditional class mode educational settings, teachers usually let students self-select their group partners or manually assign them to different groups. As discussed in the previous section, chosen grouping function is provided by the typical collaborative learning environments to support teachers to input the results of student self created or teacher created groups into the system. However, there are limitations for these methods. Student self created groups are usually formed based on friendship rather than for educational reasons [148]. In this case, students tend to avoid heterogeneous groups because they prefer to choose group partners who are like them in ethnicity, student status, gender, knowledge or competence. This can prevent one of the benefits of collaborative learning, that is, learning from other students with different strengths and backgrounds. Manually assigned groups can increase the likelihood of heterogeneous groupings, but this does not ensure that the groups work effectively together. Moreover, constraints such as large class size and time limitation may prohibit teachers from forming groups efficiently.

Compared with chosen grouping methods, computational random grouping methods increase the efficiency of the group formation process and the likelihood of heterogeneous groupings, but do not guarantee that students satisfy their individual needs. Chapman *et al.* suggest that self selected student groups tend to work better than those groups selected by random assignment [154]. Their study indicated that students in randomly assigned groups generally had more concerns about working in their groups, and had slightly less positive group attitudes and lower group outcome measures. These findings agree with the results of Mahenthiran and Rouse's study [123] which showed that random groups obtained lower group performance and satisfaction, and demonstrated smaller individual accountability than self selected groups. As discussed in the previous section, most contemporary collaborative learning environments such as LAMS [49] and Moodle [128] can provide a random grouping function for teachers to cope with group formation tasks.

There is an increasing number of research projects taking into consideration the characteristics of individual students to develop methods and tools for supporting the group formation process. These characteristics could be subject knowledge levels, cognitive features (for example, learning styles and thinking styles), and/or personality. Existing literature such as [29,84,124,130,165,168] suggest a variety of methods for group formation based on different student characteristics. A number of research studies indicated that learning styles could have a positive impact on the process of group formation for collaborative learning [7,74,139,155,165]. An extensive review of relevant literature in the impact of learning styles on group collaboration and tools that support group formation based on students' learning styles is provided in Section 2.2.3.

Next, a brief explanation of the learning style theories is presented.

### 2.2.2 Learning Style Theories

Different people prefer different ways of perceiving, taking in, processing and understanding information. These preferred ways of learning are known as *learning styles*. Existing literature provides various definitions of learning styles from different perspectives. Fleming defined learning styles as consisting of four sensory modalities: visual, auditory, reading and kinaesthetic (VARK) [66]. Riding and Cheema defined learning styles as deep-rooted features of the cognitive structure of a person's mind including wholist-analytic and verbaliser-imager [150]. Myers and McCaulley defined learning styles as one component of personality type such as introvert-extrovert [132]. Honey and Mumford described learning styles as a preferred manner which people can have to complete any given learning task, as such a person can be classified as activist, reflector, theorist and/or pragmatist [85]. Kolb defined learning styles as an individual's preferred approaches for experience-grasping and experience-transforming which can be classified as converger, diverger, assimilator and accomodator [96]. Felder and Silverman defined learning styles as the ways people receive and process information such as visual/verbal and active/reflective [61].

Although the definitions are rather complex, learning styles can be categorized as either constitutionally-based or contextually determined [46]. The constitutionally-based learning styles such as [66,150] are deep-seated, possibly biological. They are relatively fixed and not amenable to educational change [3]. The contextually determined learning styles such as [85] are learning preferences that may change from context to context [46]. There are other theorists who believe learning styles can operate across all activities and subject areas, for example, science, engineering or art [3]. Furthermore, it can be inferred from the various definitions of learning styles that the perceptions of learning styles overlap with some other concepts such as personality and cognitive styles. Nevertheless, they are not equivalent.

### 2.2.3 Impact of Learning Styles on Group Collaboration

An increasing number of studies have explored the relationships between psychological attributes of students and group collaboration development [165,168] [4,40,84], and many of these studies reveal that such attributes (including learning styles) affect how students engage with group collaboration. This could because, as Steiner suggested, psychological features of group members form one of the determinants of a group's potential productivity, which is "the maximum level of productivity that can occur when an individual or group employs its resources to meet the task demands of a work situation" [162].

Wang *et al.* discovered that collaborative groups with higher levels of intra-group diversity of thinking styles can perform statistically significant better than randomly assigned groups and have less inter-group performance variance for completing the task of designing computer networks [168]. Chen and Caropreso conducted a study which involved 73 undergraduate students in performing three online asynchronous discussion tasks for an educational psychology course, and this study indicated that personality influences group discussion tasks both quantitatively and qualitatively [40]. Ahn also identified strong associations between personality types and group collaboration experiences [4].

Learning styles form one of the important psychology features of students that affect the learning process. Several existing case studies have shown that taking account of learning styles positively influences the effective formation of groups [7,74,135,139,165], and indicated that collaborative groups with appropriate combinations of learning styles could perform better than other types of groups on the assigned group tasks.

Alfonseca *et al.* conducted a case study, involving data gathered from 166 Computer Science students who have solved programming exercises in pairs [7]. Students were asked to select their group partners. The learning styles of the students were gathered through the Index of Learning Styles (ILS) questionnaire [62] before the group tasks started. The obtained learning style scores were used to analyse the compositions of the groups in terms of students' learning styles after the experiment was completed. The exercises were marked by the teacher who organised the course. The results suggested that learning styles affect the performance of the students when working in groups. In particular, pairs worked more effectively when the students' learning styles in the active/reflective dimension of the Felder-Silverman learning style model (FSLSM) [61] were dissimilar.

An empirical study by Papanikolaou *et al.* investigated the impact of learning styles on group formation for collaborative concept mapping activities [74,139]. This study collected data from 21 undergraduate students who had constructed concept maps on the topic "computer storage units". The students were assigned into seven groups (three students per group) that possessed various combinations of learning style type. The learning style types of the students were determined through their responses to the Honey and Mumford Learning Styles Questionnaire [85] and the Index of Learning Styles (ILS) questionnaire [62]. The group work was measured quantitatively according to two approaches for evaluating learning effectiveness of concept mapping tasks [92,163]. The findings suggested that the ideal group seemed to consist of students with a mixture of learning styles but without extreme difference (rather than students with a wide range of styles or students whose styles are similar).

Nielsen *et al.* carried out a study, gathering data from 96 undergraduate students who had participated in a team-formation process for the course on Psychological Testing, investigated the degree of student satisfaction and the ways that the students benefited from the team-formation process [135]. Students were assigned to groups based on their responses to the Danish Self-Assessment Learning Styles Inventory. The results showed that seventy-three percent of the students believed that the group formation based on their learning styles rather than random grouping had made a difference to the teamwork. Ninety-seven percent of the students agreed that they had improved understanding of the different ways of thinking by fellow students, which had prevented conflicts in the team at a personal level. This was viewed as one of the most important individual benefits by the students who took part in the focus group interviews for the study.

Furthermore, an empirical study by Taylor investigated the effects of learning styles on creating effective groups in project-based learning activities [165]. This study involved 75 students who participated in different types of groups: self-selected groups, similar learning style groups and diverse learning style groups. The learning styles of students were measured by the VARK learning style inventory [65]. The project outputs by different groups were graded by the teacher. The findings from the study indicate that diverse groups performed more effectively than the similar groups and the self-selected groups on the project output.

From the existing case studies, it is believed that learning styles are one of the important factors that affect group work. The tendency seems to be that mixed learning style groups without extreme differences work better than other types of groups. As can be inferred from Alfonseca *et al.*'s study [7], the active/reflective dimension is the most influential of the dimensions that impacts on group collaboration in the context of science and engineering education.

There are few methods and software tools developed for group formation based on students' learning styles. The PEGASUS system designed by Kyprianidou *et al.* [124] is a web-based system for supporting group activity in enhancing metacognition (students are supported to identify their learning preferences, which is utilised as a reflection framework) and group formation. The system allows the teacher to define homogeneous or heterogeneous learning style groups, and enables students to negotiate with the teacher of the group participation.

TOGETHER is a tool that can suggest a set of candidate grouping solutions for heterogeneous learning style groups in a visualized way, and allow a teacher to look for the best one through a trial-and-error process [140]. This tool applies an algorithm using heuristics to find an optimal solution for heterogeneous groups, and it requires the teacher to determine the appropriate solution based on his or her criteria. The teacher should try different criteria until he or she finds the best solution. It may be argued that TOGETHER does not provide an efficient way for building heterogeneous groups because the overall processes are rather complex and can be time-consuming for teachers to find a good enough solution. PEGASUS and TOGETHER are independent tools for supporting group formation. They do not suggest an approach from contemporary research that can automatically and efficiently form diverse learning style groups in web-based collaborative learning environments.

To our knowledge, few literature has discussed the issue of whether the impact of learning styles in forming groups more effective applying to face-to-face or online learning setting. This is because the research in the fields of online collaborative learning and incorporating learning styles in group formation have newly emerged since the recent few years which makes the above issue a new research area to be investigated further. As discussed in Section 2.2.1, some existing studies including [158,161,169] have found out that there were no significant difference in students' information exchange and satisfaction on a participant's group and course between working in face-to-face setting and online setting. Therefore, in this research, it is assumed that the effect of learning styles in forming groups applies to online setting as effectively as to face-to-face setting.

## 2.3 Review of Group Collaboration Problems

### 2.3.1 Technical Problems

Numerous studies including [42,44] have shown that collaborative group working is an important way to enhance the learning experience of students. This is because students can develop valuable skills in critical thinking and self-reflection and also develop strong team working abilities. Although empirical studies demonstrate the benefits that collaboration can bring for student learning (e.g. better learning outcomes), there are still many problems existing in group collaboration, which eventually affects the effectiveness of collaborative learning. These problems have been addressed by several studies including [6,8,80-82,93,100,118,127,142,143,151].

Some problems relating to online group collaboration are caused by factors not directly related to students. One problem area that prevents effective collaborations relates to the lack of sufficient technology support and difficulties in use of technology. An *et al.* suggested that challenges inherent in virtual communication relying solely on written language could impede online group collaboration [8]. This is because students are not able to access tones, facial expressions, and other non-verbal elements of communication that help convey emotion and meaning in face-to-face learning environments. There are other technology problems that can prohibit the effective collaboration among online participants, which include but are not limited to poor or unavailable internet connection and problems accessing the learning system [8]. Moreover, Hron and Friedrich argued that difficulties in use of technology might occur if the students participating in online collaboration do not possess or have enough computer literacy [87].

Insufficient and ambiguous instructions were also identified as one of the problems that impede online group collaboration [8]. An *et al.* pointed out that poor instructions could cause students to misunderstand the assignment and to feel they had lost the direction needed to complete it [8]. The reason for poor instruction in online environments mainly lies in the fact that most instructors have little formal training in how to successfully create and manage interaction in online courses [35]. Students who participate in online group collaboration could also face the challenge presented by working in different time zones [8]. This is because it is often difficult to find a dedicated time for all the students in a group to have online meetings.

However, these non-student-induced problems are not the main factors affecting group collaboration. The existing studies reveal that the most serious problems that students and instructors face are induced by the students themselves, and suggest that the problems induced by students must be addressed in order for effective group collaboration [6,8,80,151]. The next subsection presents a review of the student-induced group collaboration problems in detail.

### 2.3.2 Student-induced Problems

The major categories of group collaboration problems induced by students include poor motivation, lack of individual accountability and negative interdependence among group members.

**Poor Motivation**

In 2002 a national survey of educators in the US [20] ranked eighteen different factors by their level of impact on first-year students' academic performance, identifying "lack of (student) motivation" as the number one factor.

Hiltz and Turoff suggest group learning activities that are well-suited for online learning environments include online seminars (individual groups lead a discussion on a topic), collaborative exams (students construct exam questions and answer each other's questions), group projects (for example, collaborative composition of essays), case study discussions and debates [83]. Online discussion is a common and important component of the group learning activities. Al-Shalchi reported that students can behave problematically in such discussions, indicating that they possess poor motivation for the learning activities [6]. Al-Shalchi noted that some students may not participate in a discussion at all and others may take part but give short and superficial responses rather than deep reflective ones. Hassanien also pointed out that poor communication and poor attendance at group meetings are the main challenges that students face [80].

Paulus analysed the e-mails, discussion forums and chat transcripts of 10 small groups consisting of experienced distance students, noting that groups talked more about off-topic issues such as social and technology concerns than they did the concept to be learned [142]. Al-Shalchi suggested basic criteria to identify whether a student has poor motivation for online discussions, including quality of work (e.g. the post is irrelevant to the topic) and mechanics (e.g. the post contains several grammatical and/or spelling errors) [6].

**Lack of Individual Accountability**

An, Kim and Kim conducted an empirical study [8] on a sample size of 24 students enrolled in an instructional technology course. The participants formed small groups and were required to complete a four-week online group project. They were asked to comment on the problems they had faced completing the group project, and the most common problem was "lack of individual accountability". Several subcategories of this problem were addressed by the participants, including not meeting the deadlines, not completing assigned work, and lack of participation (e.g. not engaging with the online discussions).

Herrick *et al.*, based on their teaching experience of an asynchronous online class, noted that students tended to wait until the group work deadline to make postings on the group forums [81]. In the study of Gilbert *et al.* [71], students worked in pairs to conduct online discussion activities for supporting the topic of the week's readings. This study addressed the same impediment as what Herrick *et al.* noted, "Students would often only contribute to the discussion on the last day rather than consistently engaging in discourse over the entire discussion period."

**Negative Interdependence**

Burdett conducted a survey to explore the perceptions of final year university business students of their formal group work experiences [37]. The key experiences examined included group processes, learning outcomes and competencies gained. The results of the survey revealed that 26% of respondents perceived that they did most of the work in the group and that the workload was not shared fairly. This is consistent with the "free-rider" problem identified by Roberts and McInnerney [151] where one or more students in the group do little or no work and consequently decrease the group's ability to reach its full potential. Prior research including [93,118,143] also addressed the same impediment.

This negative interdependence among group members typically results in oppositional interaction (individuals obstructing each other's efforts to achieve), whereas positive interdependence can encourage members' efforts to help the group reach its goals [89]. Khandaker and Soh pointed out that the free-riding phenomenon could discourage student collaboration and student learning [93]. Johnson and Johnson further suggest that there are several ways that group members can promote each other's success, including giving and receiving feedback, challenging each other's reasoning, and exchanging resources and information [89].

As can be seen from this point, there are several problem scenarios existing which can reveal the same category of group collaboration problem. The analysis of the problem scenarios corresponding to each major category of group collaboration problems is described in detail in Chapter 5. Current literature indicates that student induced group collaboration problems are the most serious; however, it does not systematically address the main problems and provide insightful views on the factors that may lead to such problems.

## 2.4 Group Collaboration Problem Diagnosis

### 2.4.1 Interaction Analysis

Analysing group collaboration problems is a complex task because a variety of such problems exist and distinct methods or techniques are required to support the analysis of these problems. To address the required methods, research in the interaction analysis field [55,105,145] suggested the types of data that indicate the existence of various collaboration problems and the methods to obtain these data from the learning systems or environments. This field has made great strides in research that focuses on the extent of student participation in the learning process examined [21,52]. The aspects of analysis in the field of interaction analysis include the quantity and quality of student interactions with the system for performing the collaborative activities [77]. The former aspect derives activity information about student interactions with the system [32], for example, the number of accesses to the group workspace in the system by individual students. The latter aspect relates to the identification of the categories of contributions by individual students and groups in conversation-based collaboration. For example, Barros and Felisa Verdejo defined six types of contributions — proposal, contra-proposal, comment, clarification, question and agree — for analysing student contributions in a conversation-based collaborative task [21].

A number of research studies in interaction analysis for collaborative activities including [9,30,33,91,164,166] have indicated that quantitative data relating to student interactions with a collaborative learning system can account for the behaviours of individual students and collaborative groups. For example, Talavera and Gaudioso [164] suggested that the number of threads started by an individual student can indicate the degree of involvement to produce a contribution and the number of messages that a student replied to can imply a measure of how they are promoting discussion. In this thesis, the types of data that indicate the existence of various collaboration problems were derived from a review of the field in interaction analysis for collaborative activities. A detailed description of the indicators is provided in Section 6.2.2 ("indicators of collaboration problem existence").

The collaborative learning systems which support interaction analysis usually allow records of user accesses and actions performed when they are tackling the group tasks. Examples of these systems include the TrAVis system [125], the DIAS system [33] and the DEGREE system [21]. The information automatically recorded by such systems is generally comprised of the following types: the user identification, the session information, and the activity information (for example, the time and date, and who has viewed the group forum). All the information is usually stored in a relational database, and can be retrieved for producing the indicators that represent student interactions with the system through different queries combining a variety of selection criteria. Typical collaborative learning environments such as Moodle [128] adopt similar methods to capture and extract student interaction data.

Research in the interaction analysis field also provides methods, techniques and tools for qualitative analysis of the student interactions tracked from the group process examined. The common methods include discourse analysis, argumentation analysis, and content analysis. Discourse analysis is a complex field that focuses on investigating naturally-occurring language use in context [69]. Argumentation analysis places emphasis on studying the argumentative discourse, which can promote deep understanding of group learning [173]. Content analysis is defined as "a research methodology that builds on procedures to make valid inferences from text" [11]. Content analysis can be used to identify message types for conversation-based collaboration and thus to measure contributions by individual students and groups. In this thesis, diagnosing one of the major collaboration problems that were identified requires identifying the messages types for the posts created by students in group discussion forums. Thus, a content analysis technique is required, which should be capable of classifying the messages automatically. A possible technique that can be applied for identifying message types by the proposed diagnosing approach is presented in detail in Section 6.3.

In summary, the types of data that indicate the existence of the collaboration problems identified and the general methods to obtain the data from learning systems are addressed by contemporary research in the interaction analysis field. However, no research has addressed the issue of how to determine the existence of various collaboration problems identified based on the student interaction data. Therefore, one of the objectives of this doctoral study is to address various methods for diagnosing the problems for a piece of group work. Chapter 6 will present details of the proposed diagnostic approach, and determine some of the collaboration problems needed to quantitatively define the relationships between the existence of the collaboration problems and various types of student interaction data that indicate the problems. Predictive modelling offers such a methodology that can deal with this issue. Next, a brief description of the predictive modelling methodology and related work is provided.

### 2.4.2 Predictive Modelling

Predictive modelling [43,101,136] is a methodology that can produce predictive models which quantitatively define the relationships between the occurrences of an event (i.e. the response or dependent variable) and the factors that can indicate the occurrences of such an event (i.e. the predictors or independent variables). The produced predictive models can then be used to compute values of a response variable for a given set of predictors. The procedure of predictive modelling involves building a data set, which collects empirical data about the response variable and the potential predictors. Then statistical analysis techniques can be applied for estimating and validating the predictive models using the constructed data set.

The methodology of predictive modelling has been widely applied in different fields. In higher education, predictive modelling has been used in a number of areas including but not limited to enrolment management, retention and graduation analysis, and donation prediction [27,103]. In these areas, the majority of time spent on a modelling project is establishing the dataset to be used, and it usually requires at least one year of historical data for building such a dataset.

In the field of online learning, Balaji and Chakrabarti have adopted the methodology to investigate the factors that influence interactions and learning in online discussion forums [17]. The data for this study were collected from two sources. One consisted of the postings relating to the discussions on the content covered in an MBA course. The authors have given no details of what aspects of the postings were examined. The other was a post-course survey that gathered student perceptions of the various factors that affect the effectiveness of the interactions and learning in online discussion forums. Similar data collection methods were adopted for the predictive modelling process that will be presented in Section 6.2.2. Furthermore, in Liu and Cheng's study regarding the effect of group discussion on web-based collaborative learning [117], predictive modelling was used to investigate the relationship between the discussions categorised as “social talk” and “group-task-related dialogue” and the group learning outcome.

A wide variety of statistical analysis techniques are available for the predictive modelling including regression analysis [43], time series models [76] and survival analysis [95]. Regression analysis focuses on the relationship between a response variable (also known as the dependent variable) and one or more predictors (i.e. the independent variables) [43]. It was used for the predictive modelling process conducted in this thesis (Section 6.2.3) for the following reasons. First, regression analysis is applicable for the required predictive modelling task while some other statistical analysis techniques are not. The data needed for the predictive modelling task was collected at one time rather than taken over a period of time so that techniques such as time series models and survival analysis are not suitable for the modelling task. Second, regression analysis is conceptually simple but effective for the predictive modelling process while other sophisticated modelling techniques such as neural networks are surplus to requirements. Finally, there is a range of regression models available for fitting the collected data, which allows alternative ways to be adopted if a particular regression analysis technique does not work.

## 2.5 Summary

This chapter presented a review of the state of the art in the fields of collaborative learning environments and support for group collaboration. This review has identified several gaps in current research including: (i) recent work has shown that learning styles can have a positive impact on the process of group formation for collaborative group work, but it does not suggest an automated approach that can efficiently construct diverse learning style groups in web-based collaborative learning environments; (ii) there are a variety of group collaboration problems and existing studies indicate that the most serious problems are caused by students themselves, however, a systematical description of the major group collaboration problems and their causes from the perspectives of students is lacking; and (iii) diagnosing the group collaboration problems requires different methods for ascertaining the existence of these problems, however, no research has addressed an automated approach that can diagnose these identified types of group collaboration problems in a collaborative learning environment.

In the next chapter, the approach proposed for group formation based on students' learning styles is presented and the add-on tool that implemented this approach is also described.

# Chapter 3
# An Approach for Group Formation based on Learning Styles

In this chapter, a novel approach namely Intelligent Grouping based on Learning Styles (iGLS) is presented which attempts to automatically form heterogeneous groups based on students' learning styles in a collaborative learning environment (CLE). This chapter starts with an overview of the proposed iGLS approach. It then moves on to discuss the components of the iGLS approach in detail, which include the learning styles modelling component, the grouping parameter identification component and the iGLS grouping algorithm. Finally, an iGLS add-on for the Learning Activity Management System (LAMS) is described which was developed to demonstrate the feasibility of incorporating this iGLS approach into contemporary CLEs for the process of group formation.

## 3.1 Overview

From the review of existing case studies (as discussed in Section 2.2.3, i.e. "impact of learning styles on group collaboration"), mixed learning style groups tend to obtain better learning outcomes than other types of groups. Hence, the aim of this chapter is to propose a solution for group formation in a CLE which is able to formulate diverse learning style groups.

For achieving the aim of this chapter, the proposed grouping approach should address the following research questions. First, the approach should address the question of how to model students' learning styles. By the notion of 'model', the process of acquiring learning style scores from individual students is referred to. Second, it needs to identify other elements besides learning styles that should be considered for the problem of group formation together with a method to define them. Furthermore, the approach should include a method to create diverse groups of students based on their learning style scores and the identified elements that affect the group formation.

Considering these research questions, the proposed iGLS approach is composed of the following components:

- a learning styles modelling component;
- a grouping parameter identification component; and
- a grouping algorithm.

The *learning styles modelling component* is responsible for acquiring learning style scores from individual students. The *grouping parameter* *identification component* attempts to determine the method for defining the values of parameters to be used in the process of group formation. The *grouping algorithm* is the method for assigning students into heterogeneous learning style groups (i.e. students with different levels of learning style).

The overall process of applying iGLS for completing a group formation task is illustrated in Figure 3.1. This process includes extracting students' learning style scores through the learning styles modelling component, defining the values of the parameters via the grouping parameter identification component and subsequently assigning students into diverse learning style groups by the grouping algorithm. The grouping algorithm can take the students' learning style scores and the grouping parameters as input and generate the desired grouping results.

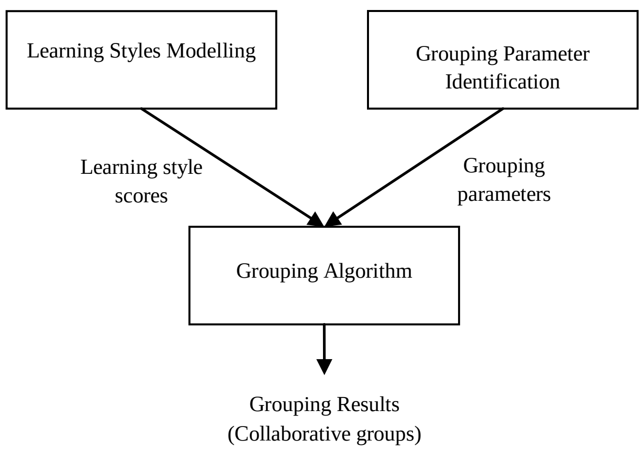


Figure 3.1. The overall process of iGLS

As the group collaboration process is assumed to be carried out with a CLE, the components of the iGLS approach are desired to fit into current CLEs. Before describing how the components of iGLS fit a CLE, the modules that constitute current CLEs for supporting teaching and learning activities are discussed below.

As mentioned in Section 2.1, the functionalities that a CLE provide are diverse, and can vary from educational administration to content management. The CLE block as shown in Figure 3.2 illustrates the functionalities that current CLEs (e.g. Moodle [128], LAMS [102] and Blackboard [26]) provide. These include administration, collaborative workplace, tools for collaborative activities and content management.

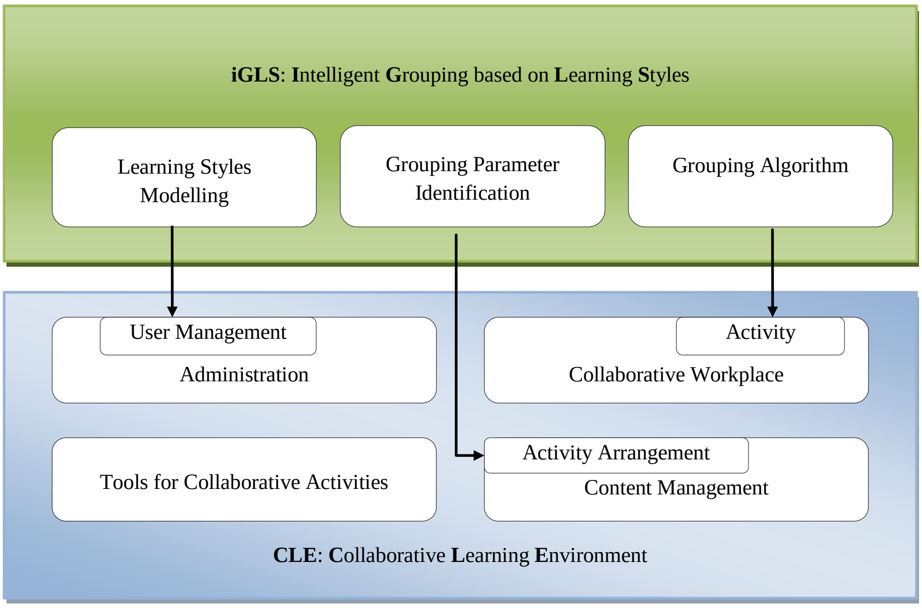


Figure 3.2. iGLS and collaborative learning environment

Each of the mentioned functionalities is supported by several modules of a CLE, which are described as follows:

- Administration:
  - user management
  - course management
  - system settings

- Collaborative workplace:
  - activity performing
- Tools for collaborative activities:
  - tools for learning activities such as chats, forums, and bulletinboards
  - tools for assessment activities such as questions, submit files, and multiple choices
- Content management:
  - learning resources management
  - collaborative activity arrangement

Figure 3.2 also illustrates how the three components of iGLS (the iGLS block) fit into a CLE for the process of group formation. The *learning styles modelling* component can be built on top of the *user management* module which supports the *administration* functionality of the underlying collaborative learning environment. The *grouping parameter identification* component can be integrated in the *activity arrangement* module which underpins the *content management* functionality of the CLE. Moreover, the *grouping algorithm* component can be incorporated into the *activity* module that supports the functionality of *collaborative workplace*. Details of the interactions between the iGLS components and a CLE are discussed later in Section 3.5.3.

In the remaining sections of this chapter, the three components of the iGLS approach, the iGLS add-on for LAMS and a scenario with the developed iGLS add-on are presented. Section 3.2 presents the categorization of learning styles that is adopted for describing students' learning styles, the reasons for choosing it and how it is applied in the learning styles modelling component. Section 3.3 identifies other elements that should be considered for the process of group formation and how the parameters representing these elements can be determined in the component for grouping parameter identification. Following that, the details of the proposed grouping algorithm are presented in Section 3.4. Furthermore, Section 3.5 discusses how the iGLS add-on for LAMS was created including a brief description of the LAMS system, the architecture of the iGLS add-on, the essential implementation issues that were decided and a concise description of the components of the developed add-on. Subsequently, a real world scenario in which the developed iGLS add-on is used for supporting the process of group formation in a LAMS system is described in Section 3.6. Finally, Section 3.7 presents a summary of this chapter.

## 3.2 Learning Styles Modelling

As discussed in Section 2.2.2 ("learning style theories"), the definitions of learning styles are very complex which lead to numerous ways of categorizing learning styles such as [85,96,132]. A categorization of learning styles is usually named as a model of learning styles. In order to describe students' learning styles, the Felder-Silverman learning style model (FSLSM) [61] is used in the proposed iGLS approach. Before discussing how this model is applied in the learning styles modelling component, a brief description of the FSLSM is presented below.

**Felder-Silverman Learning Style Model (FSLSM)**

FSLSM was initially proposed by Felder and Silverman in 1988 based on their expertise in educational psychology and experience in engineering education. The original model contained five dimensions of learning styles. Recently, this model has been modified. The current FSLSM include four dimensions of learning styles: sensing/intuitive, visual/verbal, active/reflective, and sequential/global. The review of the impact of learning styles on group collaboration (in Section 2.2.3) revealed that the active and reflective are the most influential learning styles that impact on group work [7,60,61]. Therefore, the proposed learning styles modelling component attempts to incorporate the active/reflective dimension of the FSLSM model for describing students' learning styles.

The 'active/reflective' dimension of FSLSM describes the way people convert perceived information into knowledge. Active learners prefer to learn by doing something with the information — discussing, or explaining it to others. Reflective learners prefer to review the information introspectively. More information about this dimension can be referred to [61].

Each dimension of FSLSM measures learning styles in a score between -11 and 11, increasing or decreasing 2 points in every step. All the negative values represent the scores of the active dimension and all the positive values correspond to the scores of the reflective dimension. The scale for the active/reflective dimension of the FSLSM model is illustrated in Figure 3.3.

Active Reflective

-11 -9 -7 -5 -3 -1 1 3 5 7 9 11

Figure 3.3. The active/reflective dimension of the FSLSM model

Using a scale between -11 and 11, strong and weak preferences of learning styles on a single dimension of FSLSM can be measured. If the score is valued between -3 and 3, a well balanced preference on the two styles of a dimension is indicated. If the score is valued in {-7, -5, 5, 7}, a moderate preference on the two styles of this dimension is revealed. Moreover, if the score is valued in {-11, -9, 9, 11}, a strong preference on the two styles of this dimension is shown.

There are several reasons for adopting the FSLSM model. First, FSLSM includes a dimension for identifying the active/reflective learning styles while most other learning style models do not. Second, compared with other models that contain active/reflective learning styles, FSLSM provides a sliding scale supporting a richer classification of students' styles which is more flexible than bipolar models for the balancing of learning styles in the iGLS approach. Third, FSLSM adopts the Index of Learning Styles (ILS) questionnaire [62] for measuring the described learning styles and the ILS questionnaire is shorter than the instruments used by most other models that contain the active/reflective styles such as [85] and [96]. The ILS questionnaire contains only 44 questions for measuring four pairs of learning styles while the instruments for most other models require more than 20 questions for identifying one pair of learning styles. Since students are more likely to respond to a shorter questionnaire, the ILS questionnaire is more acceptable by most students. Finally, FSLSM has become popular in technology-enhanced learning. Some researchers even argue that FSLSM is the most suitable learning styles model in technology-enhanced learning [41,98].

### A Questionnaire-based Approach for Learning Styles Modelling

As mentioned above, a questionnaire, namely ILS, is proposed by [62] to measure the learning styles categorized in the FSLSM model. The ILS questionnaire is adopted by the learning styles modelling component to acquire learning style scores from individual students. This is because a questionnaire-based approach for modelling students' learning styles is efficient and flexible and most current learning styles models adopt a questionnaire-based approach to measure students' learning styles. Moreover, the ILS questionnaire has been examined to be reliable and valid for assessing the learning styles categorized in the FSLSM model [63,108].

The ILS questionnaire consists of a total of 44 two-choice questions. These questions can be divided into four groups each of which comprises 11 questions. Each group is associated with one dimension of the FSLSM model. As only the active/reflective dimension of the FSLSM model is considered in the proposed iGLS approach, the group of questions that corresponds to the active/reflective styles in the ILS questionnaire is extracted to construct the questionnaire for the learning styles modelling component. This group of questions include 1, 5, 9, 13, 17, 21, 25, 29, 33, 37 and 41 (question number). These questions are manually grouped together according to the similarity of semantics on the active/reflective dimension of styles. For example, the questions 1 and 5 seek for the characteristic of "trying something out" for the active style and for the characteristic of "think about material" for the reflective style. The constructed questionnaire for the learning styles modelling is referred to as the learning style questionnaire (LSQ).

In the LSQ, each question includes two options ('a' or 'b'). The option 'a' represents the active style while the option 'b' corresponds to the reflective style. The learning style score on the active/reflective dimension can be computed by subtracting the responses of 'a' from that of 'b', which is an odd integer between -11 and 11. For example, if a student responds to the LSQ with 10 'a' and 1 'b', his learning style score is equal to -9. This calculated score indicates the student has a strong active style on the active/reflective dimension of the FSLSM model. The learning style scores obtained from the LSQ for individual students can be used in the proposed grouping algorithm for the process of group formation. It is compulsory for students to complete the LSQ before a grouping process starts. This is to ensure that the learning style scores of all the students who need to be grouped are obtained and the grouping process is successfully completed.

## 3.3 Grouping Parameter Identification

As mentioned in Chapter 1, group size is a key factor to be considered for the process of grouping formation [54]. Previous research such as [38,48,120] suggests that group size is positively related to group performance. However, there is disagreement about the optimal group size. Studies in personnel psychology and management such as [48] found that increasing group size could improve performance among employee involvement teams. Other studies investigating student group work in educational settings have shown that smaller groups tend to have better group performance because of a better sense of responsibilities and a deeper knowledge of the group members [72,137,156]. Furthermore, Forsyth pointed out that the size of a group can impact on the cohesion of a group [67]. Smaller groups which consist of fewer people find it easier to make agreements and to coordinate the task than larger groups.

The computational random grouping methods adopted by current collaborative learning environments has used group size as the parameter for constructing groups. For example, a LAMS system [49] allows teachers to specify the number of students per group as an input for the group formation component. Other collaborative learning environments such as Moodle [128] and Blackboard Learn [26] also adopt group size as a parameter for the group formation process.

In the process of group formation in which a class of students needs to be divided into different groups of the same size, the value of the parameter ‘group size’ can be determined in two ways. One is to determine the number of students per group directly. The other way is to determine the number of groups to be created. In the latter case, the size of a group can be calculated by dividing the total number of students by the number of groups to be created. For simplicity reasons, the former way is adopted by the grouping parameter identification component.

As can be inferred from the above discussion, it is impossible to define an optimal group size that suits all kinds of group task. Therefore, the number of students per group is used as a variable of the proposed grouping algorithm (Section 3.4). Correspondingly, the grouping parameter identification component focuses on the method to specify the value of this variable. This value can be determined by a course manager or a teacher who is responsible for organizing the group work. A suggestion of three to five students per group is made by Wessner and Pfister [170] whose studies indicate this as an appropriate size for collaborative learning activities.

Since most contemporary collaborative learning environments provide components for specifying the variables such as the number of students per group for the group formation process, the grouping parameter identification process is considered to make use of existing components provided by the collaborative learning environments for defining the values of the grouping parameter.

After the number of students per group is defined by a teacher, it is used by the iGLS grouping algorithm for creating groups of students.

## 3.4 The iGLS Grouping Algorithm

The review in Chapter 2 indicates that a method for forming heterogeneous groups based on learning styles in collaborative learning environments is lacking. Thus, the objective of the iGLS grouping algorithm is to form heterogeneous groups based on students' learning styles. That is, the proposed algorithm can divide all students into several collaborative groups which can demonstrate internal diversity. Internal group diversity refers to the feature that a single collaborative group contains students having different learning styles.

As discussed in Section 3.1, the learning styles modelling component provides the extracted students' learning style scores to the iGLS grouping algorithm, and the grouping parameter identification component offers the value of the grouping parameter to this algorithm.

There are four steps that compose the proposed algorithm, namely initializing, ordering, segmenting and assigning. A description of the four steps is provided below.

Let $L$ be the total number of students to be grouped, $N$ be the number of students per group (i.e. the defined grouping parameter), and $R$ be the remainder on dividing $L$ by $N$ ($L$, $N$, $R$ are integers).

As discussed in the previous section, past studies in group size and group performance have shown little consensus on the optimal group size [72]. Thus, the proposed algorithm does not define a constant but a variable for representing the group size (i.e. $N$).

The methods adopted by current collaborative learning environments such as student self-selection or teacher manual assignment often face the "orphan" student problem [138,148], which refers to the cases that some students are unassigned to any group after the group formation process. The proposed algorithm aims to overcome this problem. Thus, in the first step stated below, the algorithm picks $R$ students at random from the $L$ students. It then assigns these students into appropriate groups as stated in the fourth step. Consequently, the proposed algorithm does not allow any student "orphan".

**Initializing**: randomly select $R$ students from $L$; create $M$ empty groups according to the desired number of students per group, $N$, such that $M = \frac{L-R}{N}$.

As discussed in Section 3.2, the learning styles modelling component incorporates the active/reflective dimension of the FSLSM model [61] for describing students' learning styles because the active and reflective are the most influential learning styles that impacts on group work [7,60,61]. Thus, in the second step, the proposed algorithm incorporates learning style scores on the active/reflective dimension of FSLSM for sorting the students.

**Ordering**: sort the set of (*L*-*R*) students from highest to lowest learning style scores on the active/reflective dimension of FSLSM.

**Segmenting**: divide the ordered students into *N* equal segments.

The above step actually, divides the students into *N* intervals of learning style scores, which allows the selection of one student from each interval to form diverse groups of *N* students, as stated in the following step.

**Assigning**: for each of the *M* empty groups in turn randomly select one student per segment and assign them to the group, if the number of students remaining, *R*, is bigger than or equal to *N/2* then create an additional group and assign all the 'orphan' students this remainder group, otherwise compare *R* with *M*. If *R* is smaller than or equal to *M* then randomly assign each of the remaining students to one of the *M* groups. If *R* is bigger than *M* then divide *R* by *M*. If the quotient of dividing *R* by *M*, *q*, is bigger than zero and the remainder of dividing *R* by *M*, *r*, is zero then for each of the *M* groups pick *q* students randomly from *R* and assign them to the group. If *r* is non-zero, for each of the *M* groups pick *q* students randomly from *R* and assign them to the group, and randomly assign each of the *r* students to one of the *M* groups. If the quotient of dividing *R* by *M*, *q*, is equal to zero then randomly assign each of the remaining students to one of the *M* groups.

Since there is evidence that smaller groups are more effective in educational settings [111], it is assumed that where $R < N/2$ the resulting group size would not be viable and so students are assigned to existing groups. If the grouping algorithm is used to form larger groups then a threshold can be defined such that where $R \geqslant$ threshold a new "orphan" group is created. *N/2* is defined as the default threshold.

The pseudo-code of the algorithm is presented below as Algorithm 3-1.

**Algorithm 3-1: The pseudo-code of iGLS grouping algorithm**

```
// Variables:
// L: the total number of students to be grouped
// R: the remainder in the case that L is not exactly divisible by N
// M: the number of groups that are created
// N: the number of students per group
// sorted: the list of students whose learning style scores are sorted by the
function sort( )
// sl: the list of segments created
// segSize: the size of a segment
// empSeg: an empty segment that is created
// gl: the list of groups
// rNum: a random integer generated
// sgiL: the list for containing the selected group index
// s: a remaining student
// selectedGroupIndex: the index of the selected group
// gls: the size of gl

// Functions:
// read( ): read the data of the students to be grouped and the value of the
parameter 'number of students per group'
// remove( ): randomly select R students from L and remove them from L
// createGroups( ): generate the given number of empty groups
// sort( ): order the students from highest to lowest learning style scores
```

**Algorithm 3-1: The pseudo-code of iGLS grouping algorithm (Cont.)**

```
// createSL( ): create an empty list of segments
// createSegment( ): create an empty segment
// addStmS( ): add a student in sorted to an empty segment
// addtoSL( ): add a segment that contains students to a sl
// createGL( ): create an empty gl
// randomGenerator( ): generate a random number in the scope of the given
number
// addRStGroup( ): add the randomly selected student to an empty group
// addGrouptoGL( ): add an group that contains assigned students into the gl
// createGIL( ): create an empty list for containing the selected group index
// addSGI( ): add the index of the selected group to sgiL
// addRemainingStudent (gl, selectedGroupIndex, s): add the remaining student
s to the group in gl of which the index is equal to selectedGroupIndex
// addtoOrphanGroup( ): add all the remaining students to the orphan group

read( )

Initializing
remove (R, L)
if R < (N-1) then createGroups(M)
else createGroups(M+1)

Ordering
sorted ← sort(L-R)

Segmenting
sl ← createSL( )
segSize ← (L-R) / N
for each segSize of students in sorted do
    empSeg ← createSegment( )
    for each student in a segSize of sorted do
        addStmS( )
    addtoSL( )

Assigning
gl ← createGL( )
for each empty group do
    for each segment in sl do
        rNum ← randomGenerator(segSize)
        addRStGroup( )
```

**Algorithm 3-1: The pseudo-code of iGLS grouping algorithm (Cont.)**

```
        remove the selected student from the segment
    addGrouptoGL( )

if R < N/2 then
    if R <= M then
        sgiL ← createGIL( )
        for each remaining student s do
            selectedGroupIndex ← -1
            do selectedGroupIndex ← randomGenerator(gls)
            while sgiL contains selectedGroupIndex
            addSGI( )
            addRemainingStudent(gl, selectedGroupIndex, s)
    else  q ← quotient of dividing R by M
          r ← remainder of dividing R by M
          if q > 0 then
              if r = 0 then equalAssign(M, q, R)
              else equalAssign(M, q, R)
                   randomAssign (M, r)
          else if q = 0 then
              sgiL ← createGIL( )
              for each remaining student s do
                  selectedGroupIndex ← -1
                  do selectedGroupIndex ← randomGenerator(gls)
                  while sgiL contains selectedGroupIndex
                  addSGI( )
                  addRemainingStudent(gl, selectedGroupIndex, s)
else
    addtoOrphanGroup( )

return gl
```

At this point, the three components of the proposed iGLS approach — the learning styles modelling component, the grouping parameter identification component, and the iGLS grouping algorithm — have been discussed. In the following section, the iGLS add-on for LAMS that was developed is presented.

## 3.5 iGLS add-on for LAMS

### 3.5.1 Introduction

The iGLS add-on intends to demonstrate the feasibility of incorporating the proposed approach into contemporary CLEs for the process of group formation.

In order to achieve the aim, the following subsections are presented. Section 3.5.2 describes briefly the core features of the LAMS system and the reasons for adopting it. Following that, the architecture of the iGLS add-on for LAMS including the components and interactions between these components is presented in Section 3.5.3. Furthermore, Section 3.5.4 discusses the implementation issues that were addressed and the details of each component in the architecture. Exhaustive discussion on the implementation of the iGLS add-on is omitted since the focus of this section is the research ideas that it embodies.

### 3.5.2 Learning Activity Management System (LAMS)

Current collaborative learning environments include commercial systems such as Blackboard Learn [26] and open source systems such as Moodle [128] and LAMS [49]. The commercial systems were not selected as the underlying platforms for which the iGLS approach was implemented, because there lacked financial support to buy any license for this development, and the open source systems were considered to possess all the features that were needed for implementing the iGLS approach. A comparison of the relevant features of the existing open source collaborative learning environments is provided in Table 3.1.

Table 3.1 Features of open source collaborative learning environments

| | Moodle [128] | LAMS [102] | Ilias [2] | Claroline [1] |
|---|---|---|---|---|
| Programming language | PHP | Java | PHP | PHP |
| Supporting database | MySQL | MySQL | MySQL | MySQL |
| Available grouping functions | Manual or random grouping | Manual or random grouping | N/A | Manual or random grouping |
| Tools for learning activities | 13 tools (e.g. lessons, assignment, forum, chat etc.) | 22 tools (e.g. lessons, chat, forum, wiki, mind map etc.) | 10 tools (e.g. virtual classroom, chat, forum, blog etc.) | 6 tools (e.g. forum, chat, wiki, assignment etc.) |

LAMS represents a new generation of learning systems, which enables e-learning to move from a content-centred approach to an activity-sequence based approach [102]. It is a system for designing, managing and delivering online collaborative learning activities [49]. It allows teachers to create sequences of learning activities with an intuitive visual authoring environment. A range of tools are provided by LAMS to support the design of activities (as shown in the above table).

LAMS was chosen as the underlying collaborative learning environment for building the iGLS add-on. There are three reasons for this. First, LAMS is written in Java and adopts a set of Java based development tools, with which the primary researcher was most familiar. However, other systems such as Moodle are written in PHP (as shown in Table 3.1). It was more efficient for the primary researcher to accomplish the development of the iGLS add-on by adopting a familiar tool set than adopting a new one. Second, some of the existing collaborative learning environments such as Ilias [2] do not support the association of created groups with collaboration tools, which do not allow the demonstration of the developed tool in a learning scenario (the motivation scenario of the iGLS add-on for LAMS is described in Section 3.6). Finally, LAMS offers a wider range of tools to support learning activities than other systems such as Moodle (as indicated from Table 3.1), which enables the developed tool for group formation to potentially be applicable for more types of learning activities.

### 3.5.3 Architecture of the iGLS Add-on for LAMS

The iGLS add-on was built on top of a LAMS system. It implements the components of the iGLS approach for the LAMS system. The overall architecture of the iGLS add-on is shown in Figure 3.4.

As can be seen from Figure 3.4, the iGLS add-on consists of four parts: learning styles modelling, grouping parameter identification, grouping algorithm implementation and supporting table creation. There are two components of the LAMS system that support the developed add-on: the LAMS core modules and the LAMS database. Before discussing the interactions between these different components, a brief description of the LAMS core modules and the LAMS database is provided below.

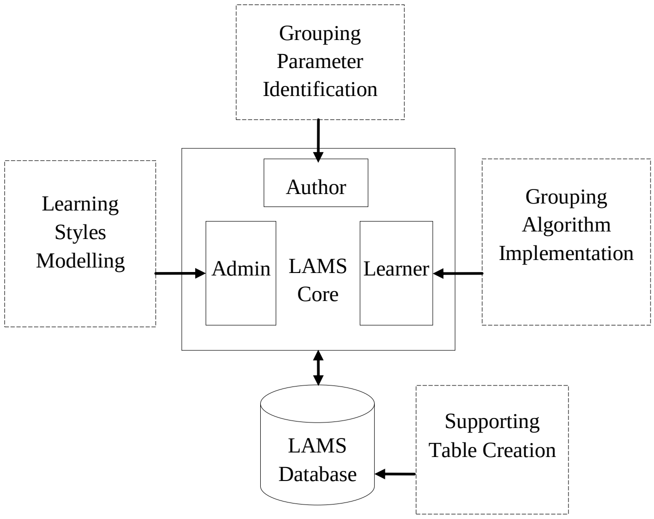


Figure 3.4. The architecture of the iGLS add-on for LAMS

The LAMS system has a modular architecture which encompasses the core modules and the tools for collaborative activities. The *LAMS core* modules are in charge of managing the arrangements of learning activities (noted as the module '*Author*'), allocating students to groups and managing students' progress in particular activities (noted as the module '*Learner*') and providing user authentication and system administration (which is noted as the module '*Admin*'). The *LAMS tools* are self-contained modules, implementing most of the functionalities for supporting collaborative activities such as chats, forums and wikis.

The *LAMS database* is the data centre of a LAMS system. It stores all the information about the LAMS system including user information and logs, system configuration, learning design and content, learning progress of students with the designed learning activities, and learning tools.

The four components of the iGLS add-on were built on different parts of the underlying LAMS system (Figure 3.4). The learning styles modelling component was incorporated in the LAMS core module 'Admin' because it is conceptually a part of user management. The component of grouping parameter identification was created on top of the LAMS core module 'Author' which is responsible for supporting the creation of learning designs. This is because the identification of a grouping parameter is viewed as a learning design in the LAMS system. Moreover, the grouping algorithm implementation component was integrated in the LAMS core module 'Learner' since LAMS 'Learner' is in charge of delivering the designed collaborative learning process to individual groups. Furthermore, the database tables that were defined by the component of supporting table creation are stored in the LAMS database.

The interactions between these above components are as follows. When a student logs into the LAMS system and starts to establish their profile of learning styles, the learning styles modelling component can deliver the LSQ (i.e. the learning style questionnaire as discussed in Section 3.2) to the student via LAMS 'Admin'. After the student has submitted the questionnaire, the learning styles modelling component can extract the student's learning style scores from the returned questionnaire. Moreover, the learning styles modelling component can store the obtained learning style scores into the tables designed for the iGLS add-on in the LAMS database. The teacher who organizes a course can define the value of the grouping parameter (i.e. the number of students per group) when he or she designs a learning process which includes group activities via LAMS 'Author'. The grouping parameter identification component can store the defined value of the grouping parameter in the LAMS database. Furthermore, when the students who take part in the designed learning process start to accomplish the collaborative activities via LAMS 'Learner', the component of the grouping algorithm implementation can assign them into diverse learning style groups based on the proposed grouping algorithm. In addition, the relevant grouping results are stored in the designed table for the iGLS add-on in the LAMS database.

### 3.5.4 Component Implementation

Since the LAMS system has been developed as a web application, the iGLS add-on was also implemented as web-based. A range of web technology was adopted for developing the add-on including Apache Struts, JSP, Java Servlet, and XML.

The Apache Struts web framework [12] enables the developed add-on to use a Model-View-Controller (MVC) architecture. This means that the code of the developed add-on was separated in three parts. The *Model* part represents the business (i.e. how to calculate students' learning styles and how to formulate collaborative groups based on the proposed grouping algorithm) or database (i.e. how to store and retrieve the obtained learning style scores and grouping results) code. The *View* part corresponds to the page design code (e.g. the web page that represents the learning style questionnaire). Moreover, the *Controller* part stands for the navigational code (e.g. forwarding a submission of the learning style questionnaire to the backend score calculation module).

JSP technology is responsible for generating dynamic web pages in terms of the presentation of the learning style scores and the grouping results to individual students. JSP technology is also in charge of creating static web pages with regard to the presentation of the LSQ and the configuration of the grouping parameters.

In addition, Java Servlet technology is responsible for handling the requests from a client and dispatching relevant responses to the client. Furthermore, XML technology is used to represent the Struts configuration for the whole application.

Next, the implementations for each component of the iGLS add-on are described. As the focus of this subsection is the implementation procedure that it embodies, concrete implementation constructs such as JSP pages, Servlet classes, and Java data access classes (for storing and retrieving data from the database) are avoided.

**Learning Styles Modelling**

Figure 3.5 illustrates the main modules that were developed for the learning styles modelling component. 'Collecting questionnaire' is a module which handles the delivery of the LSQ to individual students and collects responses to the questionnaire for further processing. The module 'calculating scores' calculates the learning style scores based on the method discussed in Section 3.2 and forwards the results to the module of 'display results' for showing the learning style scores to individual students. Additionally, the 'storing learning style scores' module can store the calculated scores to the LAMS database. These scores are stored in a table named 'lams_user_score' that was created for the iGLS add-on.

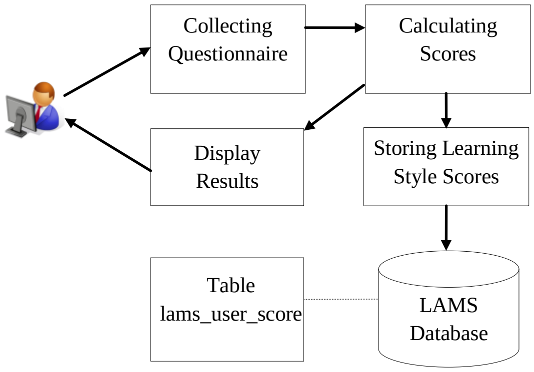


Figure 3.5. Implementation of learning styles modelling

**Grouping parameter Identification**

As mentioned in Section 3.5.3, the grouping parameter identification component was built on top of the LAMS core module 'Author' since it is the module that enables defining the parameters such as the number of groups to be created for the LAMS own grouping component. A new grouping type 'iGLS-grouping' was created which sets the number of students per group as a property. When a course manager or a teacher creates a grouping design for a learning process, the 'Author' module which incorporates the defined grouping type 'iGLS-grouping' allows them to decide the value of the parameter. This configuration can then be adopted by the grouping algorithm implementation component when a group formation process starts.

**Grouping Algorithm Implementation**

Figure 3.6 demonstrates the main modules created for implementing the iGLS grouping algorithm. The 'iGLS grouper' is the module that implements the Algorithm 3-1, which consists of several parts as shown in Figure 3.6. The middle layer of the figure shows the modules for retrieving learning style scores (namely 'learning style scores querier') and storing the grouping results (namely 'grouping results querier') with the LAMS database. After retrieving students' learning style scores from the LAMS database, the 'learning style scores querier' module can send the learning style scores to the module 'iGLS grouper' for sorting the students. After generating the grouping results, the 'iGLS grouper' can provide the results to the 'grouping results querier' to store them into the LAMS database. As shown at the bottom of Figure 3.6, a table named as 'lams_iGLS_groups' was created to store the grouping results. The table 'lams_user_score' can provide the required learning style scores for the 'iGLS grouper' module.

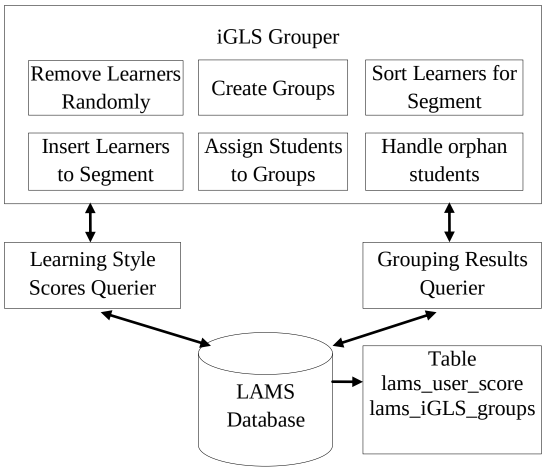


Figure 3.6. Implementation of the iGLS grouping algorithm

**Supporting Table Creation**

Two tables namely 'lams_user_score' and 'lams_iGLS_group' were created for the iGLS add-on. Since the LAMS database was created with a MySQL system, these two tables were also established in the MySQL system. As mentioned above, the table 'lams_user_score' is used to store students' learning style scores that are extracted via the learning styles modelling component. The table 'lams_iGLS_group' is used to store the grouping results which are produced by the grouping algorithm implementation component. Since the schemas for the two tables are simple, they are not presented in this subsection.

## 3.6 Demonstrating the iGLS Approach — A Real World Scenario

In order to demonstrate how the proposed iGLS approach can support the process of group formation in a collaborative learning environment, a real world scenario with the developed iGLS add-on for LAMS is presented in this section. A brief description of the scenario is provided below. Following that, the screenshots of the scenario with the LAMS system which incorporates the developed iGLS add-on are also illustrated. These screenshots attempt to demonstrate the core functionalities that were implemented in the iGLS add-on for supporting the process of group formation.

An online course named ‘Global Weather’ was created with a LAMS system with which six students were registered. The teacher who organizes the course has created an online collaborative learning lesson named ‘Cold Siberia’ through the LAMS ‘Author’ module. This lesson is comprised of two LAMS activities: a grouping activity and a multiple-choice activity. The grouping activity was configured by the teacher to adopt the iGLS grouping method for forming the collaborative groups. The teacher also defined three as the value of the grouping parameter (i.e. the number of students per group). This grouping design is used to form collaborative groups for the following multiple-choice activity. Before this lesson is started, every student who is taking this course is expected to complete the learning style questionnaire through the LAMS ‘Learner’ module. Then, the students’ learning style scores can be used for group formation by the iGLS add-on. One of the six students namely Tom wishes to start the designed online lesson at the beginning of the lesson. Tom logs into the LAMS system. Next, the iGLS add-on automatically formulates two collaborative groups according to the proposed grouping algorithm after Tom has started with the designed lesson. Subsequently, Tom can continue with the designed multiple-choice activity.

Figure 3.7 presents the screenshot of “design the learning process for the lesson ‘Cold Siberia’”. This screenshot corresponds to the visual authoring environment in the LAMS system where a teacher can design the learning process (i.e. a sequence of collaborative learning activities) of a lesson. The area of ‘properties-grouping activity’ (as shown at the bottom of this screenshot) enables the teacher to configure the properties of a grouping activity which include the title and type of the grouping activity and the parameter of the grouping activity. As discussed in Section 3.5.4, a new grouping type noted as ‘iGLS-grouping’ was defined by the iGLS add-on. Thus, the teacher can choose ‘iGLS-grouping’ as the type of the designed grouping activity and define the value of the parameter as required by the ‘iGLS-grouping’ type (i.e. number of students per group).

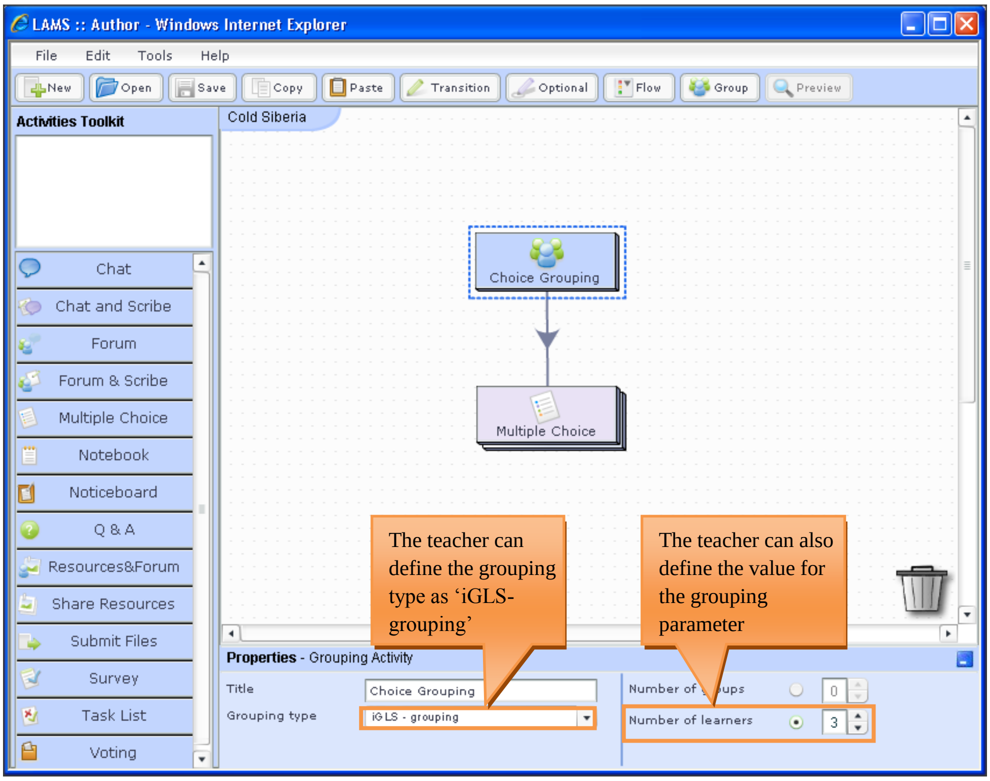


Figure 3.7. Screenshot of "design the learning process for the lesson 'Cold Siberia'"

Figure 3.8 shows the screenshot of "student profile" which is the web page for a student to edit their profile in the LAMS system. As shown on the right of this page, it provides the student (named Tom Smith) a link "take learning style questionnaire" for accessing the learning style questionnaire provided by the iGLS add-on.


Figure 3.8. Screenshot of "student profile"

Figure 3.9 illustrates the screenshot of "take learning style questionnaire". This screenshot represents the learning style questionnaire designed by the iGLS add-on. After Tom clicks on the link "take learning style questionnaire" in the above screenshot, he can access to this questionnaire. Tom should fill in the questionnaire and submit it at the end.

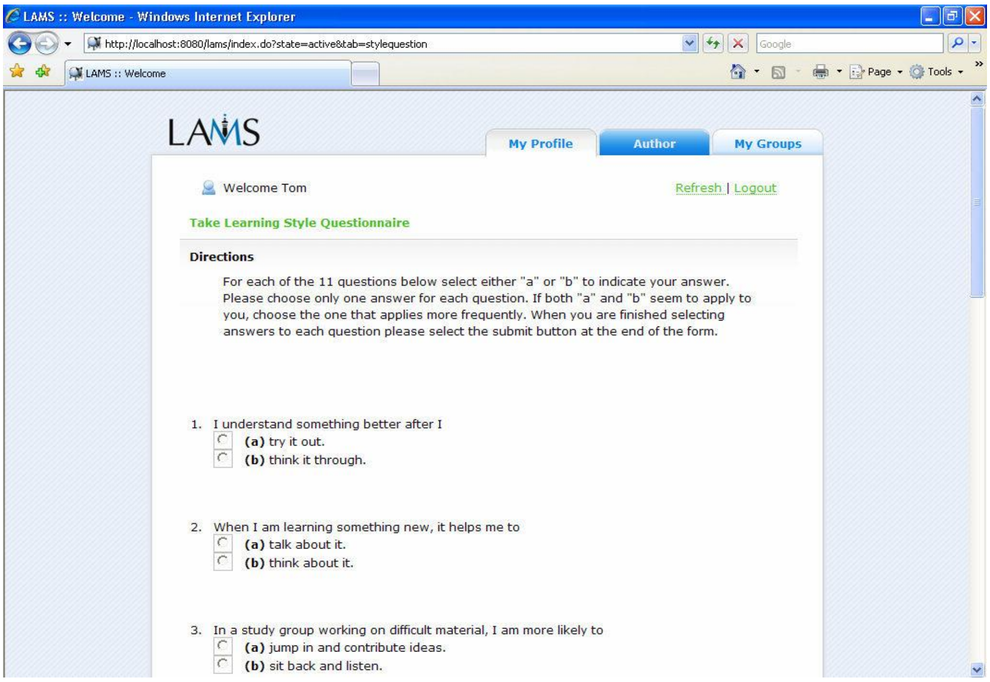


Figure 3.9. Screenshot of "take learning style questionnaire"

Figure 3.10 demonstrates the screenshot of "grouping result for the lesson of 'Cold Siberia'". As mentioned in the scenario, there are six students who registered with the online course. This screenshot shows the case when Tom who first starts with the designed lesson. In the middle of this page, the grouping results that are generated by the iGLS add-on are displayed. As can be seen from this screenshot, the six students are put into two mixed learning style groups (Groups 1 and Group 2). After that, Tom can continue with the next activity as designed in learning sequence (namely multiple-choice).

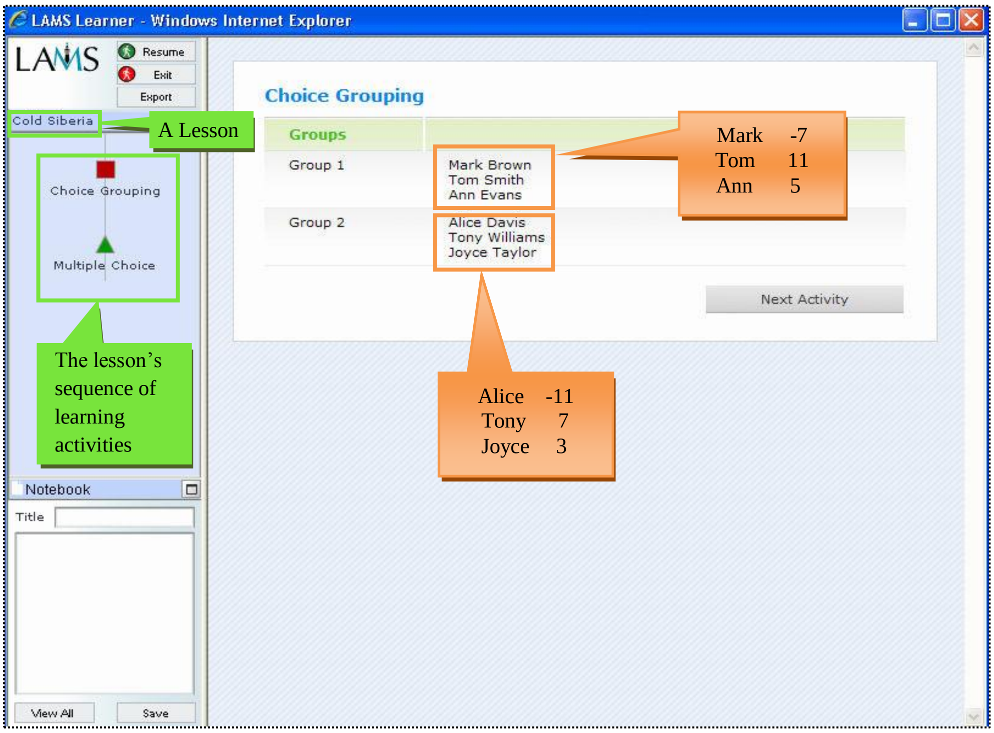


Figure 3.10. Screenshot of "grouping result for the lesson of 'Cold Siberia'"

## 3.7 Summary

In this chapter, an approach for group formation based on students' learning styles was presented. The proposed approach includes three components which respectively address the methods for acquiring learning style scores from individual students, defining the grouping parameters for the group formation process, and forming diverse learning style groups based on the obtained learning style scores in a CLE. Exhaustive discussions on these components were provided.

The iGLS add-on for LAMS and a scenario with the developed iGLS add-on were also discussed. The development of the iGLS add-on for LAMS demonstrates the feasibility of incorporating the proposed approach into contemporary CLEs for the process of group formation.

In the following chapter, the evaluation of the proposed grouping algorithm in terms of its pedagogical effectiveness for forming collaborative groups to conduct collaborative group work will be presented.

# Chapter 4

# Evaluating the Effectiveness of the iGLS Grouping Algorithm

In this chapter, an evaluation of the effectiveness of the proposed iGLS grouping algorithm is presented. Regarding the other two components of the proposed approach for group formation, no evaluation is intended in this thesis. This is because, first of all, the learning styles modelling component adopts a well established questionnaire (i.e. the ILS questionnaire) developed by Felder and Solomon for acquiring learning style scores from students (details in Section 3.2). Thus, the evaluation of the reliability and validity of this questionnaire is out of the scope of this thesis. Moreover, the grouping parameter identification component needs *real* numbers of students per group and does not consider any hypothesized value. Hence, no evaluation should be conducted for it.

This chapter begins with an introduction of its aim and objectives. It then moves on to present the methodology and the results for evaluating the iGLS grouping algorithm. Finally, an intensive analysis of the findings from the experiment is provided.

## 4.1 Introduction

As discussed in Section 2.2.3, current research with applying learning styles in group formation has focused on examining collaborative groups with different combinations of learning styles and their impact on group performance [7,53,139]. In general, two types of learning style groups have been examined in these studies. One is similar learning style groups which comprise students who possess similar learning styles. The other is diverse learning style groups which consist of students with diverse learning styles.

The proposed iGLS grouping algorithm is considered to form effective groups of students with diverse learning styles. In order to evaluate the effectiveness of the iGLS grouping algorithm for group formation, the following objectives should be addressed. First, this chapter intends to describe what kind of experiment was carried out for evaluating the iGLS grouping algorithm, who participated in the experiment and how they were recruited, what and how the experiment data were collected, and the data analysis methods that were used. Second, it attempts to present the results of the experiment that was obtained. Furthermore, it aims to analyse and interpret the findings obtained from the experiment.

The structure of the remaining chapter is as follows. Section 4.2 presents the evaluation methodology that was adopted including the design of the experiment, the participants in the experiment, the data collection procedure and the data analysis methods. Section 4.3 demonstrates the multi-dimension results that were obtained from the experiment. Following that, a reflection of the findings from the experiment is provided in Section 4.4. Finally, a summary of this chapter is presented in Section 4.5.

# 4.2 Evaluation Methodology

## 4.2.1 Experiment Design

The proposed grouping algorithm is considered to form diverse learning style groups which are assumed to work better than similar learning style groups. Hence, the research question that the present evaluation of the iGLS grouping algorithm intends to address is as follows.

*Do the diverse learning style groups formed by the iGLS grouping algorithm perform more effectively and efficiently than the similar learning style groups formed by a comparison grouping algorithm?*

In order to address this question, an experiment was conducted in which both diverse and similar learning style groups were formed, using the iGLS grouping algorithm and a comparison grouping algorithm. A detailed description of the experiment design is provided below.

In this experiment, a cohort of first year university students (aged 18+) at the University of Warwick were invited to complete two group discussion tasks relating to professional skills development. The first task was focused on the topic of “making a good scientific poster”, and the second task was titled “creating an effective PowerPoint presentation”. The participants were expected to discuss in groups the issues that they thought important on the given topics and noted their ideas on sheets of paper. A brief instruction on the two group discussion topics was given to the participants before the experiment was carried out. These include what a scientific poster and a PowerPoint presentation is comprised of respectively, the context of giving a poster and a PowerPoint presentation and the importance of presenting the two types of presentation to the audience. Before the experiment was performed, the participants were required to fill in a questionnaire to gather their learning style scores so that they could be allocated into desired groups. More information about the participants recruitment procedure is provided in Section 4.2.2.

On the experiment day, the participants were assigned into Similar Learning Style (SLS) groups manually for the first task while they were assigned into Diverse Learning Style (DLS) groups using the iGLS grouping algorithm for the second task. Lowry *et al.*’s study indicated that small groups of size three, compared with larger groups, can establish and maintain higher levels of communication quality [119]. Therefore for both the group tasks, groups of three were formed. Each student performed the two activities, in a separate group each time, once in a group consisting of students with similar learning styles, once in a group with diverse learning styles. This method was chosen in order to minimize the effects of factors other than the grouping algorithms on the final results, such as differences in participants’ backgrounds, knowledge levels and professional skills in relation to the tasks. Due to limited resources, it was difficult to get a large sample size that would not be influenced by factors that might skew the results. Furthermore, the two chosen group tasks are similar in terms of the types of activity and the difficulty for the participants to complete. This intended to minimize the effects of the factor “group task” on the final results.

Different types of data were collected from this experiment with regard to the learning achievements, collaboration processes and student feedback for examining the diverse and the similar learning style groups. A detailed description of this procedure is given in Section 4.2.3. Both quantitative and qualitative analysis methods were applied for investigating the gathered data. These methods are described in Section 4.2.4.

### 4.2.2 Population and Sampling

The underlying population that the participants of the designed experiment originated from is the first year cohort of undergraduate students in the science departments at the University of Warwick. A volunteer sampling method was applied for recruiting students from the underlying population. First year students were targetted because senior students tend to be more knowledgeable on the topics of the group tasks which can skew the experiment results. Additionally, relevant modules were taught to the first year students in the engineering departments on the similar topics to those of the group tasks. Therefore, students from these departments were excluded from the list of invited students, in order to avoid the influence of students’ previous knowledge on the experiment results.

Volunteers were drawn from four science departments — Mathematics, Physics, Chemistry and Statistics. They were requested to complete an on-line pre-study questionnaire in order to determine their learning styles before the experiment. 26 students completed the questionnaire and 20 of them subsequently completed the experiment. Based on the information collected from the pre-study questionnaire, the participants were categorised into three types based on their learning style scores for the active/reflective dimension of FSLSM: ‘active’ (from -11 to -5), ‘mild’ (from -3 to 3), and ‘reflective’ (from 5 to 11) (the score values on the dimensions of FSLSM increasing by 2 in every step). Since at least three students were obtained for each of the three types of learning styles, it was possible to form the desired similar learning style groups (i.e. ‘active’ group, ‘reflective’ group, and ‘mild’ group). Therefore, the sample was considered to be suitable for conducting the designed experiment.

### 4.2.3 Data Collection Procedure

The participants were given a brief introduction to the two discussion topics before being allocated into groups. Seven collaborative groups were formed for each task. Each group completed the task under the guidance of a tutor who was responsible for coordinating the group — keeping the audio recorder, delivering and collecting data forms, and controlling the timing of the task. The tutors were trained in advance to engage in (as far as is possible) an identical way with each group, and they were not expected to explain the topics of the tasks to the students during the group discussion processes. A single task was to be completed within a 30 minute period (a group could end the task before the time limit).

A *group record form* was used for recording the issues that the group members thought important on the given topics, the proposers of the ideas, and the total time used to complete the task. A total of 14 group record forms and 14 *audio* *recordings* of the entire group discussion process were collected for further data analysis.

A *post-study questionnaire* was given to the participants after they completed the group work, which was to ascertain (i) the factors other than learning styles that they thought might affect the group work, (ii) their participation in the two types of groups they were involved in, and (iii) the difficulties they experienced in working in the groups.

An *expert questionnaire* was produced to assess the importance levels of the issues identified in the *group record forms*, which was completed by tutors from the English department in the University of Warwick who were teaching modules on professional skills to science students. The questionnaire used a 5-point Likert scale for assessing the importance level: 1 — Not at all important; 2 — Low importance; 3 — Medium importance; 4 — High importance; and 5 — Essential. Two experts returned their responses to the *expert questionnaire* and the average scale scores were adopted for assessing the individual and group achievements.

### 4.2.4 Data Analysis Methods

In order to measure group and individual student achievements, group scores (GS) and single student scores (SSS) were calculated, using the following definitions.

$$GS = \sum_{i=1}^{t} L_i \qquad (4.1)$$

$$SSS = \sum_{j=1}^{m} L_j + \sum_{k=1}^{n} L_k / N_k \qquad (4.2)$$

In the above formulas, $t, m, n$ represent respectively the number of items proposed by a group, the number of items proposed solely by an individual student, and the number of items proposed by this student and his/her group members together; $L_i, L_j, L_k$ represent the level of importance of the proposed items $i$, $j$, $k$; and $N_k$ represents the number of people who proposed item $k$ together.

The time spent on meaningful interactions ($T_{mful}$) is equal to the total time ($T$) that a group completed a group task minus the time that a group spent on meaningless interactions ($T_{mless}$). That is, $T_{mful} = T - T_{mless}$. Examples of meaningless interactions include silence without posing anything at the end, long discussion without any concrete result, and "off-topic" discussion.

Furthermore, a content analysis of the transcriptions of the audio recordings of the group discussion was carried out. The content analysis adopted in the study was based on Bales' Interaction Process Analysis (IPA) framework [18,19], which was selected since it addresses a methodology of identifying the nature of interactions among small face-to-face group members. The framework describes group behaviours in 12 categories from the perspectives of social-emotional and task-oriented functions of groups.

The analysis process with the Bales' IPA framework involved reading and coding each group's transcript. Here, the 'coding' refers to deciding which category a message in the transcription belongs to. The unit of analysis for coding was a single simple sentence. The simple sentence should contain a complete thought presenting a reaction. Fragments of sentences or phrases were interpreted as simple sentences if they could be explained in the context of the group discussion. For example, If a group member said, “What?”, it could be interpreted, according to the context, “I do not understand you,” or “Can you repeat that?” Moreover, each of the component simple parts of a compound sentence joined by coordinators such as “and”, “but”, and “or” was assigned a category if it expresses a complete thought. For example, the following sentence was analyzed into two units: “Yeah (the first unit), but it worth a thousand words (the second unit).” Additionally, each dependent clause of a complex sentence joined by a subordinator such as “because” or a relative pronoun such as “which” was assigned a category if it presents a complete thought. For example, the following sentence was analyzed into two units: “If they just look at a load of text on a poster, that’s rather scary (the first unit), because you have to concentrate and read every single thing to get like what’s going around the world (the second unit).” Where there is more than one category that can be assigned to a simple sentence, the most applicable category was considered according to the context of the sentence. The assignment of the categories was conducted twice in order to ensure the accuracy of the coding.

Independent samples t-tests were used for identifying the differences between the SLS and DLS groups in (i) the group scores, (ii) the percentage of time spent on meaningful interactions, (iii) the total number of units of group interactions (a ‘unit’ refers to a single simple sentence in a discussion transcription), and (iv) the number of units of group interactions under each category of Bales’ IPA framework. There are several reasons for adopting the independent samples t-tests. First, the data examined for analysis (i–iv) are continuous and can determine proportions easily (e.g. ‘twice as many as’). Second, two sets of data were compared: the data belonging to the SLS groups and the data belonging to the DLS groups. Finally, the two sets of data are independent since the collaborative groups belonging to the first set are distinct from the collaborative groups in the second set (no volunteer shared both groups with any individual student).

The post-study questionnaire consists of open-ended questions for the students to remark on relevant aspects of the group work mentioned in Section 4.2.3. Different themes relating to the issues under scrutiny were extracted. The questionnaire also contains multiple-choice questions with an option for the students to add their own comments. The multiple-choice questions were used to gather some background information about the participants. The frequencies of responses to the multiple-choice questions were calculated and the student comments were analysed.

# 4.3 Results

## 4.3.1 Grouping Results

Table 4.1 and Table 4.2 summarize the grouping results of the experiment. Groups 1–7 were formed manually for the first group task (Table 4.1). Groups 8–14 were formed using the iGLS grouping algorithm for the second group task (Table 4.2).

Table 4.1 The grouping results for the first group task

| The First Group Task (SLS Groups) | | |
|---|---|---|
| Group ID | Participants (Student ID) | Group Composition (LS Scores) |
| 1 | 1, 2, 3 | (-9, -5, -5) |
| 2 | 4, 5, 6 | (11, 7, 7) |
| 3 | 8, 9, 10 | (3, 3, 3) |
| 4 | 11, 12, 13 | (-3, -3, -3) |
| 5 | 15, 16, 17 | (-1, -1, -1) |
| 6 | 18, 19, 20 | (-1, 1, 1) |
| 7 | 7, 14 | (5, -3) |

Table 4.2 The grouping results for the second group task

| The Second Group Task (DLS Groups) | | |
|---|---|---|
| Group ID | Participants (Student ID) | Group Composition (LS Scores) |
| 8 | 3, 5, 11 | (-5, 7, -3) |
| 9 | 2, 10, 19 | (-5, 3, 1) |
| 10 | 4, 14, 17 | (11, -3, -1) |
| 11 | 7, 8, 12 | (5, 3, -3) |
| 12 | 1, 9, 18 | (-9, 3, -1) |
| 13 | 6, 13, 15 | (7, -3, -1) |
| 14 | 16, 20 | (-1, 1) |

The first grouping algorithm grouped students that had the same category of learning styles and approximate learning style scores when there were many scores under one category of learning styles. As can be seen from Table 4.1, the collaborative groups formed for the first group task comprise one 'active' group (Group 1) in which all members are active students, one 'reflective' group (Group 2) in which all members are reflective students, four 'mild' groups (Group 3–6) which encompass purely 'mild' students, and a group (Group 7) of 'orphan' students (the remaining students).

The iGLS grouping algorithm grouped students of different categories of learning styles together and such groups contained students in the same intervals of learning style scores (i.e. the same segments as mentioned in Algorithm 3-1). Thus, the collaborative groups formed for the second group task were diverse groups (Group 8–13) and a group of ‘orphan’ students (Group 14).

The ‘orphan’ groups (Group 7, 14) actually consist of students of diverse (5, -3) and similar (-1, 1) learning styles respectively. Since this does not satisfy the objective of comparing similar and diverse learning style groups, the two ‘orphan’ groups are not included in the comparison of SLS and DLS groups. However, their performance is discussed later in Section 4.4 for the evaluation of the iGLS grouping algorithm.

### 4.3.2 Group Achievements

Group scores were calculated according to formula (4.1) presented in Section 4.2.4 for the SLS and DLS groups. Figure 4.1 illustrates the group scores obtained. In the scatter diagrams, the triangle points represent the SLS group scores and the square points the DLS group scores. The two dashed lines represent the average group scores of the two group tasks respectively.

For group task 1, the group scores ranged from 33 to 73, with a mean of 51 (SD = 13.25). Both the highest and the lowest groups are ‘mild’ groups. For task 2, the scores ranged between 49 and 65 with a mean of 56 (SD = 5.49). The difference between the highest and lowest scores is smaller than that of the SLS groups.

The DLS groups gained a higher average group score than the SLS groups, but the higher SD of the latter reflects the larger spread of values for the SLS groups. An independent samples t-test was conducted to compare the two sets of groups, but this test indicated that there was not a significant difference between the group scores: t(10) = -0.882, p = 0.398 > 0.05.

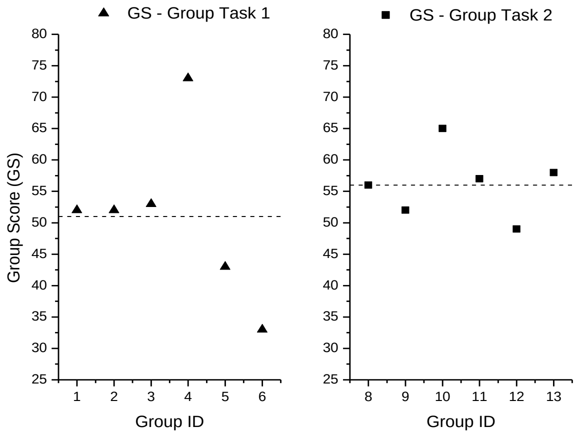


Figure 4.1. The group scores by SLS groups (Group Task 1) and DLS groups (Group Task 2)

Besides the group scores, the percentage of time spent on meaningful interactions (MIs) by the SLS groups and DLS groups was also analysed. This is illustrated in Figure 4.2, in which the two horizontal straight lines are the mean values.

For the first group task, the percentage of time spent on MIs ranged from 62% to 89%, with a mean of 73% (SD = 10.67%). Group 1, which spent most time on MIs is an 'active' group, whereas; the 'reflective' group (Group 2) spent the same as the average value and the 'mild' groups (Group 3–5) spent less than the average value on MIs. This supports the claim that 'active' students tend to engage more with group work. It is also interesting to see that although reflective students may prefer to work alone, they were not the worst performing group in terms of MIs when they were grouped together.

For the second group task, the percentage of time ranged from 76% to 91% with a mean of 84% (SD = 5.83 %), with only two of the groups below the mean value. The higher mean value obtained by the DLS groups indicates they tend to be keener to discuss the topic than the SLS groups. Furthermore, the smaller SD that the DLS groups demonstrated reveals that their values are more close to the mean.

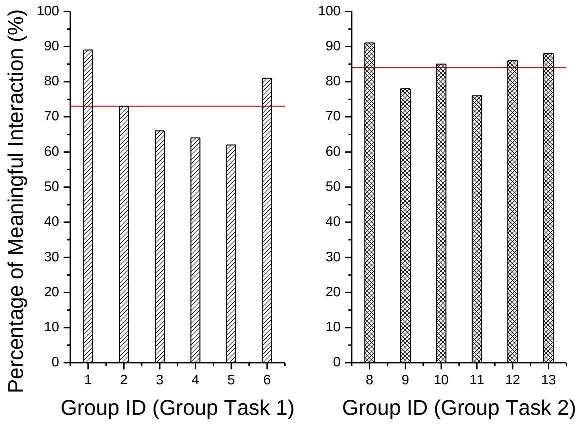


Figure 4.2. Percentage of meaningful interactions by SLS groups and DLS groups

An independent samples t-test shows that there was a significant difference between the percentages of time on MIs by the SLS and DLS groups: $t(10) = -2.316$, $p = 0.043 < 0.05$. These results suggest that DLS groups tend to spend significantly more time on meaningful interactions than on meaningless interactions.

### 4.3.3 Individual Student Achievements

Single student scores for the two types of groups were obtained from formula (4.2) (Figure 4.3). In this vertical drop line diagram, the 'square' symbols represent the single student scores for group task 1 and the 'diamond' symbols represent the single student scores for group task 2. The distance between the two symbols in a vertical line shows the difference between the student scores of a single student for the two group tasks.

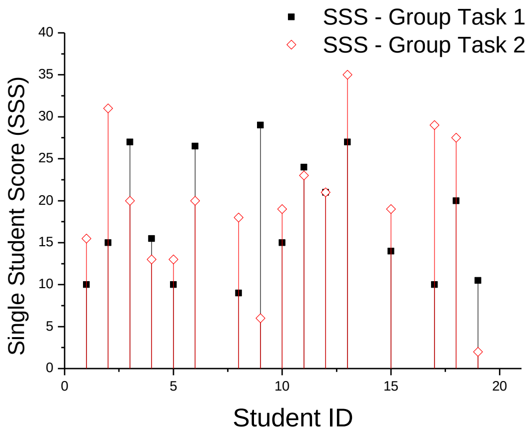


Figure 4.3. The single student scores of each participant in the SLS and DLS groups

As illustrated in Figure 4.3, 9 students (56%, *N*=16) gained higher student scores from the DLS groups than they obtained in the SLS groups, and 66.7% of ‘active’ students, 60% of ‘mild’ students and 33.3% of ‘reflective’ students gained higher individual student scores in the DLS groups. This finding suggests that ‘active’ students are most likely to obtain higher individual achievements in DLS groups than in SLS groups. Furthermore, ‘mild’ and ‘reflective’ students have also demonstrated their potential to achieve higher individual results in DLS groups.

The scores for the SLS groups ranged from 9 to 29 ($M$ = 17.72, $SD$ =7.18), and for the DLS groups from 2 to 35 ($M$ = 19.5, $SD$ =8.69).

### 4.3.4 Qualitative Findings from Group Processes

**Patterns of Group Interactions**

The content analysis identified the categories and the number of units of group interactions for each group (Table 4.3 for similar groups and Table 4.4 for diverse groups). According to the Bales' IPA framework [19], group interactions can be divided into 12 categories. Categories 1–3 represent positive social-emotional interactions respectively for showing solidarity, tension release, and agreeing; categories 4–6 correspond to task-oriented interactions attempting to give suggestion, opinion and orientation for the solution individually; categories 7–9 indicate task-oriented interactions asking for orientation, opinion and suggestion correspondingly; and categories 10–12 represent negative social-emotional interactions for showing disagreement, tension and antagonism.

Table 4.3 Similar groups—units of interactions categorised under categories 1–12 of the Bales IPA Framework [18]

| Category [19] | Group ID (Similar Groups) | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | Mean |
| 1 | 1 | 1 | 0 | 4 | 0 | 4 | 1.67 |
| 2 | 0 | 6 | 0 | 0 | 0 | 5 | 1.83 |
| 3 | 44 | 77 | 43 | 47 | 34 | 48 | 48.83 |
| 4 | 31 | 38 | 15 | 28 | 15 | 21 | 24.67 |
| 5 | 73 | 39 | 46 | 53 | 31 | 79 | 53.5 |
| 6 | 77 | 67 | 59 | 51 | 50 | 85 | 64.83 |
| 7 | 6 | 7 | 6 | 8 | 17 | 10 | 9 |
| 8 | 2 | 8 | 1 | 4 | 7 | 8 | 5 |
| 9 | 4 | 6 | 0 | 2 | 3 | 4 | 3.17 |
| 10 | 5 | 11 | 6 | 4 | 6 | 4 | 6 |
| 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Total | 243 | 260 | 176 | 201 | 163 | 268 | |

Table 4.4 Diverse groups—units of interactions categorised under categories 1–12 of the Bales IPA Framework [18]

| Category [19] | Group ID (Diverse Groups) | | | | | | |
|---|---|---|---|---|---|---|---|
| | 8 | 9 | 10 | 11 | 12 | 13 | Mean |
| 1 | 3 | 2 | 6 | 5 | 4 | 1 | 3.5 |
| 2 | 4 | 1 | 0 | 3 | 0 | 19 | 4.5 |
| 3 | 68 | 16 | 33 | 22 | 59 | 51 | 41.5 |
| 4 | 23 | 13 | 15 | 19 | 23 | 23 | 19.33 |
| 5 | 85 | 21 | 38 | 32 | 76 | 68 | 53.33 |
| 6 | 82 | 30 | 23 | 54 | 82 | 67 | 56.33 |
| 7 | 2 | 6 | 0 | 30 | 4 | 20 | 10.33 |
| 8 | 4 | 5 | 3 | 3 | 2 | 4 | 3.5 |
| 9 | 0 | 2 | 0 | 2 | 2 | 7 | 2.17 |
| 10 | 8 | 3 | 0 | 0 | 2 | 0 | 2.17 |
| 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Total | 279 | 99 | 118 | 170 | 254 | 260 | |

Most of the group interactions, regardless of the SLS and the DLS groups, fall under categories 3–6, indicating that both the SLS and DLS groups concentrated mainly on giving suggestions, opinions, orientations and agreements. Neither type of group had a contribution under category 11 or 12, which reveals that there were no negative social-emotional reactions existing such as showing tensions or antagonisms. On average, the SLS groups interacted much more under category 8 (‘asking for opinions’) and category 10 (‘showing disagreement’), and less under category 1 (‘showing solidarity’) and category 2 (‘showing tension release’) than the DLS groups.

Two ‘mild’ groups (6 and 5) had the largest and the least number of units of interactions respectively for group task 1. The average number of units of interaction by the SLS groups is 218 while that by the DLS groups is 197. A possible reason for this difference is that the SLS groups spent a longer time completing the group task on average and thus produced more units of interactions.

No significant difference is found between the total number of units of interactions by similar groups and diverse groups: $t(10) = 0.594$, $p = 0.565 > 0.05$.

Moreover, independent samples t-tests were carried out to compare the numbers of units of interactions regarding individual categories by the SLS and DLS groups in Table 4.5.

There is a significant difference found between the numbers of units of interactions under category 10 by the similar groups and the diverse groups: $t(10) = 2.307$, $p = 0.044 < 0.05$, but for the other categories there are no significant differences (and since no interactions were identified, no statistics were calculated for categories 11 and 12).

Table 4.5 Results of the t-tests to compare the number of units of interactions

| Category of Group Interactions | t | df | Sig. (2-tailed) | Mean Difference |
|---|---|---|---|---|
| 1 | -1.701 | 10 | .120 | -1.833 |
| 2 | -.835 | 10 | .423 | -2.667 |
| 3 | .702 | 10 | .499 | 7.333 |
| 4 | 1.270 | 7.2 | .243 | 5.333 |
| 5 | .013 | 10 | .990 | .167 |
| 6 | .714 | 10 | .491 | 8.500 |
| 7 | -.258 | 6.2 | .805 | -1.333 |
| 8 | 1.123 | 6.1 | .303 | 1.500 |
| 9 | .748 | 10 | .472 | 1.000 |
| 10 | 2.307 | 10 | .044* | 3.830 |

* $p < 0.05$

**Problems of Group Collaborations**

The problems that commonly existed in the group collaborations of the two types of groups were also investigated. It is interesting to note that more than half (66.7%) of the SLS groups had a common problem — students gave little feedback on each other’s thoughts, and most students in those four groups (Group 2–5) made fewer contributions than the mean value of interactions (53.5) under category 5 (namely, giving opinions). However, ‘giving little feedback on each other’s thoughts’ was not a common problem for the DLS groups. Additionally, no other common problems have been found among the DLS groups.

**Conflict Handling**

Another aspect that may indicate effective group processes is the handling of conflicts, which involves how group members deal with arguments about the solutions to group tasks. Through analysing the audio recordings and corresponding transcriptions of the group discussions, it was found that both the SLS groups and the DLS groups engaged in some arguments several times on average. The total number of arguments for the SLS groups was eight and for the DLS groups it was also eight. The average number of arguments was the same for the two types of groups. The groups that had arguments included the SLS Groups 2–6 and the DLS Groups 8–9 and 12.

Further analysis of the group arguments revealed that the DLS groups tended to think through solutions since they argued much longer and deeper than the SLS groups. Some DLS groups tended to discuss one solution for different times during the whole discussion process. This indicates that even if the problem was not solved at some point, the group members would discuss again later and try to agree. However, the SLS groups did not handle the conflicts as actively as the DLS groups, and most groups had very short disputations which culminated in the opponents’ opinions being accepted silently and passively.

### 4.3.5 Student Feedback

The post-study questionnaire was analysed to gather some background information about the participants and their feedback about participating in the group tasks.

**Student Views on the Factors That Might Affect the Group Work**

Among the 20 respondents, seven students did not think there were factors other than learning styles that would affect the group work, but the remaining 13 students provided their comments to this question. Units of meaning were generated from the student original remarks and further grouped into several themes. The number of respondents (the left column), the themes of related factors (the middle column) and the factors under each theme (the right column) are presented in Table 4.6.

Table 4.6 A summary of the factors that might affect the group work

| Number of Respondents | Themes | Factors |
|---|---|---|
| 8: | Student-related factors | • Familiarity with group members.<br>• The subjects that the students were studying.<br>• Student inspiration for the given topics.<br>• Whether the participants were home or international students.<br>• The suggestions that the first speaker proposed. |
| 5: | Environment-related factors | • The location where the tasks were completed.<br>• The group members had equal chance to give opinions.<br>• The communication between group members before the starting of a task.<br>• The atmosphere of conducting the task. |
| 2: | Task-related factors | • The types of the group tasks.<br>• The difficulty of the group tasks. |
| 2: | Group-related factors | The size of the learning groups. |
| 1: | Tutor-related factors | Whether the tutor was friendly. |

In terms of the student-related factors, the ‘familiarity with group members’ was mentioned by multiple students. Two of them believed that group members would collaborate better if they were strangers, since they could try to elaborate as much as possible to bring the points across. However, another student thought that it would be harder to communicate with group members if they were strangers. Further analysis of the multiple-choice questions on the student relationships revealed that the composition of groups were similar in terms of the student familiarity with group members (SLS groups include four 'stranger' and two 'mixed' groups while DLS groups contain three 'stranger' and three 'mixed' groups).

Two students remarked on the factor 'the subjects that the students were studying'. One of the students believed that students who did different subjects would show different viewpoints and approaches, which was fruitful for the group work. However, the other student thought that students doing the same subject could make discussions livelier since they had the same line of thought. There was no obvious difference between the group compositions in terms of the subjects of the students in the similar and the diverse groups.

It was mentioned by one student that more inspiration on the task topic would make it easier for students to put points forward. One student stated that 'whether the participants were home or international students' might affect the group work, but failed to give further explanation on how it might affect. Another viewpoint is that group members tended to stick to what the first speaker proposed and were often biased towards the first speaker's proposal. These viewpoints were only proposed by individual respondents, suggesting that they were not major factors that the student perceived would affect the group work.

In terms of the environment-related factors, two students commented that more productivity can be achieved if the places where the group work takes place are clean and separate. Note that an independent comfortable lecture or office room was provided for each group, and there were no obvious differences between the locations where the groups performed the group tasks. Other environment-related factors represent student concerns of the non-physical environmental elements that would affect the group work such as the communication between group members before starting the task and the atmosphere of conducting a task.

The respondents also mentioned task-related factors that would affect the group work, namely the types and difficulty of the group tasks. It was mentioned that the discussion tasks were good and interactive, and that the students were satisfied with the types of the group work. Moreover, the two discussion tasks were on similar topics and designed to have the same level of difficulty. Thus, there seems no apparent difference between the types and difficulty of the group tasks for the SLS and the DLS groups.

Group size was viewed as a factor, and one student remarked that breaking down into groups of three was an ideal way to enable each member to express their own ideas. Another student commented that breaking down in groups of three made the members feel at ease. From this perspective, the students believed there were several benefits to having a small size for the collaborative groups.

It was also pointed out that the perceived friendliness of the tutors might affect the group work. In the experiment, this factor was minimized by instructing the tutors to treat all the students politely and equally, and not to provide any personal suggestions on the given topics.

### Student Preferences Regarding the Types of Groups

The results of the voting by the students for their preferences regarding their participations are displayed in Figure 4.4. Nearly half of the students (43.75%, N = 16) preferred the DLS groups that they participated in compared to 25% of the students who preferred the SLS groups. 18.75% had equal preferences to the two types of groups and 12.5% of the students expressed no preferences.

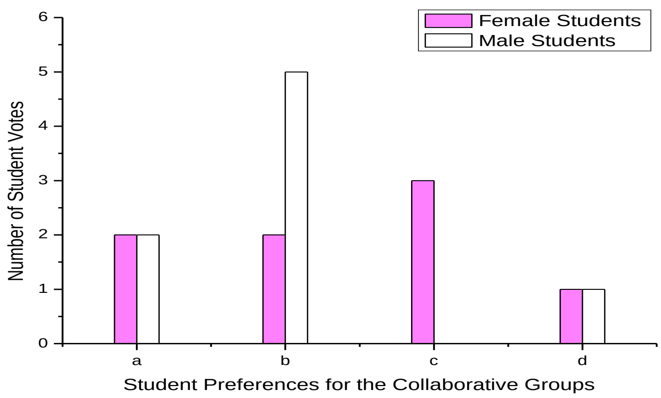


Figure 4.4. Student preferences for the collaborative groups (a. preferred the SLS group; b. preferred the DLS group; c. preferred equally for the SLS and DLS groups; d. expressed no preferences)

Further analysis on the student remarks revealed several reasons why the students preferred the diverse groups. First, the group members' ideas were widespread and diverse. One student remarked, "We had totally different ideas and opinions. It was very interesting to hear the pros and cons of one's ideas. The ideas were very widespread and diverse." Another student emphasized, "It was a more open discussion where it could stimulate more ideas and bring out the best of me." Second, there was friendlier atmosphere such as one student explained, "Friendly interactions between the group members. We were still talking even after the exercise was over ... We proposed our ideas in a constructive, fluent and smooth manner." Another student also claimed that it was a calm, friendly atmosphere and everyone listened to each other. A third student agreed that the atmosphere was friendlier. Thirdly, the group members were very active and enthusiastic. Finally, the group members had an equal chance to share their ideas. One student remarked "Everyone got to participate and express their opinions."

**Difficulties with the Collaborative Groups**

All the respondents stated that they had no difficulties with the groups they participated in, suggesting that this is not an issue which contributes to differences between the SLS and the DLS groups.

## 4.4 Discussion

This section presents an analysis of the methodology and findings of the present experiment for evaluating the effectiveness of the proposed iGLS grouping algorithm.

In this experiment, group discussion tasks were organized to investigate the performance of the collaborative groups that were formulated. There are several reasons for this. First, group discussion is a common collaborative activity that has been widely adopted in face-to-face and online collaborative learning. Second, most of the existing empirical studies have been focused on a specific type of collaborative activity in terms of examining the impact of group formation methods on group collaboration. This is because conducting a study for a particular type of collaborative activity is considered to be realistic and is able to provide sufficient data for developing an in-depth understanding of the examined group formation method. Examples of these empirical studies include Alfonseca *et al.*'s study [7] for which the students were expected to solve two programming exercises in groups and Papanikolaou *et al.*'s study [139] for which the students co-constructed concept maps in groups. Finally, wide generalisations are not the goals of this evaluation but rather to understand intensively the impact of the proposed grouping algorithm on group formation for a given situation. The findings from this experiment can then be generalised for the same kind of situations.

Moreover, the present empirical study has developed an in-depth understanding of the group collaborations by SLS groups and DLS groups. Various aspects of the group collaborations have been investigated to compare the performance of the two types of groups.

The first aspect compared was group achievement. The higher average group score obtained by the DLS groups agrees with the results of Alfonseca *et al.* [7] and Papanikolaou *et al.* [139] regarding the group achievement of mixed learning style groups. Although Robertson [152] has argued that forming groups with similar or different learning styles does not appear to influence the quality of the work, most existing studies such as [7,74,139,155] have shown that it may be more beneficial for individuals to work in a group containing individuals with different learning styles. The finding that the DLS groups have spent significantly more time on meaningful interactions may explain why they were more efficient in accomplishing the group task than the SLS groups.

The second aspect examined was the individual level of achievement. The finding that the majority of 'active' and 'mild' students gained higher student scores in the DLS groups demonstrates that 'active' and 'mild' are the types of students who tend to obtain the highest individual benefits in diverse learning style groups. To our knowledge there is no published research on the differences between individual achievements within different types of learning style groups.

The group collaboration processes have been further analysed for providing inside views on the interactions and relationships between group members in the two types of groups. The finding that the similar groups had demonstrated significantly more negative social-emotional reactions in showing disagreements disagrees with the results of Nielsen *et al.* [135] which reported that the work process of heterogeneous learning style groups was more challenging than that of homogeneous learning style groups. However, the team formation presented by Nielsen *et al.* was loosely linked to the course of study by a learning styles test and by knowledge transfer in the form of lectures. Their conclusion does not reflect the real situations where students work in collaborative process-oriented exercises. The participants in Nielsen *et al.*'s study expressed that if the team formation processes were firmly integrated with their classes for team activities they would have gained additional benefits from the process.

The difference between demonstrating the problem of giving little feedback in the two types of groups suggests that the members of the DLS groups formed by the iGLS grouping algorithm tend to be more enthusiastic about giving feedback on each other's thoughts during the group process. This finding implies that the heterogeneous approach, although challenging for the group process, can stimulate the students to bring out the best of their potential to contribute to the group work.

The finding that both the DLS and SLS groups had controversies and the DLS groups seemed to produce more critical discussions and constructive arguments than the SLS groups is consistent with literature on constructive controversy [58].

Although the students have suggested several factors other than learning styles that might affect the group work, most of the factors of obvious potential relevance to group collaborations have been addressed in the experiment by distributing students among groups evenly and randomly. It is also indicated that the DLS groups formed by the iGLS grouping algorithm had a greater student enjoyment than the SLS group members.

Although the ‘orphan’ groups (Groups 7 and 14) are excluded from the analysis of the SLS and DLS groups in this chapter, the researchers have examined the results inclusive of the ‘orphan’ groups with regard to learning achievements, collaboration processes and student feedback. There are no significant difference found between the presented results and the results inclusive of the ‘orphan’ groups. That indicates that the groups formed by the iGLS grouping algorithm tend to gain better learning achievements, more effective collaboration processes and greater student enjoyment than the groups formed by the comparison algorithm for group discussion tasks.

Furthermore, the smaller range of values both in the group scores and in the percentage of time spent on meaningful interactions suggests that the iGLS grouping algorithm tends to construct collaborative groups which can demonstrate lower inter-group difference regarding the group scores and the percentage of time spent on meaningful interactions. The finding that the majority of ‘active’ and ‘mild’ students as well as a few ‘reflective’ students gained higher individual score suggests that the iGLS grouping algorithm could mostly stimulate ‘active’ and ‘mild’ students but also could influence the performance of ‘reflective’ students.

## 4.5 Summary

This chapter investigates the effectiveness of the iGLS grouping algorithm which incorporates learning styles in forming diverse groups. A collaborative process-oriented experiment with current undergraduate students in the UK has been conducted. In this experiment, the participating students were invited to accomplish two group discussion tasks separately in diverse learning style groups formed by this grouping algorithm and in similar learning style groups formed manually. A thorough analysis of the results reveals several differences between the learning achievements, collaboration processes and student feedback for the diverse and the similar learning style groups, particularly with respect to the quality of group interactions. The findings suggest that the targetted grouping algorithm tends to form collaborative groups which seem to demonstrate better learning achievements and more effective group collaboration processes for conducting group discussion tasks.

In the following chapter, the details of a survey which was conducted to identify major student-induced group collaboration problems and their causes and the findings from the survey are presented.

# Chapter 5
# A Student Perspective on Group Collaboration Problems and Causes

In this chapter, the methodology and results of a nationwide survey in the UK is reported, which revealed student perceptions of group collaboration problems with online group work and the factors that can cause such problems. This is what current literature fails to adequately address (as discussed in Chapter 2). The findings from the survey were used to create an XML-based representation of the linkages between the problems and their causes identified. The survey results are important for diagnosing group collaboration problems because they address the major types of group collaboration problems to be diagnosed and suggest parts of the diagnostic products for students which will be discussed in Chapter 6.

## 5.1 Introduction

Through a thorough review of literature in Section 2.3, three major categories of group collaboration problems have been identified including ‘poor motivation’, ‘lack of individual accountability’ and ‘negative interdependence’. This review also indicates that there are several problem scenarios existing which can reveal the same category of group collaboration problem. Next, a brief summary of the problem scenarios identified regarding each category of group collaboration problem is provided.

Concerning ‘poor motivation’, two problem scenarios were identified. The first describes a scenario in which all the members in a collaborative group could post with an asynchronous collaboration tool (e.g. forums, wikis and blogs) to discuss a given learning topic and a student in the group made a post irrelevant to the learning topic. The second denotes a situation in which the members in a collaborative group were expected to provide in-depth reflective responses to a discussion on a given learning topic or material and one of the group members made a post that contained several grammatical and/or spelling errors which was difficult to understand. These two scenarios were revealed from several studies in online group work including [6,100,142].

Regarding ‘lack of individual accountability’, three problem scenarios were recognized. The first represents a situation in which the members of a collaborative group discussed online to accomplish a piece of group work with an asynchronous collaboration tool and an individual student hadn’t contributed much during the online discussions. The second scenario describes a situation in which a deadline was set for a piece of group work and the members needed to complete the work together (no role division within the group), and one member was negligent in meeting the deadline. Furthermore, the final scenario can be explained as that each member in a collaborative group was allocated with a role to complete the group work and one student did not complete his or her assigned work. These problem scenarios were identified from research [8,81,127] regarding the common collaboration problems that were faced by students participating in an online group project.

In terms of ‘negative interdependence’, two problem scenarios were identified. One depicts a situation in which a collaborative group was assigned a piece of group work and all the members were desired to discuss the solutions together; however, they had given little feedback to each other about each other’s thoughts. The other denotes a situation where the workload of a collaborative group was not shared fairly; one student in the group had made most of the work and other members did little or no work. These two scenarios reveal the problems possessed by individual groups whose members have negative relationships with regard to collaboration. The first scenario was identified from [8,82] which noted that limited student participation in online discussion appears to be a persistent problem. The second scenario is known as the “free-rider” problem identified by Roberts and McInnerney [151] as one of the common problems of online group learning. Other studies that also noted these two problem scenarios include [93,118,143].

As can be seen from the above discussion, a total of seven problem scenarios corresponding to several sub-categories of group collaboration problems were identified from the literature. The survey presented in this chapter addressed the seven problem scenarios and the factors that may cause these problems.

The structure of the remaining sections is organized as below. Section 5.2 presents the methodology that was applied for conducting the survey-based study.

This includes several aspects: (i) the general research design including the type and scope of survey that was used, the administration of the survey and the ethical consent for this project; (ii) the targets of the survey and the method of inviting the participants to take the survey; (iii) the data collection instrument and procedure adopted; (iv) and the data analysis techniques that were applied.

Following that, Section 5.3 presents the results that were obtained from the survey. Four aspects of results are presented. First, Section 5.3.1 summarizes the demographic information about the respondents. Second, Section 5.3.2 describes students' views on the seven problem scenarios (i.e. whether they have experienced the problems or not) and what factors can cause such problems. Moreover, the associations between student backgrounds and their perceptions of the factors are discussed in Section 5.3.3. Finally, Section 5.3.4 analyses the popularity of various asynchronous collaboration tools that the students had previously used for completing the group work.

Section 5.4 discusses how the set of major group collaboration problems and their causes were determined from the survey results. In Section 5.5, a detailed description of the XML-based representation is provided, which includes the motivation for adopting XML for the representation, the hierarchical structure of the XML elements, a code fragment of the XML representation and the validation of the XML created. This section also discusses the potential applications of the XML-based representation. In addition, a summary of this chapter is provided in Section 5.6.

## 5.2 Methodology

### 5.2.1 Research Design

An online survey was developed for this study. Considering the size of the potential respondents, the survey was comprised mostly of semi-closed questions requiring multiple-choice responses and additional comments from students where applicable. Although this type of survey is heavy on time early in devising, piloting and refining it, it enables the data to be processed and statistics to be calculated comparatively rapidly at the stage of analysing the results of the survey.

The main body of this survey addressed questions corresponding to the seven group collaboration problem scenarios identified from literature (as discussed in Section 5.1). It also contained questions requiring background information about the students and their previous experiences with online group work such as the types of asynchronous collaboration tools used. Details of the design of this survey are described in Section 5.2.3. Moreover, this survey was refined through a pilot study before it was established online and distributed to the participants.

The survey was administered with a web-based survey tool. The web-based approach was adopted since it can provide a greater response speed and the same or better quality data as compared to mail surveys. The conduct of this survey project followed the primary researcher's university guidance on ethical issues and ethical consent was approved by the researcher's department.

### 5.2.2 Participants

The online survey was distributed via e-mail invitations to university students across the UK enrolled mainly on computing degree courses. The invitation e-mail contained the purpose of the study and the link to the URL where the survey was located. It is estimated that the United Kingdom has approximately 110 HEIs with computing departments, and communication with students was facilitated by the UK Higher Education Academy Subject Centre for Information and Computer Sciences and its department representatives. A total of 173 students at more than 18 different universities in the UK responded to the online survey. Detailed information about the participants is presented in Section 5.3.1.

### 5.2.3 Data Collection

The survey was distributed late in 2009, and the responses to the survey were collected during a period of seven weeks. The survey consisted of nineteen questions. Survey questions one through seven gathered demographic information about the participants. This information included: age, gender, subject, education background, ethnic origin, whether the respondent is native English speaker or not, and the university they are studying at. The set of responses chosen for ethnic origin was that used by the primary researcher's institution and by other UK universities.

Survey question eight sought to collect information on the types of asynchronous learning tools (e.g. forums, wikis, and blogs) that students had previously used when working on collaborative group work. Questions nine through twelve gathered information about how the students' groups had been formed. These questions were used to gather more information about the previous group experience of the participants, which were not the purposes of this chapter. Thus, the analysis of these questions is excluded from this chapter.

The final seven questions were in the form of describing small scenarios corresponding to the seven sub-categories of group collaboration problems requiring multiple-choice responses. The factors that may cause the occurrence of such a problem scenario were represented as the set of choices of responses for a scenario question. The respondents were asked to select, from the set of choices of responses, the factors which in their opinion results in such a situation. The factors addressed for each problem scenario in the survey were defined based on the primary researcher's knowledge and refined through the pilot study that was carried out. Because of the wide possible variety (of the causes of a problem), a text box was provided under each scenario question for the respondents to offer alternative opinions so that additional factors leading to each scenario could also be identified from the survey.

### 5.2.4 Data Analysis Methods

A quantitative analysis of the survey responses was carried out. Descriptive statistics were applied to gather three aspects of information from the responses to the survey: (i) demographic information on the participants; (ii) student perceptions of the factors causing the group collaboration problems; and (iii) information on the types of asynchronous learning tools that the students had previously used when working on online group work.

Since the background of the participants involved in the survey varies largely, it would be important to see whether the student perceptions of the factors resulting in the problems vary between students with different background. This could provide further implications when generalising the results on the underlying population where the survey sample originated from. Correspondingly, cross-tabulations [64] were set up between the respondents' backgrounds and their perceptions of the factors causing the problems in group collaboration. The Pearson chi-square tests [64] were applied to the cross-tabulations to examine the associations between student background and their perceptions of the factors.

## 5.3 Survey Results

### 5.3.1 Participants' Demographic Information

A total of 173 students responded, most of whom (87% of the total) were students from 18 universities in the UK, (13% did not identify their university). Additionally, 87% of the respondents were studying computing related subjects and others were studying subjects including mathematics, information management, project management, mobile telecommunications management, digital film production, information and library studies, film and TV, and historical and archival studies. Apart from the 22 respondents who did not provide their university names and four who chose not to provide their ethnic origins, all the other demographic questions were answered by all participants, and these are summarised in Table 5.1.

Table 5.1 Demographic characteristics of participants (*N*=173)

| Characteristics | Frequency | Percentage |
|---|---|---|
| ***Age at time of survey (years)*** | | |
| 18-20 | 63 | 36.4% |
| 21-30 | 85 | 49.2% |
| 31-40 | 17 | 9.8% |
| 41-57 | 8 | 4.6% |
| ***Gender*** | | |
| Male | 125 | 72.3% |
| Female | 48 | 27.7% |
| ***Education*** | | |
| Undergraduate | 130 | 75.1% |
| Masters Student | 41 | 23.7% |
| Doctoral Student | 1 | 0.6% |
| Non-degree Student | 1 | 0.6% |
| ***Ethnic Origin*** | | |
| White | 108 | 62.4% |
| Indian | 16 | 9.3% |
| Pakistani | 10 | 5.8% |
| Black African | 9 | 5.2% |
| Other Ethnic Background | 26 | 15% |
| I'd rather not answer | 4 | 2.3% |
| ***English*** | | |
| Native English Speaker | 125 | 72.3% |
| Non-Native English Speaker | 48 | 27.7% |

### 5.3.2 Perceptions on the Problem Scenarios and the Factors Causing the Problems

As mentioned in Section 5.2.3, the seven sub-categories of group collaboration problems were addressed as small scenarios in the survey. The responses for the seven scenarios are summarised in Figure 5.1. As can be seen from Figure 5.1, the responses for each scenario are illustrated with an individual bar chart of which the x-axis represents the set of choices of responses and the y-axis represents the number of responses. Additionally, the list of the most top rated factors for all the scenarios is presented at the bottom right of Figure 5.1. Next, an analysis of the student perceptions of each of the problem scenarios is provided.

The first (of two) scenarios which addressed poor motivation was 'post irrelevant to the learning topic scenario'. Although more than half of the respondents (52%, *N*=173) had not experienced scenario 1 (S1-D), the factor 'misunderstood the topic' (S1-A) gained the highest rate of responses (10.4%), followed by 'used the forum to send personal messages to group members' (S1-C) and 'posted the message in the wrong place' (S1-B). One respondent suggested an additional factor – "may be for asking questions or spreading news" (S1-E).

The second scenario, 'post contains grammatical and/or spelling errors' had not been experienced by only 14.5% of the respondents (S2-F), and 'English was poor' (S2-A) gained the highest rate of responses (35.3%), followed by 'he or she was careless' (S2-C), 'used text speak' (S2-D) and 'he or she thought these errors would not affect the final assignment scores' (S2-B). The factor 'did not have much time to finish the assignment' gained the lowest rate of responses (S2-E). Two respondents suggested dyslexia (S2-G).

The next three scenarios address 'lack of individual accountability'. Scenario 3, 'not contributing much in online discussions scenario' had not been experienced by 31.2% (S3-F). The factor 'did not have enough time' gained the highest rate of responses (16.8%, S3-E), followed by 'too shy to be involved in the communication' (S3-A), 'I have done my part of the work, no need to communicate with others' (S3-C) and 'I was too lazy' (S3-D). The factor 'disagreed with others on the discussion topic' gained the lowest rate of responses (S3-B). Additionally, several other factors were suggested by the respondents (S3-G), including dislike of non face-to-face communication, a perception that the student their comments are not needed, the pressure of doing other work, a comment that the student didn't want to get caught in the crossfire (of the discussion), and "clunkiness" of the online discussion tool.

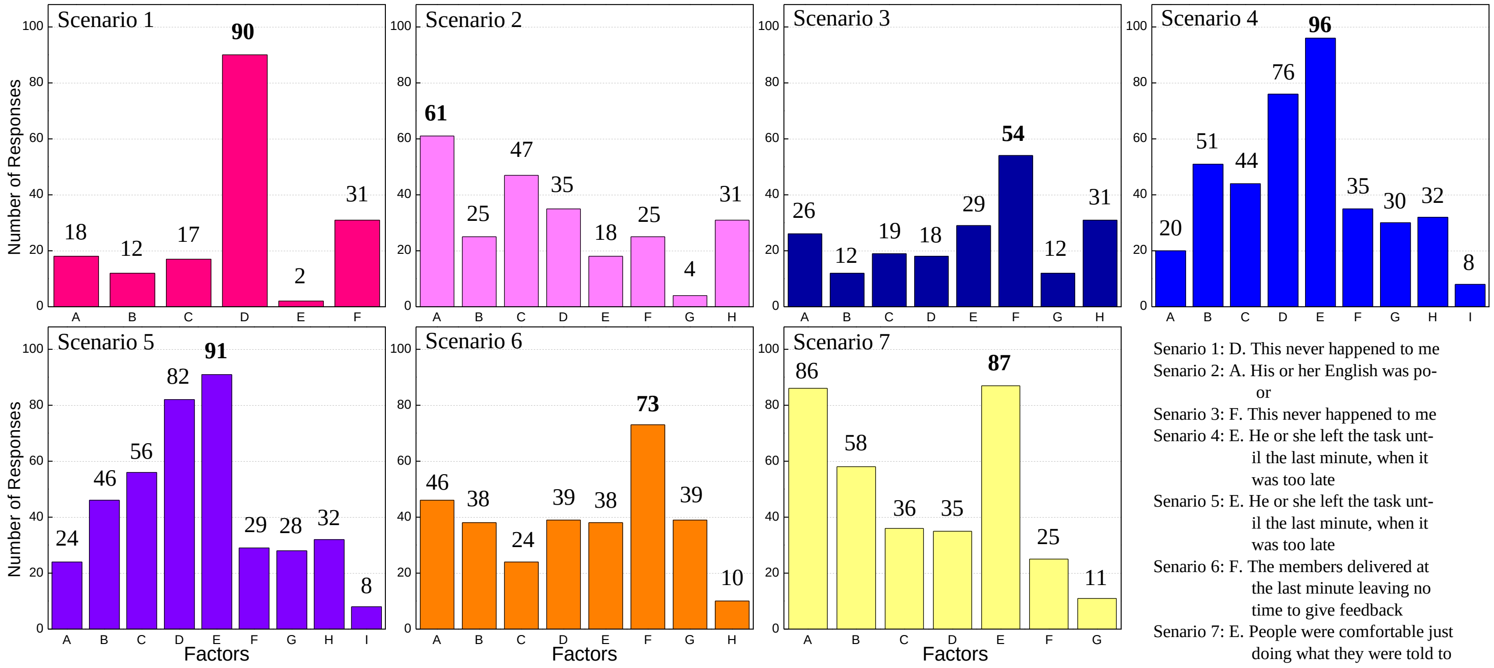


Figure 5.1. Scenarios and their associated responses. As the lengths of the actual descriptions for each scenario and factors are large, we only present the id number of the scenarios and the most top rated factor of each scenario.

Scenario 4, 'not meeting the deadlines' was not experienced by only 18.5% (S4-H). The most popular response was 'left the task until the last minute, when it was too late' (55.5%, S4-E), followed by 'laziness' (S4-D) and 'did not wish to do the work' (S4-B). 'The factor 'forgot the deadline' (S4-A) gained the lowest rate of responses. Additionally, a few respondents suggested the factors 'poor group management' and 'lack of personal organizational skills' (S4-I).

The next scenario, 'not completing the assigned work scenario', also was not experienced by only 18.5% (S5-H). It elicited 'left the task until the last minute, when it was too late' (S5-E) as the most popular response (52.6%), followed by 'laziness' (S5-D), 'did not understand what to do' (S5-C), and 'did not wish to do the work' (S5-B). The factor 'forgot the deadline' gained the lowest rate of responses (S5-A). Other suggestions (S5-I) by the respondents included attempting to "pawn the work on to other group mates", ineffective progress tracking at meetings, the difficulty of the tasks, and "had delusions of grandeur, could not actually finish anything".

Finally, two scenarios addressed the negative interdependence problem. The first, 'little feedback on each other's task work', which only 22.5% had not experienced (S6-G), the factor 'the members delivered at the last minute leaving no time to give feedback' gained the highest rate of responses (42.2%, S6-F), followed by 'they did not like to communicate with each other' (S6-A) and 'group members were too lazy' (S6-D). The lowest rate of responses (S6-C) identified 'differences in language made communication difficult'. Other suggestions (S6-H) included unwillingness to criticise, a tense social situation – "everyone walking on eggshells", shyness, and unawareness of team working skills such as use of praise and encouragement.

Scenario 7, 'single student dominating the group scenario', which again was not experienced by a small minority of 14.5% (S7-F), the factor 'people were comfortable just doing what they were told to' was the most popular (50.3%, S7-E), followed by 'this person was the strongest academically' (S7-A) and 'other members of the group did not like to argue' (S7-B). The factor 'other members were too lazy to challenge that person' (S7-D) has the lowest rate of responses. Other suggestions (S7-G) identified the student being selected as a group leader, feeling the most confident, naturally taking command "almost subconsciously", the student being the best at organization/decision making, and having higher energy levels than the rest of the group.

In addition, a low proportion (17.9%) of the total respondents have never used any asynchronous learning tools to complete online group work (S1-F, S2-H and S3-H), so they did not provide responses to scenario 1 through scenario 3 which describe the problems in collaboration with asynchronous collaboration tools.

### 5.3.3 Associations between Student Background and Their Perceptions on the Factors

The students' perceptions on the factors causing problems in group collaboration (i.e. responses to the scenario questions) are grouped by the scenarios since each scenario question represents a subcategory of the problems that were identified. In order to test whether the actual distribution of perceptions on each scenario differs significantly by student background, Pearson chi-square values ($\chi^2$) and their significance levels ($\rho$) were computed. The Pearson chi-square test was adopted since the two variables being examined for each scenario are both categorical (not continuous). Table 5.2 summarises the chi-square values ($\chi^2$) and the significance levels ($\rho$) for various cases. The row heads represent the scenarios addressed; the column heads represent the characteristics of age, gender and English capability.

Table 5.2 Associations between students' characteristics and their perceptions on the factors

| | **Age** | | **Gender** | | **Native English speaker or not** | |
|---|---|---|---|---|---|---|
| | $\chi^2$ | $\rho$ | $\chi^2$ | $\rho$ | $\chi^2$ | $\rho$ |
| **scenario 1** | 2.297 | .971 | 2.664 | .616 | 3.637 | .457 |
| **scenario 2** | 5.213 | .950 | 3.288 | .772 | 6.890 | .331 |
| **scenario 3** | 5.017 | .957 | 26.102 | .000* | 8.494 | .204 |
| **scenario 4** | 39.297 | .001* | 5.573 | .695 | 6.039 | .643 |
| **scenario 5** | 11.293 | .791 | 16.034 | .042* | 11.632 | .168 |
| **scenario 6** | 7.004 | .935 | 11.515 | .118 | 9.735 | .204 |
| **scenario 7** | 4.684 | .585 | 6.860 | .077 | .205 | .977 |

* $\rho$ <0.05

Based on the results shown in Table 5.2, no statistically significant association has been found between the student backgrounds and their perceptions on the factors causing the problems addressed in the seven scenarios ($\rho$ > 0.05). There are three exceptions here. Student gender is associated with the perceptions of the students on the factors causing the problem addressed in scenario 3 ($\chi^2$ = 26.102, $\rho$ = 0.000 < 0.05). Examining the pattern of data it is noted that more male students preferred factors 'this never happened to me' and 'other'. More female students tended to choose the factor 'I was too shy to be involved in the communication'. Student age is associated with the perceptions of the students on the factors causing the problem addressed in scenario 4 ($\chi^2$ = 39.297, $\rho$ = 0.001 < 0.05). A further analysis of the data reveals that more younger students (age 18-20) preferred the factors ‘he or she forgot the deadline’ and ‘he or she did not wish to do the work’. More older students (age 21-57) preferred the factors ‘this never happened to me’ and ‘other’. There is also a statistically significant association found between gender of the students and the perceptions of the students on the factors causing the problem addressed in scenario 5 ($\chi^2$ = 16.034, $\rho$ = 0.042 < 0.05). It indicates that more male students preferred the factors including ‘This never happened to me’ and ‘other’ than the female students did.

### 5.3.4 The Popularity of Various Asynchronous Collaboration Tools

This subsection reported the respondents’ perceptions of the types of asynchronous collaboration tools that they have previously used when working on online group work.

The relevant survey question (i.e. question eight) was provided with multiple choices. Three types of tools were predefined for this question since they are the common types of asynchronous collaboration tools for supporting online group work. These include forums, wikis and blogs. Two other choices were also presented. One is allowing the respondents to choose when they had never used any asynchronous collaboration tool. The other was followed by a text box which enabled the respondents to comment on additional tools which were not listed. A summary of the types of asynchronous collaboration tools identified and the numbers of respondents for them is illustrated in Figure 5.2.

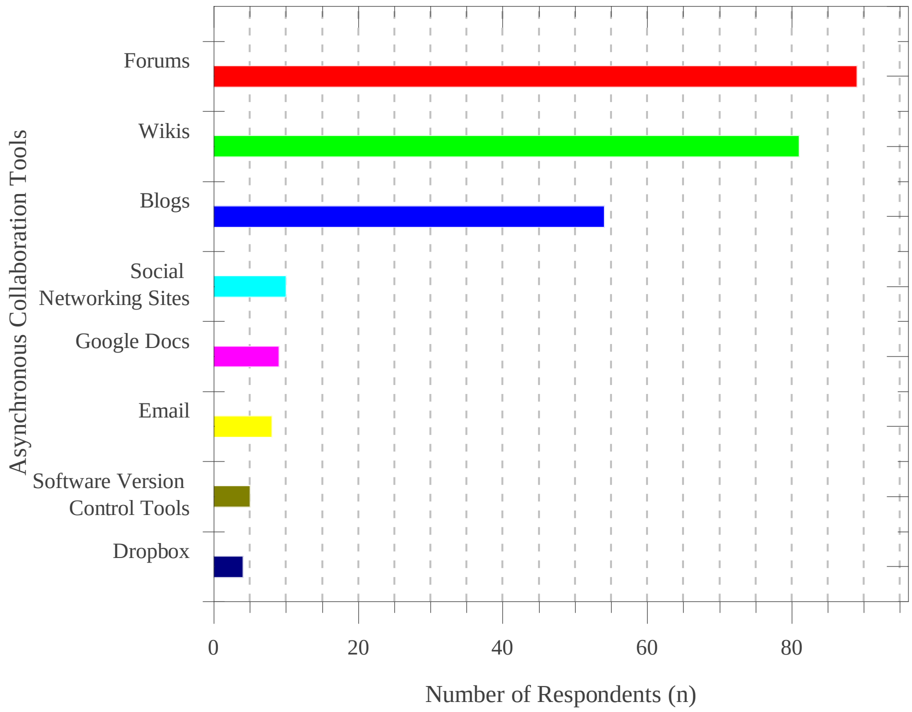


Figure 5.2. Types of asynchronous collaboration tools and the number of students who have previously used them when working on online group work

As shown in Figure 5.2, forums were identified as the most frequently used type of asynchronous collaboration tool that was adopted by the respondents for completing online group work (n=89), followed by wikis (n=81) and blogs (n=54). Moreover, five types of asynchronous collaboration tool were suggested by the respondents. They include social networking sites (e.g. Facebook) (n=10), Google Docs (n=9), email (n=8), software version control tools such as SVN (n=5) and Dropbox (n=4).

Furthermore, a total of 31 respondents had never used any asynchronous collaboration tool for accomplishing their group work. Therefore, their choices (i.e. 'I've never used any asynchronous collaboration tool) were excluded from the results illustrated in Figure 5.2. The data provided by one student who chose the options of ‘forums’, ‘wikis’ and ‘I’ve never used any tools’ together was considered invalid and thus also not included in the final results.

## 5.4 Major Group Collaboration Problems and Their Causes

This section attempts to present the major group collaboration problems and their causes from the findings of the survey. By ‘major’, we mean that more than half of the respondents have experienced one of the problem scenarios referred to.

In terms of the first scenario (i.e. ‘post irrelevant to the learning topic scenario’), 52% of the students ($N$=173) have never experienced it. Apart from this scenario, all the other problem scenarios have been experienced by most of the students who responded to the survey. Therefore, the remaining six problem scenarios (Scenario 2–7 in Section 5.3.2) are identified as the major group collaboration problems.

In order to provide references for the subsequent chapters (Chapter 6–7), a concise name and a symbol are assigned to each of the major group collaboration problems identified (Table 5.3). In Table 5.3, the first four names and symbols represent the types of collaboration problems possessed by individual students and the last two describe the problems for individual collaborative groups.

Table 5.3 Names and symbols of the major group collaboration problems

| Problem Symbol | Problem Name | Scenario Code |
|---|---|---|
| CP-1 | not contributing much in online discussions | Scenario 3 |
| CP-2 | not actively meeting the deadlines | Scenario 4 |
| CP-3 | not actively completing the assigned work | Scenario 5 |
| CP-4 | post contains grammatical and/or spelling errors | Scenario 2 |
| CP-5 | little feedback on each other's task work | Scenario 6 |
| CP-6 | single student dominating the group | Scenario 7 |

As can be seen from Section 5.3.2, various factors were identified through the present survey for each of the major group collaboration problems. In general, the numbers of responses for the factors are different regarding the same major group collaboration problem. This enables the determination of the importance levels of all the factors that can cause such a collaboration problem. Detailed information about the linkages between the major group collaboration problems and their causes is provided in the next section.

## 5.5 Representing the Collaboration Problem-Cause Linkages

Having identified the major types of group collaboration problems and the factors that can cause such problems, this section proposes a representation of the linkages between the major problems and their causes identified, and discusses the potential applications of this representation.

### 5.5.1 An XML-based Representation of the Linkages

Extensible Markup Language (XML) can be defined as a set of rules for encoding documents in a machine-readable form [78]. The set of rules expresses the constraints on the content and structure of documents. A common use of XML is in identifying, storing and structuring information [56]. This is because XML is a metalanguage which allows a user to design own markup for describing the identity of the component parts of a document (e.g. “this is a book”, “this is a magazine”). Moreover, XML is supported by an international standard (W3C XML 1.0 Specification) so it will remain available and processable as a data format. Additionally, as XML allows its entities to nest, it can be used to structure any kind of hierarchical information. These features of XML drove the adoption of it in representing the linkages between the major collaboration problems and their causes identified in this research.

As can be inferred from Section 5.3.2, there are several factors that can lead to a single type of collaboration problem and the influence level of these factors for causing the problem can be various. Some of the collaboration problems (CP-1–CP-4) are possessed by individual students and the others belong to individual collaborative groups (CP-5–CP-6). The collaboration problems, causes (the factors), and the influence levels of the causes were defined as the elements in the XML representation. The hierarchical structure of the elements is illustrated below in Figure 5.3.

In Figure 5.3, the top-level elements refer to the major group collaboration problems. The reason for this is that the collaboration problems were recognised to comprise elements in which other concepts (for example, causes, the influence level of causes) were logically composed. The causes of a collaboration problem were defined as the subordinate elements of the problem, which accommodates the one-to-many relationships between the collaboration problems and their causes.

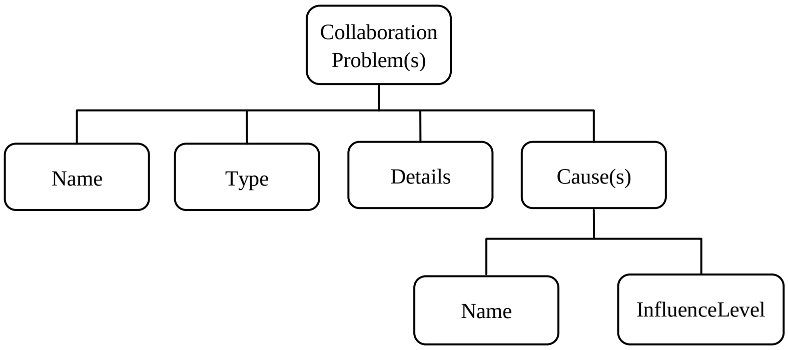


Figure 5.3. A hierarchical structure of the elements

The bottom-level elements encompass the names and the influence level of the causes. The influence level of the causes was defined using a Likert scale listing five items: 1 — Very Strong; 2 — Strong; 3 — Moderate; 4 — Weak; and 5 — Very Weak. The determination of the Likert values was based on the finding from the survey regarding student perceptions on the factors causing the collaboration problems (Section 5.3.2). In particular, the percentage of the number of responses on a factor leading to a problem scenario to the total number of sensible responses to the problem scenario was calculated. Take Scenario 4 in Figure 5.1 as an example, the number of responses to the factor A is 20 and the total number of valid responses for the scenario is 360 (responses to the factor H: "this never happened to me" was excluded from the total number for the purpose of calculating influence level of the factors). Therefore, the desired percentage for the factor A is 5.56% (20/360). Since the percentages for all the factors ranged from

0.32% to 32.10%, the schema shown in the following table was adopted for determining the Likert values of the influence level of the causes.

Table 5.4 Schema for determining the influence level

| **Percentage of responses on a factor to the total responses on a problem scenario** | **Likert items** |
|---|---|
| 20% ~ 32.10% | Very strong |
| 10% ~ 20% (not included) | Strong |
| 6% ~ 10% (not included) | Moderate |
| 1% ~ 6% (not included) | Weak |
| 0 ~ 1% (not included) | Very weak |

Part of the XML representation of the linkages between the collaboration problems and their causes identified is presented in Code Fragment 1. The + symbol suggests that there are additional data which are not shown here.

The format of the XML representation is described in the XML schema designed (*linkageSchema.xsd*). This schema defines a set of rules to constrain the format of the XML representation, including what elements can be included, the data types that the elements should belong to, the structure of the elements and how elements are to be used in documents (for example, the order and occurrence of elements). The XML representation was well formed (correct syntax) and complied with the XML schema defined via an XML validation check.

From a review of the literature, no related XML-based representations of the linkages between major group collaboration problems and their causes were identified. The defined XML representation is novel in that it provides a unique perspective on the influence level of the causes of different collaboration problems and a machine-readable form of the major collaboration problems and their causes.

```
<ProblemBase>
  <CollaborationProblem id="CP-1">
      <name>Not contributing much in online discussions</name>
      <type>Student problem</type>
      <details>… an individual student does not contribute much during the online discussions.</details>
+     <causes>
  </CollaborationProblem>
  <CollaborationProblem id="CP-2">
      <name>Not actively meeting the deadlines</name>
      <type>Student problem</type>
      <details>… one member fails to meet the deadline.</details>
      <causes>
        <cause id="CE-11">
            <name>Left the task until the last minute when it was too late</name>
            <influenceLevel>Very strong</influenceLevel>
        </cause>
        <cause id="CE-12">
            <name>Laziness</name>
            <influenceLevel>Very strong</influenceLevel>
        </cause>
        <cause id="CE-13">
            <name>Did not wish to do the work</name>
            <influenceLevel>Strong</influenceLevel>
        </cause>
        <cause id="CE-14">
            <name>Did not understand what to do</name>
            <influenceLevel>Strong</influenceLevel>
        </cause>
        <cause id="CE-15">
            <name>Did not like to work together with other group members</name>
            <influenceLevel>Moderate</influenceLevel>
        </cause>
        <cause id="CE-16">
            <name>Did not have the ability to work with others to improve the final product</name>
            <influenceLevel>Moderate</influenceLevel>
        </cause>
        …
      </causes>
  </CollaborationProblem>
+ <CollaborationProblem id="CP-3">
+ <CollaborationProblem id="CP-4">
+ <CollaborationProblem id="CP-5">
+ <CollaborationProblem id="CP-6">
</ProblemBase>
```

Code Fragment 1: XML representation of the linkages

### 5.5.2 Discussing the Potential Applications of the XML-based Representation

The developed XML representation of the linkages between major collaboration problems and their causes mainly has two aspects of usage. The first aspect is in applying the XML representation in applications for supporting student self-reflection on a collaborative learning process. One possible application of this is to present the potential causes of the collaboration problems that are identified for individual students and groups who participate in a piece of collaborative group work investigated. Given one collaboration problem as specified in the XML representation, it is capable of analysing the potential causes associated with the problem and reporting them to the problematic students. Thereafter, the students who read the reports can reflect on their participations regarding the collaborative learning process examined. The proposed approach for diagnosing group collaboration problems (Chapter 6) has incorporated this method for encompassing the causes of various collaboration problems as part of the diagnostic products that will be presented to the problematic students.

The second aspect of usage is in adopting the XML representation in applications for facilitating a collaborative learning process. A possible way of facilitating a collaborative learning process is to suggest appropriate learning advice to students that are identified as possessing different collaboration problems. Different learning advice can be predefined referring to the causes of a collaboration problem. Since the influence level of the causes of a collaboration problem varies, the appropriateness of different learning advice for facilitation is considered to be different. Then, a mechanism can be established for selecting appropriate learning advice to moderate different collaboration problems. The selected learning advice together with the identified collaboration problems can be provided to the problematic students. Thus, these students are able to reflect on their actions in the collaborative learning process and take the advice to improve their learning. In summary, this aspect leads to a new question for future research which focuses on the investigation of an approach for facilitating collaborative learning processes based on the linkages between group collaboration problems and their causes as specified in the XML representation.

## 5.6 Summary

In this chapter, a student perspective on student-induced group collaboration problems and their causes was presented. This study carried out a nationwide survey in the UK to address this issue. The methodology and the results of the survey were elaborated in detail. The findings from the survey enabled the identification of the major student-induced group collaboration problems and their causes in online group work. Moreover, an XML-based representation of the linkages between the identified problems and their causes was created, which has potential usage in applications for supporting student self-reflection and facilitating the collaborative process in online collaborative learning.

The next chapter will present a novel approach for diagnosing the identified group collaboration problems in a collaborative learning environment.

# Chapter 6
# An Approach for Diagnosing Group Collaboration Problems

In this chapter, a novel approach namely the Group Collaboration Problem Diagnosis (GCPD) for automatically diagnosing these identified types of group collaboration problems in a collaborative learning environment (CLE) is presented.

This chapter begins with an overview of the proposed GCPD approach. It then continues with a detailed description of the components that constitute the GCPD approach, including a diagnostic mechanism, a data collection and processing component, and a presentation of diagnostic products component. Finally, a tool namely GroupDoctor which was developed as a proof of concept of the core research ideas that underpin the proposed GCPD approach is described.

## 6.1 Overview

At the time of the investigation conducted for the survey (2009), forums were identified as the most frequently used tool for supporting web-based collaborative group work in a Higher Education context (Chapter 5). Therefore, the focus of this research is to examine group work that is undertaken with collaborative learning forums. Therefore, the aim of this chapter is to address an approach for automatically diagnosing collaboration problems in group work that is undertaken in collaborative learning forums.

As discussed in Section 2.4.1 (“interaction analysis”), student interactions with a CLE can account for the behaviours of individual students and collaborative groups. In order to achieve the aim of this chapter, the main research question faced is how to ascertain the existence of different collaboration problems based on student interactions with a collaborative learning forum. Additionally, the proposed approach should address the subsidiary questions which are complementary to achieving the overall goal. These questions include how to collect desired student interaction data from a CLE for the diagnostic procedure and what diagnostic products can be presented to the participants and in which ways they can be presented.

In order to address these research questions, the proposed GCPD approach encompasses the following components:

- a diagnostic mechanism;
- a data collection and processing component; and

- a presentation of diagnostic products component.

The *diagnostic mechanism* is a component which addresses the methods for ascertaining the existence of group collaboration problems based on student interactions with a collaborative learning forum. The *data collection and processing component* attempts to provide solutions to collect the desired student interaction data from a CLE. The *presentation of diagnostic products* component is responsible for presenting the diagnostic products to different participants in an appropriate way.

Considering these components, distinct methods were adopted for exploring the solutions for them. For the diagnosis mechanism, since a variety of collaboration problems have been identified, a hybrid methodology was adopted for building the mechanism. An introduction to the hybrid methodology is presented in Section 6.2.1.

Concerning the data collection and processing component, the data collection requirements (i.e. what types of data to be collected) were derived from the diagnosis mechanism established. Moreover, as a typical CLE can record and maintain the logs about student interactions (as discussed in Section 2.1 and 2.4.1), solutions to obtain the desired data were proposed based on collecting and processing the logs from a CLE.

In terms of presenting the diagnostic products, the content and format of the presentation was determined according to the types of participants who are involved in a piece of group work.

Furthermore, in order to show how the proposed GCPD components can be applied to a diagnosis process in the context of a CLE (where the collaborative learning forums for supporting the examined group work are embedded), Figure 6.1 is presented accordingly.

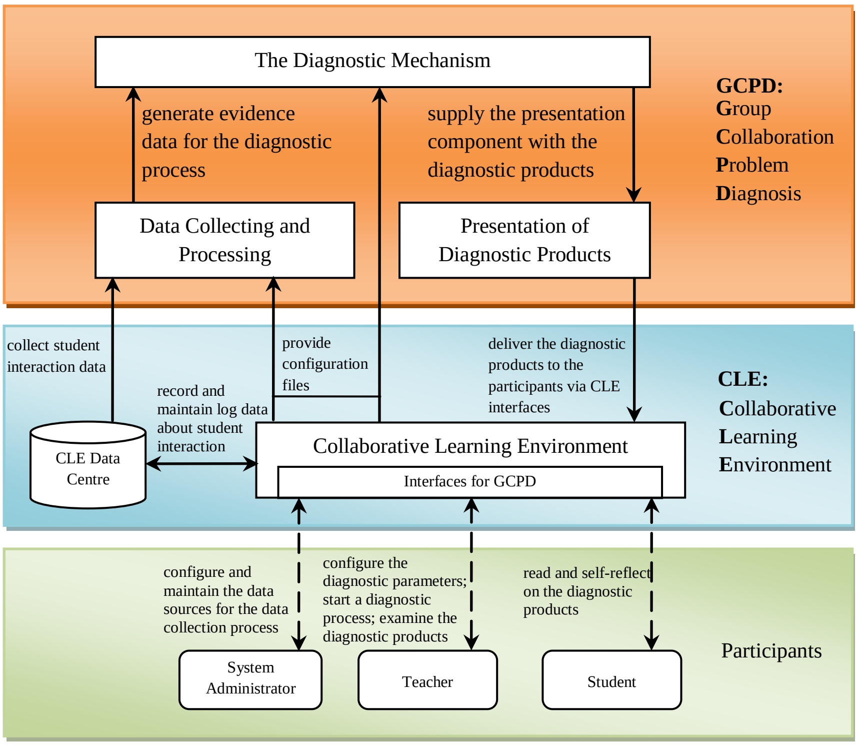


Figure 6.1. An overall view of the GCPD components and the diagnostic process

Figure 6.1 comprises three blocks, including the GCPD block (at the top), the CLE block (in the middle), and the Participants block (at the bottom). The GCPD block represents the GCPD components and the interactions between them for accomplishing a diagnostic task. The CLE block stands for a collaborative learning environment where all the activities related to the examined group work are carried out. The Participants block corresponds to the human users of the CLE and their interactions with the CLE for configuring, starting and making use of the diagnostic process.

Concerning the complexity of Figure 6.1, a bottom-up and then top-down order is adopted to illustrate the working flow of a diagnostic process with the multiple components of the GCPD approach.

As can be seen from the bottom block of this figure, the participants consist of system administrator, teacher and student. Before starting a diagnostic process, the system administrator who maintains a CLE should configure and maintain the data sources for the data collection process. The results of the configuration by the system administrator are kept by the data collection and processing component. When performing a diagnostic task, the teacher who is in charge of the examined group work is expected to configure the diagnostic parameters for the diagnostic mechanism. User interfaces for the GCPD components can be provided via the CLE to these participants.

While the group work goes on, the CLE can record and maintain data about student interactions with the supporting collaborative learning forums in the data centre of the CLE (as shown in the middle block). After receiving the command from the teacher to start a diagnostic process, the data collection and processing component begins to collect student interaction data from the CLE using the configuration of the data sources pre-defined by the system administrator. With the completion of this process, the data collection and processing component moves on to provide the gathered data to the diagnostic mechanism (as shown in the top block).

After receiving the data, the diagnostic mechanism begins to analyse the collaboration problems with the established diagnostic mechanism and produces the diagnostic results. The diagnostic results are then sent to the presentation component (as illustrated in the top block).

Consequently, the presentation component can generate the final diagnostic products based on the diagnosis results and deliver them to the participants via interfaces for the presentation component (as shown in the middle block).

With the presented diagnostic products, the teacher can assess the performances of individual students and collaborative groups for the examined group work and the students can reflect on their own learning actions (represented in the bottom block).

In the following sections, the three components of the proposed GCPD approach are discussed in detail and an implementation of the core components of the GCPD approach is also presented. Section 6.2 presents the methodology used for establishing the diagnostic mechanism and the diagnostic mechanism itself. Section 6.3 describes the types of student interaction data desired for the data collection process as well as different methods and processes that the data collection and processing component can adopt for obtaining these data. Following that, Section 6.4 discusses various types of diagnostic products that are produced for different participants by the presentation of diagnostic products component and the formats that they can be presented. Furthermore, Section 6.5 presents how the GroupDoctor tool was created including the functionalities that the tool attempts to provide and the essential implementation issues determined and a case study with the developed tool. Finally, a summary of the contents presented in this chapter is provided in Section 6.6.

# 6.2 The Diagnostic Mechanism

## 6.2.1 Introduction

Having identified six types of student-induced collaboration problems from the survey presented in Chapter 5, the diagnostic mechanism is thus expected to propose corresponding methods for ascertaining the existence of these problems. Before discussing the methodology adopted for building the mechanism, the six types of collaboration problems identified are reiterated. They include ‘not contributing much in online discussions’ (as referred to CP-1), ‘not actively meeting the deadlines’ (CP-2), ‘not actively completing the assigned work’ (CP-3), ‘post contains grammatical and/or spelling errors’ (CP-4), ‘little feedback on each other’s task work’ (CP-5), and ‘single student dominating the group’ (CP-6). The first four problems (CP-1, CP-2, CP-3, and CP-4) belong to individual student problems that may occur, and the last two problems (CP-5 and CP-6) are types of group problems.

Regarding the first three problems (CP-1, CP-2, and CP-3), the relationships between the existence of one of the problems and certain types of student interaction data should be determined. As discussed in Section 2.4.2 (“predictive modelling”), predictive modelling [43,136] offers such a methodology that can quantitatively define the relationships between the existence of the collaboration problems (i.e. the response or dependent variable) and various types of student interaction data that indicate the problems (i.e. the predictors or independent variables). The process of predictive modelling involves building a data set to collect empirical data about the response variables and the potential predictors, and applying appropriate statistical analysis techniques on the data set to estimate and validate the predictive models. The subsection presented next, includes a description of the procedures for establishing such a data set namely *Forum*.

Concerning the fourth problem—'post contains grammatical and/or spelling errors' (CP-4) — a method for identifying grammatical and spelling errors is desired. Existing grammar checkers and spelling checkers provide a solution for this. They can be adopted in the proposed diagnostic mechanism to verify written texts for grammatical and spelling correctness. In this situation, no extra methods need to be defined for diagnosing the problem. In other words, if the content of a post is verified by a grammar and spelling checker and identified to have one or more grammatical or spelling error, it can indicate that the student who created the post has the problem. However, popular grammar checkers and spelling checkers are often criticised for their incorrectly identification of correct texts as errors or failure to spot errors. The problems with these checkers mainly lie in that they devote most of their effort to spot the easiest errors such as split infinitives and masculine third-person singular pronouns and less effort to catch something subtle and tricky such as the incorrect use of words considering the context in which the words occur. The validity of the grammar and spelling checkers is beyond this thesis and needs further investigation. A description on the grammar and spelling checker adopted in the diagnostic mechanism is presented in Section 6.2.5.

Finally, in consideration of the last two problems (CP-5 and CP-6), methods for deciding whether an individual group has a particular type of relevant problem or not should be identified. As the two problems 'little feedback on each other's task work' and 'single student dominated the group' are both relevant to student participation in a collaborative group, an analysis of the problem scenarios and a further literature review can identify the indicators which reveal the existence of the problems. A detailed description of this procedure is presented in the subsection "indicators of collaboration problem existence" (in Section 6.2.2). Moreover, two algorithms can be developed incorporating these identified indicators for diagnosing the two problems respectively. The designed algorithms require pre-definition of some parameters for the diagnostic process. For example, the number of posts produced by a group on a group forum that can be defined as relatively few. The definition of 'few' depends on the features of the group work examined such as the time period that the group work lasts for and the numbers of the posts made by other groups. The teacher who examines the group work is responsible for defining the values of the desired parameters. Section 6.2.4 discusses the two proposed algorithms in detail.

As can be seen from this point, two different procedures were followed for exploring the methods for diagnosing the first three problems and the last two problems. The reason for this is given below. Performing predictive modelling requires a large data set to ensure the validity of the estimated predictive models. However, the collected data for individual groups (i.e. 18 groups) is relatively small compared to the data collected for individual students (i.e. 87 students). It was impossible to draw valid predictive models on the relatively small data set for individual groups. Hence, an alternative procedure was adopted (as discussed above) in order to ensure the validity of the proposed method.

In summary, the proposed diagnostic mechanism consists of the predictive models established for diagnosing the problems CP-1, CP-2, CP-3; the algorithms defined for diagnosing the problems CP-5, CP-6; and the grammar and spelling checker adopted for diagnosing the problem CP-4. Next, the process to construct the *Forum* data set is described.

### 6.2.2 Constructing the *Forum* Data Set

The purposes for constructing the *Forum* data set are two-fold: collecting data for the predictive modelling procedure that is discussed in Section 6.2.3, and gathering data for the evaluation of the proposed diagnostic mechanism which is addressed in Chapter 8. The *Forum* data set contains two kinds of data. The first is student interaction data which were collected from a learning forum system on which a web-based computer science group project was undertaken. The second is the data relating to assessment of group collaboration problems, and were gathered through a questionnaire delivered to the students who participated in the group project.

**Indicators of Collaboration Problem Existence**

In order to discover the types of student interaction data that potentially indicates the existence of the collaboration problems, an analysis of the problem scenarios and a further literature review were carried out.

As discussed in Section 2.4.1, quantitative data related to student interactions with a forum system can account for the behaviours of individual students and collaborative groups [30,33,91,164,166]. Talavera and Gaudioso [164] suggested that the number of threads started by an individual student can indicate the degree of involvement to produce a contribution and the number of messages that a student replied can imply a measure of how they are promoting discussion. In addition to this, Nakahara *et al.* [91] pointed out another three indicators in their study that can reveal the degree of participation in an online BBS forum: the "number of posts", the "number of times posts are read" and "ratio of total forum posts created to replies". In other studies including [30,33], the number of messages has also been noted as an indication of activity for individual students or groups.

Furthermore, Bratitsis and Dimitracopoulou's study [33] on computer-supported interaction analysis for forums suggested that the proportion of the number of posts made by an individual student to the overall number of posts made by the group that the student belongs to can reveal the contribution status of the student for the group activity and also evidence whether the student has actively participated in the group activity or not. Additionally, Bratitsis and Dimitracopoulou also noted in [55] that the number of posts made by a student and the number of times that the student read a post during a time period can identify the participation peak for this period.

Apart from the indicators identified from literature, some hypothetical indicators were proposed to complete the list of indicators. These hypothetical indicators are expected to be related to the existence of the collaboration problems in question. Among these indicators, some are quantitative data related to student interactions with a forum system. Here are two examples of the quantitative hypothetical indicators: the number of times that an individual student logged in to a group forum (noted as 'forum_login') and the percentage of the size of a group that is defined as relative majority (noted as 'percentage_groupsize_most'). The other hypothetical indicators are qualitative data related to student interactions with a forum system. For example, the pattern of the participation peak over a time period for an individual student (noted as 'timeperiod_post_pattern') is such a qualitative hypothetical indicator.

Table 6.1 provides a summary of the indicators identified for each collaboration problem. As discussed in the previous subsection, existing grammar and spelling checkers can be adopted for diagnosing the problem CP-4. Therefore, no extra indicators are defined for the problem CP-4 in Table 6.1.

Table 6.1 Indicators for each collaboration problem identified in Chapter 5

| Problem No. | Problem Name | Indicators |
|---|---|---|
| CP-1 | 'not contributing much in online discussions' | post_create, post_reply, forum_view, thread_view, forum_login, ratio_stupost_grpost |
| CP-2 | 'not actively meeting the deadlines' | post_create, post_reply, forum_view, thread_view, forum_login, timeperiod_post_pattern, timeperiod_view_pattern |
| CP-3 | 'not actively completing the assigned work' | post_create, post_reply, forum_view, thread_view, forum_login, ratio_stupost_grpost |
| CP-5 | 'little feedback on each other's task work' | group_post, group_feedback, average_group_feedback, student_reply, percentage_groupsize_most, percentage_avegroupfeedback_large |
| CP-6 | 'single student dominating the group' | group_post, student_over_post_most, student_post, average_group_post, grouppost_few, percentage_grouppost_most, percentage_groupsize_most |

The next subsection presents the data collection and preparation procedure for defining the *Forum* data set according to the indicators listed in Table 6.1.

**Data Collection and Preparation**

The data collection procedure aimed to collect the two kinds of data that were pointed out earlier: data relating to the indicators and data about the assessment of the collaboration problems. Next, the background about the group project which the data were collected from is presented.

The group project was a part of a first year undergraduate module in the Department of Computer Science at the University of Warwick. The group project started at the beginning of Term 1 for the academic year 2010-2011 and completed in the middle of December, 2010. A total of 95 students took part in this module. These students were allocated into 19 groups at the beginning of the term (i.e. five students per group). The task for each group was to construct a set of questions for other groups to answer and also answer some questions authored by other groups on a collaborative learning forum that was assigned to each group. The questions posed should relate to the concepts of the operating system UNIX which were taught in lectures and practiced during lab sessions for this module. The private group forum was used for group discussions relating to the group project. A general forum was also set up so that all the groups were able to post their questions and answers decided on. Both the private group forums and the general forum were created and maintained using the Warwick Forums system.

The Warwick Forums is a discussion group system. It provides a structured tool for asynchronous collaboration. Similar to a collaborative learning environment, the Warwick Forums system can capture data about student interactions with the system such as the number of times a user has viewed threads in a forum, the number of times a user has logged in to a forum, as well as all the messages posted in a forum including the time when a user started a thread or replied to a message. The system provides functionalities of exporting these data in two formats. The statistics of student interactions with a forum can be exported into a CSV file and the forum messages can be exported as an XML file.

Apart from the above procedure, a questionnaire was designed for collecting data about the problems that the students and their groups experienced in the group project. The questionnaire was targeted for the students who participated in the group project. Moreover, the questionnaire was completed at the end of Term 1.

The questionnaire consisted of 18 statements which were organized in five groups. Each of the first four groups consisted of four statements. Each statement represented one of the collaboration problems to be judged for an individual student (i.e. CP-1, CP-2, CP-3 or CP-4). Since there were another four students other than the respondent in a group, four groups of statements for individual students were presented. The last group encompassed two statements. Each corresponds to a collaboration problem (i.e. CP-5 or CP-6) to be judged for an individual group. Two choices (i.e. ‘Yes’ and ‘No’) were provided for each statement. If a statement was believed to be true, the respondent should choose the answer of ‘Yes’. Otherwise, the respondent should choose ‘No’.

The ethical consent for the data collection procedure was approved by the primary researcher’s department. Data were collected for 87 students who constituted 18 collaborative groups.

The data collected through the above procedure were further analysed and used to define the *Forum* data set. Particularly, the CSV files and XML files exported from the Warwick Forums system were used to define the values of indicators for the problems as specified in Table 6.1; the responses to the questionnaire were used to define variables representing the collaboration problems. However, there were some exceptions. No values were defined for the five indicators listed in Table 6.1: 'percentage_groupsize_most' and 'percentage_avegroupfeedback_large' for CP-5; 'grouppost_few', 'percentage_grouppost_most' and 'percentage_groupsize_most' for CP-6. This is because they are parameters required for the GCPD algorithms and would not be used for the predicitve modelling process.

**The *Forum* Data Set**

The constructed *Forum* data set contains five tables: *Forum-1*, *Forum-2*, *Forum-3*, *Forum-4* and *Forum-5*. The first three tables correspond to the data prepared for the problems CP-1, CP-2 and CP-3. Each of these tables defines values of a response variable (i.e. the categories of problem existence) and values of the predictors (i.e. the indicators) relating to the existence of a problem. These three tables were used for the predictive modelling process that is discussed in Section 6.2.3.

The tables *Forum-4* and *Forum-5* also define values of the variable that represent categories of problem existence and values of indicators for the problem CP-5 and CP-6. These two tables were used for evaluating the proposed GCPD algorithms (that is presented in Chapter 7).

An example of the tables defined in the *Forum* data set is illustrated in Table 6.2.

Table 6.2 Data segments from the table *Forum-1* in the *Forum* data set

| Student No. | CP-1 | post_create | post_reply | forum_view | thread_view | forum_ login | ratio_ stupost_ grpost |
|---|---|---|---|---|---|---|---|
| … | … | … | … | … | … | … | … |
| 38 | 1 | 0 | 1 | 7 | 10 | 3 | 25% |
| 39 | 2 | 1 | 5 | 45 | 41 | 4 | 55% |
| 40 | 2 | 1 | 2 | 112 | 36 | 12 | 27% |
| 41 | 2 | 0 | 0 | 6 | 3 | 2 | 0 |
| 42 | 2 | 0 | 1 | 41 | 31 | 11 | 9% |
| 43 | 2 | 0 | 1 | 9 | 8 | 4 | 9% |
| 44 | 3 | 1 | 8 | 52 | 41 | 20 | 25% |
| 45 | 1 | 0 | 1 | 13 | 26 | 4 | 3% |
| 46 | 3 | 0 | 13 | 87 | 81 | 15 | 36% |
| 47 | 1 | 0 | 8 | 40 | 64 | 18 | 22% |
| 48 | 1 | 0 | 5 | 31 | 45 | 17 | 14% |
| 49 | 1 | 0 | 3 | 116 | 71 | 23 | 8% |
| 50 | 1 | 0 | 0 | 13 | 6 | 2 | 0 |
| 51 | 1 | 0 | 0 | 7 | 5 | 2 | 0 |
| 52 | 3 | 3 | 15 | 198 | 166 | 29 | 46% |
| … | … | … | … | … | … | … | … |

In the above table, each row represents data relating to an individual student and each column corresponds to a defined variable. The response variable representing the categories of problem existence was defined as a polytomous variable. The categories include the category of 'yes' (coded as '1') which means the student has the problem; the category of 'maybe' (coded as '2') which means the student may have the problem; and the category of 'no' (coded as '3') which means the student does not have the problem. As can be seen from Table 6.2, the column 'CP-1' corresponds to the response variable that adopted such coding rules.

In the next subsection, the predictive modelling process by using the collected data in the *Forum* data set is presented.

### 6.2.3 The GCPD Predictive Models

Logistic regression has become a standard method of modelling the relationship between a binary or dichotomous response variable and one or more explanatory variables in many fields [86]. Other regression methods such as multivariate analysis and analysis of covariance [43] were not applicable for the targeted predictive modelling process and thus were not chosen for building the predictive models. For example, multivariate analysis is applicable when there are two or more quantitative response variables. However, there was only one categorical response variable for the targeted modelling process. In addition, the analysis of covariance method applies when there is only one continuous response variable. Multinomial logistic regression (MLR) is an extension of the logistic regression in the case where the response variable is nominal with more than two levels. In this study, multinomial logistic regression was adopted for building the predictive models for diagnosing the problems of CP-1, CP-2 and CP-3. This is because the response variables defined are with three categories ('yes', 'maybe', 'no'). Before proceeding with presenting the generated GCPD predictive models, the general MLR model is presented below.

**The Multinomial Logistic Regression Model**

Let $q$ be the possible categories of the response variable $Y$ and $\{x_1, x_2, \ldots, x_k\}$ be the set of $k$ predictor variables. The general multinomial logistic regression model [86] can be denoted in the form

$$\ln\left[\frac{P(Y=j|x)}{P(Y=q|x)}\right] = b_0{}^{(\mathrm{j})} + \sum_{i=1}^{k} b_i{}^{(j)} x_i\,,\ \ j = 1, \ldots, q-1 \tag{6.1}$$

where $P(Y = q|x)$ expresses the probability that the response variable $Y$ falls into the category $q$ ($q$ is used as the *reference* category); $P(Y = j|x)$ represents the probability that the response variable $Y$ falls into the category $j$ (i.e. one of the categories other than the reference category); and $b_i$ stand for the unknown MLR coefficients ($b_0$ is the intercept). The quantity on the left side of equation (6.1) is called a *logit*.

To develop the expressions for $P(Y = q|x)$ and$P(Y = j|x)$, the following definition is made

$$g_j(x) = b_0{}^{(\mathrm{j})} + \sum_{i=1}^{k} b_i{}^{(j)} x_i\,,\ \ j = 1, \ldots, q-1. \tag{6.2}$$

Based on the equations (6.1) and (6.2), the probability that the response variable $Y$ falls into the category $i$ can be derived and denoted in the form

$$P(Y = i|x) = \frac{e^{g_i(x)}}{\sum_{l=1}^{q} e^{g_l(x)}},\ \ i = 1, \ldots, q \tag{6.3}$$

where $g_q(x) = 0$.

The coefficients of the model (6.1) can be fitted by applying a model fitting method such as maximum likelihood [86]. After this is done, the logits and the probabilities of each category of the response variables can be calculated according to the equations (6.2) and (6.3). The final prediction is the category with the maximum probability.

### The Modelling Processes

Multinomial logistic regression analysis was performed on the three tables *Forum-1*, *Forum-2* and *Forum-3* in the *Forum* data set using the SPSS statistical software (version 19). The modelling on the table *Forum-1* produced the GCPD Predictive Model I for describing the relationship between the existence of the problem CP-1 and its predictors. In addition, the modelling on the table *Forum-2* produced the GCPD Predictive Model II for describing the relationship between the existence of the problem CP-2 and its predictors. Last, the modelling on the table *Forum-3* produced the GCPD Predictive Model III for describing the relationship between the existence of the problem CP-3 and its predictors. Next, results of each of the modelling processes are presented.

### The GCPD Predictive Model I

Table 6.3 presents the results of the MLR analysis for variables predicting the collaboration problem CP-1. Of the six predictor variables for the problem CP-1 listed in Table 6.1, three were able to separate the cases for problem existence: 'Yes', 'Maybe', and 'No'. The three predictors include 'post_create' (i.e. the number of posts that were created by a student in the group forum), 'post_reply' (i.e. the number of posts that were replied to by a student in the group forum), and 'thread_view' (i.e. the number of times that a student viewed the threads in a group forum). This final model was statistically significant [-2 Log likelihood=104.081; $\chi^2(6)$ =66.895; P=0.000].

The significance of the predictors in the model was measured with the Likelihood ratio tests — 'thread_view' [-2 Log likelihood=114.262; $\chi^2(2)$ =10.182; P=0.006], 'post_reply' [-2 Log likelihood=122.930; $\chi^2(2)$ =18.849; P=0.000], and ‘post_create’ [-2 Log likelihood=135.599; $\chi^2(2)$ =31.518; P=0.000]. The indicators ‘forum_view’ (i.e. the number of times that a student viewed a group forum), ‘forum_login’ (i.e. the number of times that a student logged in to the group forum) and ‘ratio_stupost_grpost’ (i.e. the ratio of the overall number of posts that a student made to the overall number of posts that a group made) failed to meet the 0.05 significance criterion and were dropped from the final model.

Table 6.3 Summary of multinomial logistic regression analysis for variables predicting the collaboration problem ‘not contributing much in online discussions’ (CP-1) (*N*=87)

| Problem CP-1[a] | | B | Std. Error | Wald | df | Sig. | Exp(B) | 95% Confidence Interval for Exp(B) | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Lower Bound | Upper Bound |
| Yes | Intercept | 1.642 | .461 | 12.665 | 1 | .000 | | | |
| | thread_view | .118 | .049 | 5.806 | 1 | .016 | 1.125 | 1.022 | 1.239 |
| | post_reply | -.934 | .334 | 7.824 | 1 | .005 | .393 | .204 | .756 |
| | post_create | -4.327 | 1.348 | 10.307 | 1 | .001 | .013 | .001 | .185 |
| Maybe | Intercept | .276 | .497 | .308 | 1 | .579 | | | |
| | thread_view | .015 | .031 | .240 | 1 | .625 | 1.015 | .956 | 1.078 |
| | post_reply | .148 | .116 | 1.644 | 1 | .200 | 1.160 | .925 | 1.455 |
| | post_create | -1.957 | .986 | 3.940 | 1 | .047 | .141 | .020 | .976 |

a. The reference category is: No.

The goodness-of-fit of the model (i.e. how well the model fits a set of observations) was measured with the Pearson chi-square test. The result of the test was not statistically significant [$\chi^2(136)$ =139.853, P=0.393], which indicates that the model fits the data well. This is due to the value of P is bigger than 0.05 and therefore the null hypothesis is not rejected. The Pearson chi-square test verifies the null hypothesis that the observed frequency distribution of the outcome categories of the response variable is consistent with a particular theoretical distribution (i.e. the chi-square distribution).

As can be seen from Table 6.3, the multinomial logit model has an important feature that it estimates $q-1$ models, which $q$ is the number of categories of the response variable $Y$.

For each response category, the unique contribution of each predictor's coefficient while holding constant the other predictors was measured by the Wald chi-square test. For the response category 'yes' relative to the reference category 'no', each of the three predictors' coefficient is statistically significant ($P < 0.05$). For the response category 'maybe' relative to the reference category 'no', only the coefficient of the predictor 'post_create' is statistically significant ($P < 0.05$).

The predictive model I that computes the probability of each response category for the problem CP-1 can be defined based on the equations (6.3), (6.2) and the coefficients obtained from the MLR analysis (as presented in the third column of Table 6.3). The established predictive model I comprises the following equations (6.4)—(6.8). The equations (6.4), (6.5) and (6.6) correspond to the probability of the first response category ('yes'), the probability of the second response category ('maybe') and the probability of the last response category ('no') respectively

$$P(Y=1|x) = \frac{e^{g_1(x)}}{1+e^{g_1(x)}+e^{g_2(x)}}, \tag{6.4}$$

$$P(Y=2|x) = \frac{e^{g_2(x)}}{1+e^{g_1(x)}+e^{g_2(x)}}, \tag{6.5}$$

$$P(Y=3|x)=\frac{1}{1+e^{g_1(x)}+e^{g_2(x)}} \tag{6.6}$$

and the equations (6.7), (6.8) represent the logits of $g_1(x)$, $g_2(x)$

$$g_1(x)=1.642+0.118x_1-0.934x_2-4.327x_3, \tag{6.7}$$

$$g_2(x)=0.276+0.015x_1+0.148x_2-1.957x_3, \tag{6.8}$$

where $x_1, x_2, x_3$ represent the predictor variables ‘thread_view’, ‘post_reply’ and ‘post_create’ correspondingly.

The odds ratio (i.e. the exponentiation of the coefficients—$Exp(B)$) for the predictor variables, indicating how likely an outcome of the response variable is to fall in the comparison category or the reference category while the predictor variable in question increases are also presented in Table 6.3. If the odds ratio of a coefficient $>$ 1, it indicates that the outcome of the response variable is more likely to fall in the comparison category as the predictor variable increases. If the odds ratio of a coefficient $<$ 1, it indicates that the reference category is more likely than the comparison category as the predictor variable increases. For example, the odds ratio of the coefficient -4.327 is 0.013 $<$ 1, and thus the outcome of the response variable is more likely to fall in the reference category (‘no’) as the predictor variable ‘post_create’ increases. In other words, as the number of posts created by a student increases the possibility that the student does not have the problem of ‘not contributing much in online discussions’ increases.

The confidence interval for an individual odds ratio reflects whether the predictor variable in question significantly affects the odds ratio. As can be seen from Table 6.3, the conventional 0.05 standard for statistical significance was adopted. The lower bound and the upper bound of the confidence interval of an odds ratio are presented. If the interval includes one, it indicates that the predictor variable in question does not significantly affect the odds ratio. For example, the confidence interval for the predictor variable 'thread_view' in the 'maybe' category group is between 0.956 and 1.078, which includes one. Therefore, the predictor variable 'thread_view' does not significant affect the odds ratio $Exp(B)$.

**The GCPD Predictive Model II**

Table 6.4 presents the results of the MLR analysis for variables predicting the collaboration problem CP-2. Of the seven predictor variables for the problem CP-2 listed in Table 6.1, two were able to separate the cases for problem existence: 'Yes', 'Maybe', and 'No'. The two predictors are 'post_reply' and 'post_create'. This final model was statistically significant [-2 Log likelihood=89.591; $\chi^2(4)$ =71.891; P=0.000].

The significance of the two predictors in the model was 'post_reply' [-2 Log likelihood=111.482; $x^2(2)$ =21.891; P=0.000], and 'post_create' [-2 Log likelihood=108.269; $x^2(2)$ =18.678; P=0.000]. The indicators 'forum_view', 'thread_view', 'forum_login', 'timeperiod_post_pattern' (i.e. the pattern of posting that a student made during a particular time period) and 'timeperiod_view_pattern' (i.e. the pattern of viewing that a student had during a particular time period) failed to meet the 0.05 significance criterion and were dropped from the final model.

Table 6.4 Summary of multinomial logistic regression analysis for variables predicting the collaboration problem 'not actively meeting the deadlines' (CP-2) (*N*=87)

| Problem CP-2[a] | | B | Std. Error | Wald | df | Sig. | Exp(B) | 95% Confidence Interval for Exp(B) | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Lower Bound | Upper Bound |
| Yes | Intercept | 3.794 | .775 | 23.939 | 1 | .000 | | | |
| | post_reply | -.846 | .228 | 13.801 | 1 | .000 | .429 | .275 | .671 |
| | post_create | -1.851 | .713 | 6.740 | 1 | .009 | .157 | .039 | .635 |
| Maybe | Intercept | 1.699 | .786 | 4.668 | 1 | .031 | | | |
| | post_reply | -.307 | .172 | 3.180 | 1 | .075 | .736 | .525 | 1.031 |
| | post_create | -.749 | .362 | 4.282 | 1 | .039 | .473 | .233 | .961 |

a. The reference category is: No.

The goodness-of-fit of the model was measured by the Pearson chi-square test. The result of the test was not statistically significant [$\chi^2(138)$ =142.815, P=0.372], which indicates that the model fits the data well. This is due to the value of P is bigger than 0.05. Therefore, the null hypothesis is not rejected, which states that the observed frequency distribution of the response variable is consistent with the chi-square distribution.

With regard to the unique contribution of each predictor's coefficient while holding constant the other predictors, for the response category 'yes' relative to the reference category 'no', each of the two predictors' coefficient is statistically significant ($P < 0.01$). For the response category 'maybe' relative to the reference category 'no', only the coefficient of the predictor 'post_create' is statistically significant ($P < 0.05$).

The predictive model II which computes the probability of each response category for the problem CP-2 can be defined based on the equations (6.3), (6.2) and the coefficients obtained from the MLR analysis (as presented in the third column of Table 6.4). The predictive model II consists of three same regression equations as (6.4)—(6.6) and another two logit equations (6.9)—(6.10). The logit equations take the following forms

$$g_1(x) = 3.794 - 0.846x_1 - 1.851x_2, \tag{6.9}$$

$$g_2(x) = 1.699 - 0.307x_1 - 0.749x_2 \tag{6.10}$$

where $x_1, x_2$ represent the predictor variables 'post_reply' and 'post_create' correspondingly.

The odds ratio for the predictor variables are presented in the column of $Exp(B)$ in the Table 6.4. It is revealed from this table that the odds ratios of the coefficients for the predictor variables in the first category group ('yes') and in the second category group ('maybe') are smaller than one, and thus the outcome response category is more likely to fall in the reference category ('no') as the predictor variable increases. In other words, as a predictor variable increases the possibility that the student does not have the problem of 'not actively meeting the deadlines' increases.

Furthermore, it suggests from Table 6.4 that the confidence intervals at the significance level of 0.05 for the odds ratios of the predictor variables for the first category group ('yes') do not include the number of one. Therefore, the predictor variables in question significantly affect the odds ratios. However, for the second category group ('maybe'), only the predictor variable 'post_create' significantly affect its odds ratio while the predictor variable 'post_reply' does not significantly affect its odds ratio since the confidence interval for its odds ratio includes one.

## The GCPD Predictive Model III

Table 6.5 presents the results of the MLR analysis for variables predicting the collaboration problem CP-3. Of the six predictor variables for the problem CP-3 listed in Table 6.1, two were able to separate the cases for problem existence: ‘Yes’, ‘Maybe’, and ‘No’. The two predictors include ‘post_reply’ and ‘post_create’. This final model was statistically significant [-2 Log likelihood=58.203; $\chi^2(4)$ =107.920; P=0.000].

The two identified predictors were statistically significant: ‘post_reply’ [-2 Log likelihood=95.120; $x^2(2)$ =36.917; P=0.000], and ‘post_create’ [-2 Log likelihood=99.183; $x^2(2)$ =40.980; P=0.000]. The indicators ‘forum_view’, ‘thread_view’, ‘forum_login’, and ‘ratio_stupost_grpost’ failed to meet the 0.05 significance criterion and were dropped from the final model.

Table 6.5 Summary of multinomial logistic regression analysis for variables predicting the collaboration problem ‘not actively completing the assigned work’ (CP-3) (*N*=87)

| Problem CP-3[a] | | B | Std. Error | Wald | df | Sig. | Exp(B) | 95% Confidence Interval for Exp(B) | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Lower Bound | Upper Bound |
| Yes | Intercept | 7.459 | 1.921 | 15.084 | 1 | .000 | | | |
| | post_reply | -1.637 | .426 | 14.762 | 1 | .000 | .195 | .084 | .449 |
| | post_create | -5.136 | 1.703 | 9.098 | 1 | .003 | .006 | .000 | .166 |
| Maybe | Intercept | 4.338 | 1.829 | 5.628 | 1 | .018 | | | |
| | post_reply | -.555 | .314 | 3.116 | 1 | .078 | .574 | .310 | 1.063 |
| | post_create | -3.137 | 1.279 | 6.020 | 1 | .014 | .043 | .004 | .532 |

a. The reference category is: No.

The goodness-of-fit of the model was measured by the Pearson chi-square test. The result of the test was not statistically significant [$\chi^2(138)$ =71.263, P=1.000], which indicates that the model fits the data well.

For the response category ‘yes’ relative to the reference category ‘no’, each of the two predictors’ coefficient is statistically significant ($P < 0.01$). For the response category ‘maybe’ relative to the reference category ‘no’, only the coefficient of the predictor ‘post_create’ is statistically significant ($P < 0.05$). The predictive model III which computes the probability of each response category for the problem CP-3 consists of three regression equations same as (6.4)—(6.6) and two logit equations (6.11)—(6.12). The logit equations take the following forms

$$g_1(x) = 7.459 - 1.637x_1 - 5.136x_2, \tag{6.11}$$

$$g_2(x) = 4.338 - 0.555x_1 - 3.137x_2 \tag{6.12}$$

where $x_1, x_2$ represent the predictor variables ‘post_reply’ and ‘post_create’ correspondingly.

The odds ratio for the predictor variables are presented in the column of $Exp(B)$ in the Table 6.5. It is revealed from this table that the odds ratios of the coefficients for the predictor variables in the first category group (‘yes’) and in the second category group (‘maybe’) are smaller than one, and thus the outcome response variable is more likely to fall in the reference category (‘no’) as the predictor variable increases. In other words, as a predictor variable increases the possibility that the student does not have the problem of ‘not actively completing the assigned work’ increases.

As can be seen from Table 6.5, for the first category group (‘yes’), the confidence intervals at the significance level of 0.05 for the odds ratios of the predictor variables do not include the number of one. Therefore, the predictor variables significantly affect the odds ratios. However, for the second category group (‘maybe’), only the predictor variable ‘post_create’ significantly affect its odds ratio while the predictor variable ‘post_reply’ does not significantly affect its odds ratio since the confidence interval for its odds ratio includes one.

Having presented the GCPD predictive models for diagnosing the collaboration problems CP-1, CP-2 and CP-3, the next subsection introduces the algorithms defined for diagnosing the collaboration problems CP-5 and CP-6.

### 6.2.4 The GCPD Algorithms

A set of indicators was identified respectively for the collaboration problems CP-5 and CP-6 (as presented in Table 6.1). Based on this, two algorithms were defined for diagnosing the two problems individually. Next, a detailed description of the two proposed diagnosis algorithms is provided.

**The CP-5 Diagnosis Algorithm**

Concerning the problem ‘little feedback on each other’s task work’ (CP-5), four continuous variables indicating the activity of a collaborative group were identified (Table 6.1) including ‘group_post’ — the overall number of posts produced by a group, ‘group_feedback’ — the overall number of items of feedback provided by a group, ‘average_group_feedback’ — the average number of items of feedback for all the groups participating in the group work, and ‘student_reply’ — the number of students who have replied to any post in the group forum.

Apart from these indicator variables, some parameters were also presented (Table 6.1). These parameters include ‘percentage_groupsize_most’ — the percentage of the size of a group defining relative majority and ‘percentage_avegroupfeedback_large’ — the percentage of the average number of items of feedback by all groups for defining relatively large number of items of feedback produced by a group. For example, a teacher can define 110% as the percentage of the average number of items of feedback made by all groups for judging whether the number of feedback produced by a group is relatively large or not. The two parameters should be determined based on the features of the group work investigated such as the size of a group and the time period that the group work lasts for.

A diagnosis algorithm namely the CP-5 diagnosis algorithm for ascertaining the existence of the problem CP-5, is proposed incorporating the identified indicators and parameters. The CP-5 diagnosis algorithm is proposed on the assumption that feedback on the work of individual students (e.g. opinions and suggestions) can be obtained before proceeding with this algorithm. The data collection and processing component of the GCPD approach (presented later in Section 6.3) will describe the method adopted for obtaining the feedback from the content of messages posted in a learning forum.

The steps of the CP-5 diagnosis algorithm are illustrated in Figure 6.2 and the pseudo-code of the algorithm is provided in Algorithm 6-1. This algorithm can be illustrated in four steps: (i) compare the value of the variables 'group_post' and 'group_feedback' with zero, if either of the two variables are equal to zero, the problem exists; (ii) if both of the variables 'group_post' and 'group_feedback' are non-zero, compare the value of the variable 'group_feedback' with the value of the variable 'average_group_feedback'; if the former is smaller than the latter, the problem exists; (iii) otherwise, compare the ratio of the value of the variable 'student_reply' to the group size with the value of the parameter 'percentage_groupsize_most'; if the former is smaller than the latter, the problem exists; (iv) otherwise, compare the ratio of the value of the variable 'group_feedback' to the variable 'average_group_feedback' with the value of the parameter 'percentage_avegroupfeedback_large'; if the former is bigger than the latter, the problem does not exist; otherwise, the problem may exist.

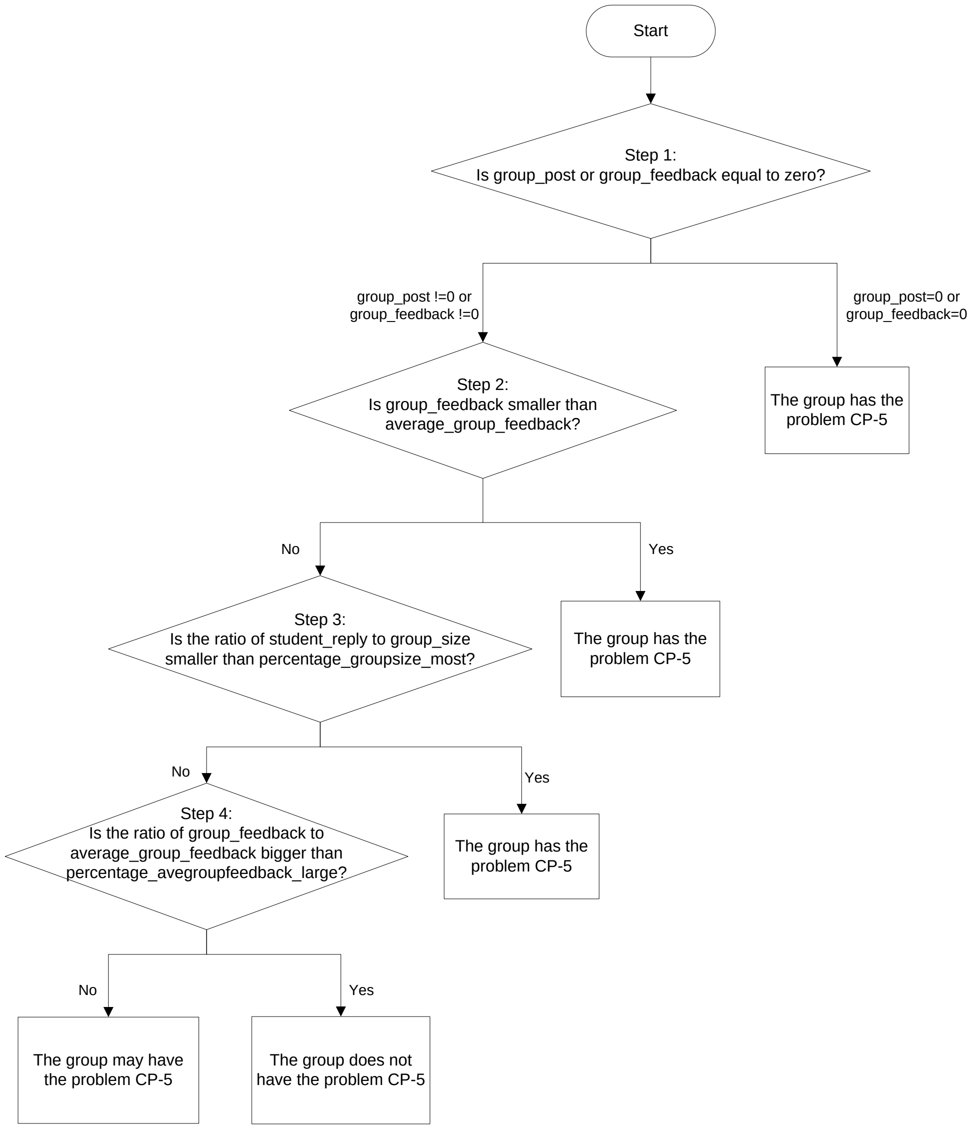


Figure 6.2. The steps of the CP-5 diagnosis algorithm

**Algorithm 6-1: The pseudo-code of CP-5 diagnosis algorithm**

// Variables:
// op: *the overall number of posts produced by a group*
// of: *the overall number of items of feedback given by a group*
// af: *the average number of items of feedback for all the groups participating in the group project*
// sr: *the number of students who have replied to any post on the group forum*
// gs: *the size of a group examined*
// p1: *parameter 1— the percentage of the size of a group defining relative majority*
// p2: *parameter 2— the percentage of the average number of items of feedback by all groups for defining relatively large number of items of feedback produced by a group*
// result: *an assigned code representing the result of the diagnosis process*

// Functions:
// read( ): *read the data of a group regarding op, of, af, sr, gs, p1, p2 given the ID for the group*

```
Initializing
read(group ID)

Diagnosing
if op = 0 or of = 0 then
    result ← 1
else
    if of < af then
        result ← 1
    else
        if (sr/gs) < p1 then
            result ← 1
        else
            if of /af > p2 then
                result ← 3
            else
                result ← 2
return result
```

The code '1' represents the problem CP-5 exists for the group.
The code '2' represents the problem CP-5 may exist for the group.
The code '3' represents the problem CP-5 does not exist for the group.

### The CP-6 Diagnosis Algorithm

Concerning the problem 'single student dominating the group' (CP-6), four continuous variables indicating the activity of individual groups were identified (Table 6.1) including 'group_post' — the overall number of posts produced by a group, 'student_over_post_most' — the number of students who posted over the majority of the posts produced by a group, 'student_post' — the number of students who have posted in the group forum, and 'average_group_post' — the average number of posts for all the groups participating in the group work.

Similar to the CP-5 diagnosis algorithm, some parameters were also defined as well as the above indicator variables (Table 6.1). These parameters include 'grouppost_few' — the number of posts that can be defined as relatively few for a piece of group work, 'percentage_grouppost_most' — the percentage of the number of posts made by a group that can be defined as relative majority, and 'percentage_groupsize_most' — the percentage of the size of a group defining relative majority of a group. For example, a teacher can define 10 for 'grouppost_few', 50% for 'percentage_grouppost_most' and 50% for 'percentage_groupsize_most' for the group work examined.

A diagnosis algorithm namely the CP-6 diagnosis algorithm is proposed for ascertaining the existence of the problem CP-6 incorporating the identified indicators and the defined parameters.

The steps of the CP-6 diagnosis algorithm are illustrated in Figure 6.3 and the pseudo-code of the algorithm is provided in Algorithm 6-2. This algorithm can be illustrated in four steps: (i) compare the value of the variable 'group_post' with the variable 'grouppost_few'; if the value of 'group_post' is smaller than or equal to the value of ‘grouppost_few’, the problem CP-6 does not exist; (ii) otherwise, compare the value of the variable ‘student_over_post_most’ with the number of one; if the value of ‘student_over_post_most’ is not equal to one, the problem does not exist; (iii) otherwise, compare the ratio of the value of the variable ‘student_post’ to the variable ‘group_size’ with the value of the parameter ‘percentage_groupsize_most’; if the former is bigger than the latter, the problem exists; (iv) otherwise, compare the value of the variable ‘group_post’ with the value of the parameter ‘average_group_post’; if the former is smaller than the latter, the problem may exist; otherwise, the problem does not exist.

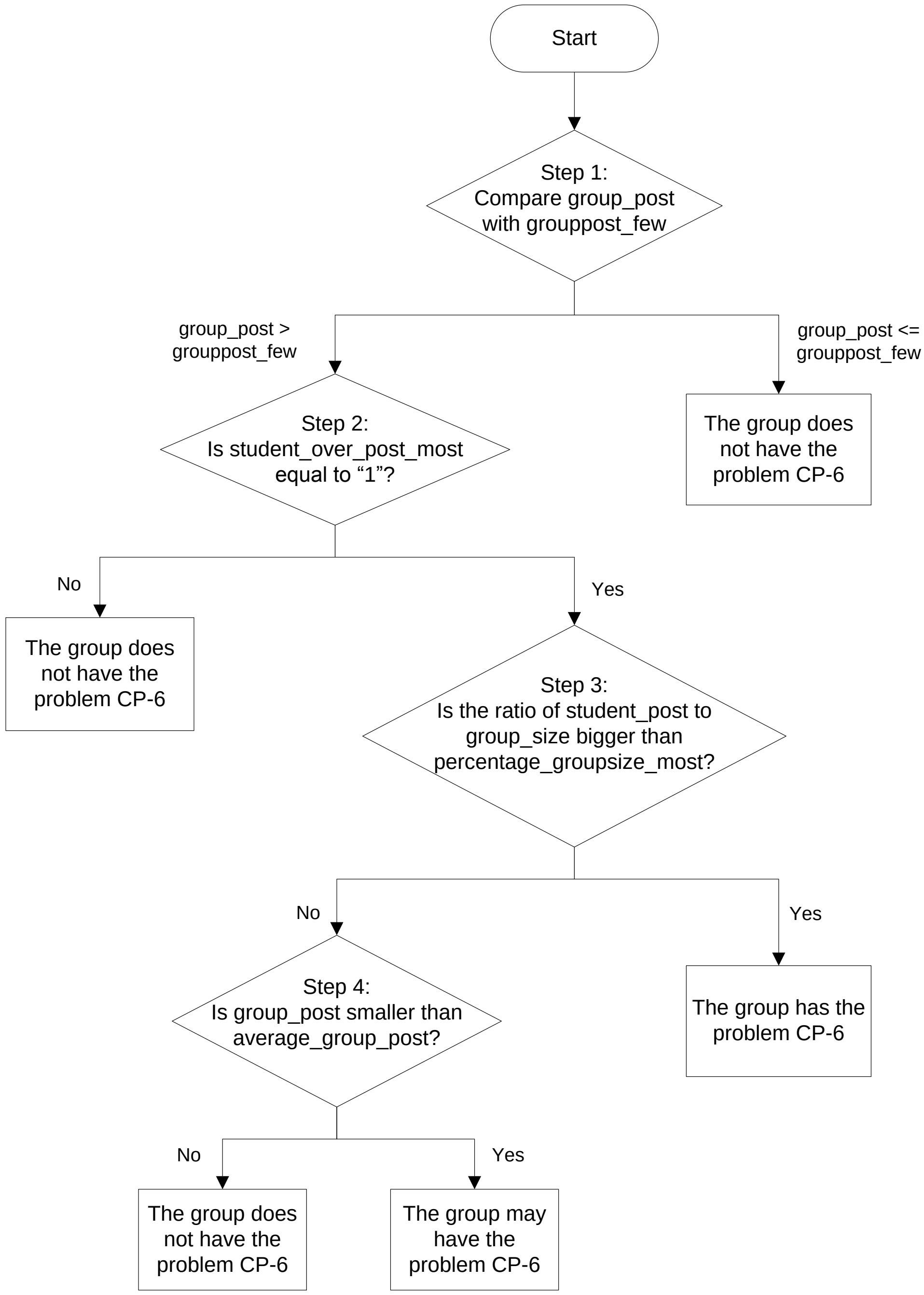


Figure 6.3. The steps of the CP-6 diagnosis algorithm

**Algorithm 6-2: The pseudo-code of the CP-6 diagnosis algorithm**

// Variables**:**
// op: *the overall number of posts produced by a group*
// som: *the number of students who posted over the majority of the posts produced by a group*
// sp: *the number of students who have posted on the group forum*
// gs: *the size of a group examined*
// ap: *the average number of posts for all the groups participating in the group project*
// p3: *parameter 3—the number of posts that can be defined as relatively few for a group project*
// p4: *parameter 4—the percentage of the overall number of posts made by a group for defining relative majority*
// p5: *parameter 5— the percentage of the size of a group defining relative majority of a group*
//result: *an assigned code representing the result of the diagnosis process*

// Functions:
// read( ): *read the data of a group regarding op, som, sp, gs, ap, p3, p5 given the ID for the group*

```
Initializing
read(group ID)

Diagnosing
if op ≤ p3 then
    result ← 3
else
    if som = 1 then
        if sp/gs > p5 then
            result ← 1
        else
            if op < ap then
                result ← 2
            else
                result ← 3
else result ← 3

return result
```

The code '1'represents the problem CP-6 exists for the group.
The code '2'represents the problem CP-6 may exist for the group.
The code '3'represents the problem CP-6 does not exist for the group.

### 6.2.5 The Grammar and Spelling Checker

In terms of the collaboration problem ‘post contains grammatical and/or spelling errors’ (CP-4), the diagnosis process is briefly described in Figure 6.4. The messages of posts collected for individual students (through the data collection and processing component) are sent to the grammar and spelling checker. After receiving these messages, the grammar and spelling checker starts to analyse the grammatical and spelling errors in the messages using supporting technology such as natural language processing techniques. The grammatical and spelling errors identified are used to identify the students that have the problem CP-4.

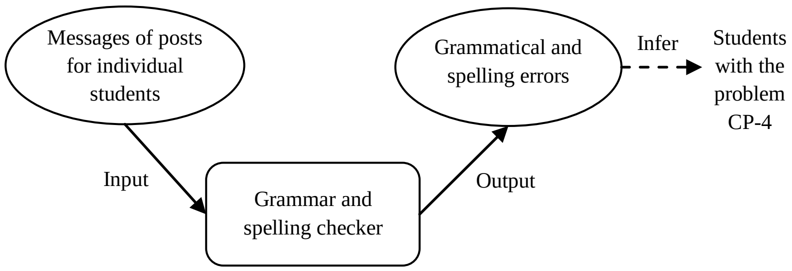


Figure 6.4. The process for diagnosing the collaboration problem CP-4

Existing grammar and spelling checkers were examined for selecting such a checker that can be adopted in the diagnostic mechanism for diagnosing the problem CP-4. A brief discussion on this examination is presented below. Exhaustive discussions on the selected grammar and spelling checker are avoided because this is not the main research question for this thesis.

Although commercial software such as Microsoft Office 2007 and Grammarly [14] provide the desired functionalities of grammar and spell checking, they can not be easily used by new applications in terms of the expense for buying the licenses and the integration of two applications. However, open source grammar and spelling checkers are more convenient to be adopted by new applications, particularly for research applications. This is because open source software is usually free of use for research purposes and provides software libraries or services that can be directly used by new applications.

The open source software ‘After the Deadline’ [16] is selected for checking the grammatical and spelling errors in the diagnostic mechanism. There are several reasons for this. First, it provides solutions for tackling both the grammar checking and the spell checking problems in one piece of software. Compared with this, most other open source software (e.g. Aspell [15], Jazzy [88], Hunspell [68], and Language Tool [133]) only provide the solution for either grammar checking or spell checking. Second, After the Deadline demonstrates similar or even better accuracy for grammar and spell checking than most other open source software according to [131]. Furthermore, After the Deadline checks the common grammatical and spelling errors encountered in daily uses. As the posts that are checked are constructed by students for discussing the group work in an informal way, too complicated grammar rules such as those for professional proofreading applications should be avoided so as not to over demand the students for grammar and spelling accuracy. Finally, After the Deadline is a kind of sever software that can be run as a server and provides service APIs that can be directly called by any other application for grammar and spelling checking which do not require complicated integration.

Figure 6.5 shows the architecture of grammar and spelling checking by adopting an After the Deadline server for diagnosing the problem CP-4. In this architecture, the application implementing the GCPD components can talk to an After the Deadline server. (The machine runs this application is noted as the GCPD machine). The GCPD application sends requests of grammar and spelling checking to the After the Deadline server. The requests contain data in the format of plain text or html for the messages of posts created by individual students. After receiving the requests from the GCPD application, the After the Deadline server starts to perform the grammar and spell checking, and then sends the responses in the format of XML to the GCPD application. The responses include data relating to the number of grammar errors and the number of spelling errors for the students who created the posts.

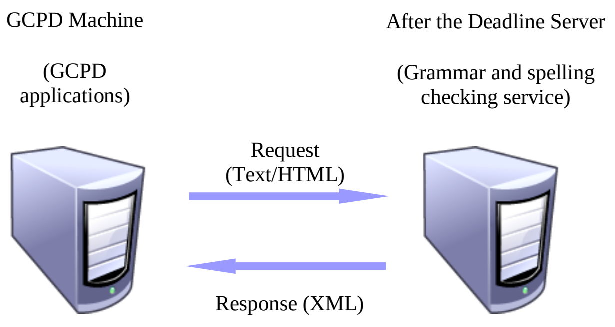


Figure 6.5. The architecture of grammar and spelling checking

This architecture demonstrates a convenient way that the open source software After the Deadline can be used by the GCPD application for conducting the grammar and spell checking for diagnosing the problem CP-4. In addition to this, the After the Deadline software also provides APIs for sharing its functionalities of grammar and spell checking.

## 6.3 Data Collection and Processing

In this section, the methods and processes adopted by the data collection and processing component for gathering the required data for the diagnosis process are presented. Before moving on to present these methods and processes, the types of data to be collected are described below.

The types of data to be collected were derived from the diagnostic mechanism presented in the previous section. Table 6.6 illustrates the six collaboration problems that are examined, the types of data to be collected for each category of problems and the relevant methods in the diagnostic mechanism which these types of data was derived from.

Table 6.6 The types of data derived from the diagnostic mechanism for diagnosing the collaboration problems that are examined

| Problem No. | Types of data to be collected | Relevant method in the diagnostic mechanism |
|---|---|---|
| CP-1 | thread_view, post_reply, post_create | The GCPD predictive model I |
| CP-2 | post_reply, post_create | The GCPD predictive model II |
| CP-3 | post_reply, post_create | The GCPD predictive model III |
| CP-4 | messages of posts | The grammar and spelling checker |
| CP-5 | op, of, af, sr, gs | The CP-5 diagnosis algorithm |
| CP-6 | op, som, sp, gs, ap | The CP-6 diagnosis algorithm |

The methods of obtaining the data are distinct. For the first four problems (CP-1 to CP-4), the required data can be directly collected from the data centre of a CLE (as discussed in Section 2.4.1). For the last two problems (CP-5 and CP-6), the data relating to the variable ‘gs’ (i.e. the size of a collaborative group) can be obtained from a CLE and other data can be obtained by carrying out basic calculations on the collected data. There is one exception here. For obtaining the overall items of feedback given by an individual group in a group forum (i.e. the variable 'of'), an automatic message type identification technique should be adopted (which is discussed later in this section). Moreover, the average items of feedback for all the groups which participate in the group work examined (i.e. the variable 'af') can be calculated based on the data relating to the variable 'of'.

The process of gathering the required data from the data centre of a CLE is illustrated in Figure 6.6.

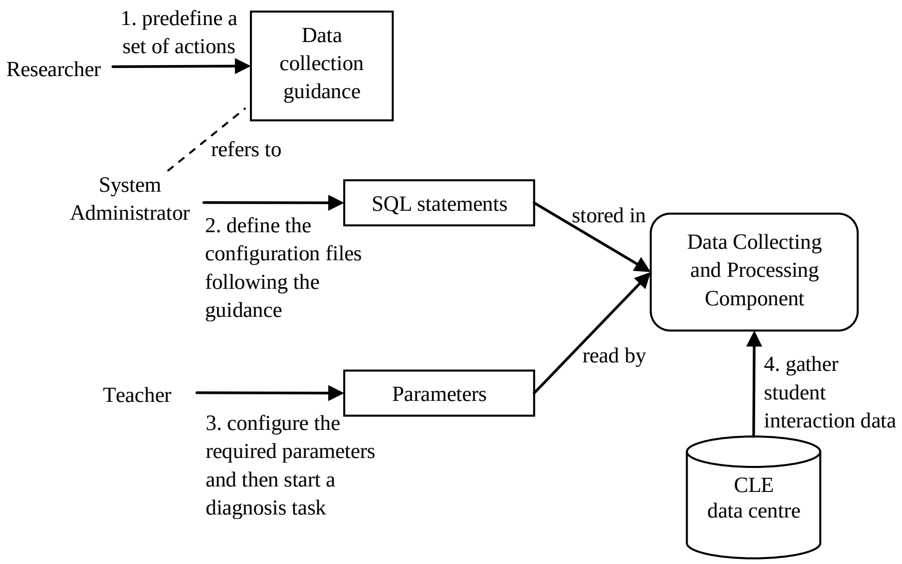


Figure 6.6. The process of gathering data from a CLE data centre

As can be seen from this figure, the data collection process consists of four steps.

Step 1: predefine the guidance for data collection. This is completed by the researcher. This guidance specifies a set of actions representing the flow, which is understandable by the data collection and processing component, for obtaining the types of required data (Table 6.6) from a CLE.

Step 2: define a series of SQL statements according to the data collection guidance. These defined SQL statements are noted as the configuration files in Figure 6.1. The system administrator who is familiar with the database schema of a CLE should complete this step before any diagnosis task is performed. The defined SQL statements are then stored in the data collection and processing component.

Since most contemporary collaborative learning environments such as Moodle, LAMS and Blackboard use a relational database (e.g. MySQL) for storing all the information about teaching and learning activities, SQL statements are chosen for configuring the data sources for the data collection task.

Step 3: configure the parameters that are needed for the diagnosis procedure and start performing a diagnosis task. The teacher who is in charge of the group work examined can configure these parameters including parameters p1–p5 as defined in Algorithm 6-1 and Algorithm 6-2.

Particularly, the parameter p4 — *the percentage of the overall number of posts made by a group for defining relative majority* (defined in Algorithm 6-2) is to determine the values of the type of data 'som'— *the number of students who posted over the majority of the posts produced by a group* (defined in Algorithm 6-2) for the data collection process. The other parameters are used by the diagnostic mechanism.

Step 4: gather student interaction data from the data centre of a CLE. This step is accomplished automatically by the data collection and processing component by executing the predefined SQL statements.

In order to show how Step 2 works, an example is given below for illustrating the data collection guidance defined for one type of the data to be collected from a CLE and relevant SQL statements that can be defined by the system administrator of the CLE.

In this example, the type of data 'thread_view' is examined. A Moodle system [128], which is a web-based CLE, is assumed to provide relevant collaborative learning forums for performing the group work. The Moodle system stores the student interaction data that result from the group work. The guidance for collecting data about the variable 'thread_view' is described as follows.

| **Data Collection Guidance (thread_view)** | |
|---|---|
| **Get information about groups and group members** | The constant course_id is known as the identifier for the selected course.<br><br>First, identify the table that stores information about the groups allocated for the course, and write a SQL statement to retrieve the IDs of all the groups.<br><br>Next, identify the table that stores information about the members of a group and write a SQL statement to retrieve the members' IDs (the group id is known as group_id). |
| **Obtain information about group forums and forum threads** | First, identify the table that stores information about forum discussions, and write a SQL statement to retrieve the forum id for a group (course_id and group_id are known as the constants).<br><br>Next, write a SQL statement to retrieve all the discussions (i.e. threads) in a group forum (the group forum's id is known as forum_id). |
| **Retrieving log information about a student viewing a group forum thread** | First, identify the table that stores log information about forum usages, and write a SQL statement to calculate the number of times that a user views a group forum discussion during a time period.<br><br>The user's id is known as user_id, the forum discussion's id is given as thread_id, and the timestamps for the start and end of the time period are timestamp_start and timestamp_end. |

Following the steps in the guidance, the system administrator of the Moodle system can define a series of SQL statements as below for collecting data about the variable 'thread_view'.

| **SQL Definitions (thread_view)** | |
|---|---|
| **Get information about groups and members** | 1. SELECT id<br>FROM mdl_groups<br>WHERE courseid = course_id;<br>2. SELECT userid<br>FROM mdl_groups_members<br>WHERE groupid = group_id. |
| **Obtain information about group forums and forum threads** | 3. SELECT forum<br>FROM mdl_forum_discussions<br>WHERE course = course_id AND groupid = group_id;<br>4. SELECT id<br>FROM mdl_forum_discussions<br>WHERE forum = forum_id. |
| **Retrieving log information about a student viewing a group forum thread** | 5. SELECT COUNT(id)<br>FROM mdl_log<br>WHERE userid = user_id AND time >= timestamp_start AND time <= timestamp_end AND module = "forum" AND action = "view discussion" AND info = thread_id. |

The method of using a data collection guidance and subsequently defining relevant SQL statements based on the guidance makes the data collection and processing component flexible for collecting data from various CLEs, which have distinct data structures of their data centres.

Through the described methods for data collection, data relating to the four problems CP-1–CP-4 can be obtained. As described above, basic calculations can be carried out on these data to obtain other data relating to the problems CP-5 and CP-6 except the variables 'of' and 'af'. For example, the total number of posts created and replied to by all the students in a group sum up the overall number of posts created by the group (i.e. ‘op’).

In terms of obtaining data relating to the variables ‘of’ and ‘af’ for the problem CP-5, Li *et al.*’s [104] technique for message type identification can be applied. This approach attempts to automatically classify messages that are posted in collaborative learning forums. The classification of messages is based on a process of keywords matching and pattern matching. In Li *et al.*’s approach, keywords matching and pattern matching techniques are used at the same time. They were applied to discover the most usual patterns and keywords that were identified for analysing the messages which belong to ‘feedback’. Extensive discussions on the approach are available in [104,106,175].

## 6.4 Presentation of Diagnostic Products

As mentioned in Section 6.1, the presentation of diagnostic products is user centred. The users include teachers and students who participate in the group work that is analysed. The goal of the presentation of diagnostic products to teachers is to provide an illustrative and overall view of how individual students or groups perform in the group work, whereas the presentation to students attempts to enable them reflect on their own problems and the possible causes for such problems. Therefore, distinct diagnostic products are delivered to the teachers and the students.

There are two kinds of diagnostic products presented to the teachers, which include:

- *Student and/or Group Problems* The list of the students and groups that are identified to have or may have any of the collaboration problems and the relating problems are presented.
- *Statistics on the Diagnosing Results* Some basic statistics about the diagnosing results are also provided, including the percentage of groups that have, may have and do not have a particular type of problems, and the percentage of students that have, may have and do not have shown a particular type of problems.

The diagnostic products presented to the students are comprised of the following items.

- *Student and/or Group Problems* The types of problems that are identified for an individual student and/or the problems that are identified for the group that the student belongs to.
- *Causes of the Problems* The potential causes to the identified problems are also presented to the students, which are suggested based on the collaboration problem-cause linkages discussed in Chapter 5.

The presentation of the above diagnostic products can be done in several ways. The types of presentation forms include textual, numerical and diagrammatically visualized. A combination of these methods can be applied. For example, the list of student and group problems can be described using tables while statistics on the diagnosing results can be illustrated using a diagrammatically visualized way such as pie charts with additional numerical annotations.

At this point, the three components of the proposed GCPD approach—the diagnostic mechanism, the data collection and processing component, and the presentation of diagnostic products component—have been extensively discussed.

In the following section, the tool that was developed as an implementation of the core components of the proposed GCPD approach is presented.

## 6.5 The GCPD Implementation

### 6.5.1 Introduction

Having addressed the proposed GCPD approach in detail, this section presents a tool namely GroupDoctor that was developed. This tool was built as a proof-of-concept of the core research ideas that constitute the GCPD approach.

The aim of this section is two-fold. First, it intends to describe how the tool was produced. This includes discussing the functionalities that the tool attempts to provide, and explaining how the essential implementation issues were determined such as the type of application that the tool was designed as and the underlying technology that underpins the development of the tool. Second, it aims to give a brief description on the GroupDoctor tool itself.

In order to achieve the aim, the following subsections are presented. Section 6.5.2 presents the implementation scope of the GroupDoctor tool, which comprises its functionalities and the solutions adopted for the implementation issues that were encountered. Subsequently, Section 6.5.3 illustrates how the GroupDoctor tool works in a real world scenario for diagnosing collaboration problems. Since the focus of this section is the research ideas that it embodies, comprehensive discussions on the tool's development were omitted.

### 6.5.2 Implementation Scope

The implementation scope of the GroupDoctor tool was determined based on two aspects. The first aspect that was considered is to implement the core components of the GCPD approach that correspond to the main research question raised in this chapter. As discussed in Section 6.1, the main research question that this chapter attempts to tackle is how to be ascertained of the existence of different collaboration problems based on student interactions with a collaborative learning forum. The second aspect concerned is to provide a demonstration on how the complex diagnostic processes can be supported and used by an end user. Based on these two aspects, the GroupDoctor tool was designed to implement the diagnostic mechanism encompassing the established three predictive models (the GCPD Predictive Model I, II, and III as presented in Section 6.2.3) and the proposed two diagnosis algorithms (the CP-5 diagnosis algorithm and the CP-6 diagnosis algorithm as described in Section 6.2.4). The GroupDoctor tool also intended to implement the presentation of the diagnostic products for teachers who can use the tool to assess collaboration problems for collaborative group work.

In terms of the grammar and spelling checkers adopted in the proposed diagnostic mechanism and the data collection and processing component, they are the subordinate components that support the diagnostic mechanism. Hence, they were not implemented in the GroupDoctor tool.

**Functionality**

An example scenario is described below to illustrate the functionalities that the GroupDoctor tool attempts to provide. Jack is the teacher who organizes the group work that is examined. At one day after the group work began, Jack wishes to assess the collaboration problems for the students and groups who are participating in the examined group work. He then opens the web browser on his desktop computer and logs in to the GroupDoctor system for starting a diagnosing task. After he logs in, Jack chooses to perform a new diagnosis task. Then, he selects the data files containing the student interaction data which are prepared and uploads them to the GroupDoctor system. Next, the system asks him for configuring some parameters for the diagnosis task. Jack inputs the values for the parameters and clicks the 'diagnose' button for executing the diagnosis process. After the diagnosis process is completed, Jack can view the diagnostic results as tables and diagrams using his web browser which are delivered from the GroupDoctor system.

As can be seen from the above scenario, the GroupDoctor tool attempts to provide the following functionalities. First, it provides an *authentication* functionality which controls user access to the system. Second, it encompasses a *data uploading* functionality which allows a user to select and upload data files to the system. The data files correspond to the student interaction data collected for analysing a group project. The data files to be uploaded should meet a standard data format so that they can be processed by the GroupDoctor tool. Furthermore, the GroupDoctor tool offers a *configuration* functionality which allows users to set the values of the parameters required and a *diagnosis* functionality which takes as inputs the data files uploaded and the values of the parameters configured, and then analyses the existence of the collaboration problems based on the diagnostic mechanism proposed. Finally, the GroupDoctor tool contains a *presentation* functionality which delivers the final diagnostic products to teachers in an illustrative way such as tables and diagrams.

**Implementation Issues**

By the notion of type of application, the meaning of desktop or web application is referred to. The GroupDoctor tool was designed as a web application since it offers much convenience for teachers to perform diagnosis tasks anywhere and anytime provided that a web browser is installed and the Internet is connected. Moreover, it allows future extensions of the GroupDoctor tool which can be efficiently integrated in or linked to a web-based CLE for online collaborative group work.

A Java-based tool set was used for the development of the GroupDoctor web application. Eclipse Java EE IDE [57] was used as the development environment for completing the programming tasks. The dynamic web content technology including JSP and Java Servlets was adopted for implementing the web application. Moreover, JSP technology is responsible for generating dynamic web pages in terms of the presentation of the diagnostic products for this application. JSP is also used for generating the static web pages for this application in terms of user log-ins and configuration of the parameters for a group project. Additionally, Java Servlet technology is responsible for handling the requests from a client and dispatching relevant responses to the client in terms of authenticating users, saving the uploaded data files and conducting the diagnosis based on the diagnostic mechanism. Finally, Apache Tomcat Server [13] was applied for deploying and running the web application.

### 6.5.3 The GroupDoctor Tool

In order to demonstrate how a diagnosis task is supported by the GroupDoctor tool, the screenshots of a case study with this tool are presented in this subsection. These screenshots intends to demonstrate the core functionalities implemented in the

GroupDoctor tool. The data used in this case study was collected in the *Forum* data set (as described in Section 6.2.2).

Figure 6.7 demonstrates the GroupDoctor diagnosis setting page. This page is entered after a teacher chooses to perform a new diagnosis task. It embodies two of the functionalities that were implemented in the application: the data uploading functionality and the configuration functionality. On the left of the page it contains a list of the data files that have been uploaded to the application server. A teacher can select from those files as the required student interaction data for the diagnosis process. If there are no files uploaded before, the teacher can use the 'Choose File' and 'Upload' buttons below the list to upload a new data file. Moreover, the data files should be prepared offline by the teacher. On the right of the page it presents a group of radio buttons for the teacher to specify the course for which the parameters are defined and a set of input boxes for the teacher to define the values for the parameters desired. After the teacher clicks the 'Diagnose' button, the client (i.e. the browser) will send out the diagnosing request and the application server will start to analyse the problems after receiving this request.

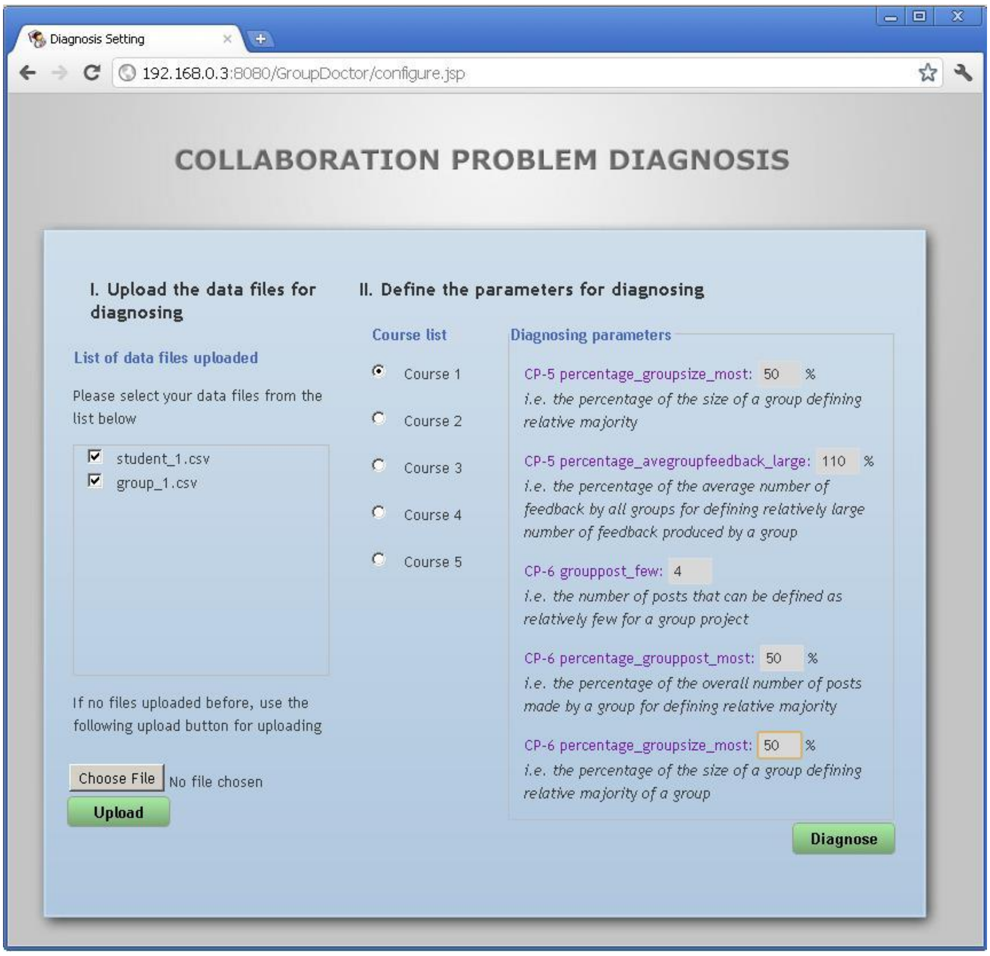


Figure 6.7. GroupDoctor Diagnosis Setting screenshot

The diagnostic results and some basic statistics on the results (as discussed in Section 6.4) are presented in the screenshot of Figure 6.8. Two tables are provided on the left of this web page, representing the problems for individual groups and students respectively. Five pie charts are drawn on the right of the web page. Each pie chart corresponds to the ratios of the groups or students identified as one of the categories of problem existence (i.e. ‘Yes’, ‘Maybe’ and ‘No’) to the total number of groups and students that were analysed. For example, on the top right of this screenshot, the pie chart (for Problem 6) illustrates three ratios. The green segment of this pie chart suggests that 61.1% of the groups did not have the problem CP-6. The red segment indicates that 27.8% of the groups were identified to have the problem CP-6. In addition, the blue segment shows that 11.1% of the groups may have the problem CP-6. The names of the collaboration problems analysed are noted at the bottom of this web page.

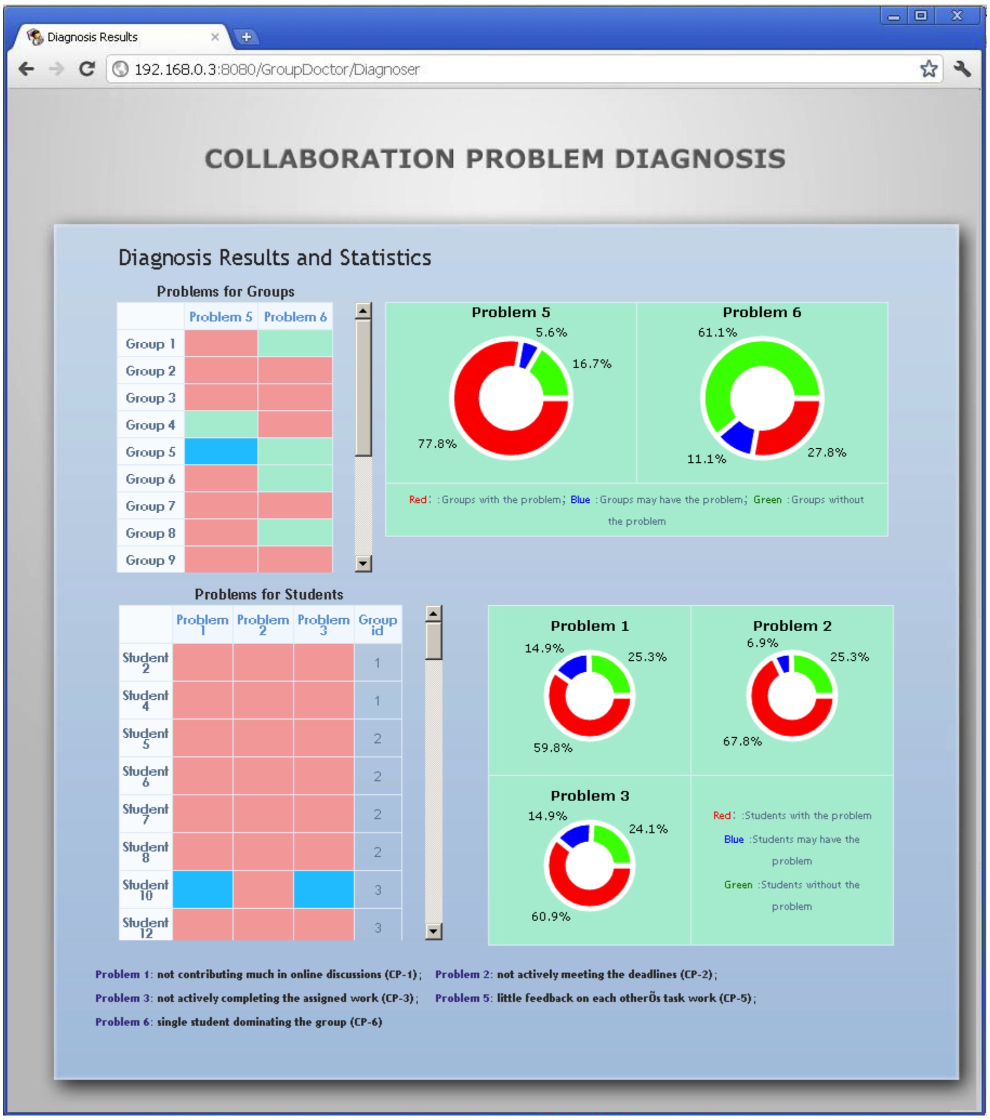


Figure 6.8. GroupDoctor Diagnosis Results screenshot

## 6.6 Summary

This chapter presented an approach for automatically diagnosing group collaboration problems. The proposed approach mainly intends to address effective methods for ascertaining the existence of the six collaboration problems as identified in Chapter 5 based on student interactions with a collaborative learning forum. Correspondingly, a diagnostic mechanism is proposed to achieve this objective. Exhaustive discussions on the diagnostic mechanism were presented. In addition to this, two supporting components in the proposed approach were also described. These components address the methods for collecting student interaction data from a CLE that are required by the diagnosis mechanism and the methods for presenting the diagnostic products to the participants of the group work examined.

The implementation of the GroupDoctor tool and a case study with the developed tool were also reported. The development of the GroupDoctor tool demonstrates the feasibility of applying the diagnostic mechanism for conducting diagnosis tasks.

The next chapter will discuss the evaluation of the proposed diagnostic mechanism, which encompasses an assessment of the validity of the GCPD predictive models and the diagnostic accuracy of the GCPD algorithms.

# Chapter 7

# Evaluating the Validity of the GCPD Predictive Models and the Diagnostic Accuracy of the GCPD Algorithms

As the proposed diagnostic mechanism (Section 6.2) comprises different methods for ascertaining the existence of various types of collaboration problems (as identified in Chapter 5), the evaluation of this mechanism can be a complex process which combines distinct evaluation methods for assessing the different parts of this mechanism. Since the grammar and spelling checker (Section 6.2.5) is not the main research goal for the proposed diagnostic mechanism, the evaluation of the grammar and spelling checker is out of the focus of this thesis. Therefore, the evaluation of the diagnostic mechanism focuses on investigating the established GCPD predictive models (Section 6.2.3) and the GCPD algorithms (Section 6.2.4). In this chapter, the methods and results for evaluating the validity of the GCPD predictive models and the diagnostic accuracy of the GCPD algorithms are presented.

## 7.1 Introduction

Before addressing the aim of this chapter, a summary of the initial assessment of the GCPD predictive models that was discussed in Section 6.2.3 is provided below. This assessment not only examined the statistical significance and goodness-of-fit of the established predictive models, but also investigated the statistical significance of individual predictors in the final predictive models. The findings reveal that the three predictive models that were developed through the predictive modelling process are statistically significant and they fit the development data well. The findings also indicate that the predictors included in the final models significantly affect the predictions of the collaboration problems that are examined.

The results of this initial assessment demonstrate the overall fit of the established predictive models. The notion of 'fit' refers to how a predictive model fits a representative sample from the underlying population and meets the assumptions of the adopted predictive modelling method (i.e. multinomial logistic regression analysis). Besides the assessment of the fit, it is important to determine the reproducibility of the established models for the underlying population before the models are applied for future predictions of the examined collaboration problems. The reproducibility of a predictive model refers to the overall performance of the model on the data where the model was derived from and the validity of the model on independent data which are similar to the data where the model originated from [86].

In terms of the proposed GCPD algorithms, as the objectives of the algorithms are to ascertain the existence of the collaboration problems CP-5 and

CP-6, the core evaluation question faced is how accurate the proposed algorithms are able to classify the existence of the examined problems.

Therefore, the aim of this chapter is to evaluate the reproducibility of the GCPD predictive models and the diagnostic accuracy of the GCPD algorithms. For achieving the aim of this chapter, the following objectives should be addressed. First, this chapter intends to explain the design of the experiments that were carried out for the evaluation, the testing dataset that was used in the experiments, the data collection procedure from the designed experiments and the data analysis methods that were adopted. Second, this chapter attempts to address the results of the experiments that were performed. Finally, it aims to provide an overarching reflection on the evaluation findings including the assessment of fit and the reproducibility of the GCPD predictive models, and the diagnostic accuracy of the GCPD algorithms.

The remaining sections of this chapter are organized as follows. Section 7.2 discusses the evaluation methods including the experiment design, how the testing dataset was obtained, how the experiments were conducted and the methods applied for analysing the results from the data collected through the experiment procedure. Section 7.3 discusses the results that were obtained. Following that, Section 7.4 presents the reflections on the evaluation results. Finally, a summary of this chapter is provided in Section 7.5.

## 7.2 Evaluation Methods

### 7.2.1 Experiment Design

Concerning the different evaluation objectives, distinct methods were adopted for guiding relevant experiments. For evaluating the reproducibility of the established predictive models, two validation techniques were adopted which include the apparent validation technique and the split-sample validation technique. The two validation techniques were used to examine two different aspects of the reproducibility of the established predictive models. The apparent validation technique is used to assess the overall performance of the predictive models on the data where the models were derived from [86]. The split-sample validation technique intends to examine the validity of the predictive models on independent data which are similar to the data where the models originated from [79]. Additionally, for evaluating the diagnostic accuracy of the GCPD algorithms, a comparison-based approach which was suggested by [104] was adopted. Brief descriptions of each of the evaluation methods are presented below.

The apparent validation technique refers to the method to assess the performance of a predictive model directly in the sample where it was derived from [86]. That is, 100% of the sample data that were used to develop the model are used to test the model. In such an apparent validation, a developed multinomial logistic regression (MLR) model is used to calculate the probabilities of response categories that represent the existence of a collaboration problem using data relating to the predictors in the model which were collected in the data sample. Then, the predicted response category for the examined collaboration problem belonging to an event (i.e. an individual student) can be determined by selecting the response category with the maximum probability. If there is a tie, the category with the smallest category number is chosen [160]. Following that, the predicted response category and the observed response category for all the events in the data sample are used to create a classification table and the overall rate of correct classification for the examined predictive model can be calculated based on this classification table. A detailed explanation on the classification table and the formula to compute the overall rate of correct classification is provided in Section 7.2.4.

With split-sample validation, the assessing of the model performance was carried out in a random part of the sample, with model development in the other part [79]. The sub-sample used to develop a predictive model is known as the estimation sample. The other part is called the validation sample which was used to validate the estimation model. The new estimation model can be built using the same method as the original predictive model (i.e. MLR). Then the established estimation model was applied on the validation sample to obtain a classification table and the overall rate of correct classification following the same procedure as the apparent validation did. As can be seen from this point, the split-sample validation enables validation of a predictive model on similar but independent data.

The comparison-based approach adopted for evaluating the diagnostic accuracy of the GCPD algorithms attempts to conduct an experimental study and compare the diagnostic results provided by the proposed algorithms with the results provided by assessors of the collaboration problems (i.e. CP-5 and CP-6). Regarding the experimental study, a dataset that contains values of the variable representing categories of problem existence for one of the collaboration problem (judged by assessors) and other variables (i.e. the indicators) as required by an individual algorithm is desired for both of the GCPD algorithms. With the indicators from such a dataset an individual algorithm can generate the diagnostic results (i.e. the diagnostic values relating to the problem existence). Then, the diagnostic results can be compared with the results provided by assessors of the collaboration problems. Based on this comparison, a rate of correct classification for problem diagnosis can be calculated for the diagnosis algorithm that is examined.

Next, the details of the testing dataset that was used in the designed experiments are presented.

### 7.2.2 The Testing Dataset

As mentioned in Section 6.2.2, the *Forum* data set was constructed for the predictive modelling process (Section 6.2.3) and also for the evaluation of the proposed diagnostic mechanism that was expected to be discussed in this chapter. The testing dataset applied in this chapter originates from the constructed *Forum* data set. Additional operations including randomly splitting and defining missing values (for the parameters required by the GCPD algorithms) were performed on the *Forum* data set to obtain the complete testing dataset.

To reiterate, the *Forum* data set contains five tables: *Forum*-1, *Forum*-2, *Forum*-3, *Forum*-4 and *Forum*-5. Details of the *Forum* data set can be referred to Section 6.2.2. A brief discussion of the process to create the testing dataset based on the *Forum* data set is provided below.

As the first three tables in the *Forum* data set were used to construct the GCPD predictive model I, II and III respectively and the full dataset for model development is desired for the apparent validation procedure, no additional operations were performed on the tables *Forum*-1, *Forum*-2 and *Forum*-3 and they were used directly for the apparent validation.

For the split-sample validation, two data splitting options are available. One is referred as the split-half method and the other is referred as the split 1/3 method, where 50% or 33.33% of the data sample is used as the independent evaluation part for the MLR model that was estimated on the 50% or 66.67% of the sample correspondingly. Considering the sample size of the tables *Forum*-1, *Forum*-2 and *Forum*-3 (in each table $N$=87), the first splitting method can produce validation samples of size 43 and the second method can generate validation samples of size 28. A small validation sample may lead to an unstable estimation of the model performance. In order to ensure the validity of the evaluation results, the first splitting method was preferred so that a relatively large validation sample can be obtained.

Therefore, each of the three tables *Forum*-1, *Forum*-2 and *Forum*-3 were randomly split into two groups: 50% estimation sample and 50% validation sample. The estimation sample and the validation sample which were generated from the table *Forum*-1 are noted as ES-1 and VS-1. Those produced from the table *Forum*-2 were noted as ES-2 and VS-2 and those created from the table *Forum*-3 are noted as ES-3 and VS-3.

In terms of evaluating the diagnostic accuracy of the GCPD algorithms, the tables *Forum*-4 and *Forum*-5 were used. As some of the variables defined in each of the tables represent the parameters that are required for a relevant diagnosis algorithm, no values were defined for them when the *Forum* data set was created (as discussed in Section 6.2.2). Hence, the values relating to these parameters were desired for evaluation purpose.

There were totally five parameters to be defined for evaluating the GCPD algorithms. These parameters were defined based on the researcher's own teaching experience. For the CP-5 diagnosis algorithm, the parameter 'percentage_groupsize_most' was defined as 50% and the parameter 'percentage_avegroupfeedback_large' was specified as 110%. The first value was defined as 50% because the common standard for defining "majority" as more than half of a group was used. The second value was defined as 110% because only 4 of 18 groups in the test dataset contributed more than the average number of items of feedback and so a slightly bigger than the average number of feedback (i.e. 10% more) was defined as the relatively large number of items of feedback produced by a group. For the CP-6 diagnosis algorithm, the parameter 'grouppost_few' was defined as four, the parameter 'percentage_grouppost_most' was set as 50%, and the parameter 'percentage_groupsize_most' was determined as 50%. The first value was specified as four because four was the pivot which divided the values in the test dataset (i.e. the number of posts made by the collaborative groups) into two groups: one group of values that were close to or more than the average number of posts by all groups and the other group of values that were much smaller than the average number. The reasons for defining the second and third values as 50% were similar to the definition of the value of the parameter 'percentage_groupsize_most' (CP-5) as addressed above.

The outputs of the diagnosis algorithms can be variable when different values are defined for the above diagnosis parameters which means the outputs of the algorithms are sensitive to the values chosen for the parameters. A further analysis of the outputs of the two algorithms by changing the values of each individual parameter while holding the other parameters constant using the test dataset was carried out. It indicates that the sensitivity of the two algorithms to different individual parameters are dissimilar. In terms of the parameters 'percentage_groupsize_most' and 'percentage_grouppost_most', the possible values of either of the parameters range from 1% to 100% and the outputs of the algorithms are variable when one parameter takes values from different subranges. There are four subranges that either of the parameters can pick values from, which can produce four different outputs of the corresponding algorithm. In terms of the parameter 'percentage_avegroupfeedback_large', it has a lower bound of 100% but has no upper bound. There are four subranges that this parameter can pick values from, which can produce four different outputs of the corresponding algorithm. In terms of the parameter 'grouppost_few', it has a lower bound of 1 but has no upper bound. There are eight subranges that this parameter can pick values from, which can produce eight different outputs of the corresponding algorithm.

The definition of the values for the required parameters was given by the primary researcher, who was the organizer of the group work and checked the progress of the group work regularly. Therefore, the researcher has the closest overview of it and it is believed that the values defined for this evaluation fit into the setting where the test data originate from.

### 7.2.3 Experiment Procedure

In this subsection, the procedures that were carried out for collecting data from the designed experiment are discussed.

Regarding the apparent validation, similar processes were performed for examining the three GCPD predictive models. To simplify the discussion, the apparent validation process for the predictive model I is presented below. 100% of the data kept in the table *Forum*-1 was used to generate a *classification table* which cross-classifies the observed response variable with a polytomous variable whose values were derived from the estimated multinomial logistic probabilities. This procedure was assisted by the SPSS statistical software (version 19). After the entire process was completed, three classification tables were gathered respectively for the predictive models I, II and III.

Compared with the apparent validation, the split-sample validation was more complex. The split-sample validation for examining the predictive model I is described below to exemplify the overall process since similar data collection processes were applied to the other two GCPD predictive models.

An *estimation model* was built from the estimation sample ES-1 and then applied to the validation sample VS-1 to predict the response categories of problem existence. Following that, a classification table was established which cross-classifies the observed response variable (defined in the validation sample VS-1) with a polytomous variable corresponding to the predicted response categories of problem existence.

After the entire split-sample validation procedure was completed, a total of three new estimation models were developed using the estimation samples ES-1, ES-2 and ES-3 and three classification tables were created by applying the estimation models on the three validation samples VS-1, VS-2 and VS-3.

Considering the experiment design for the proposed GCPD algorithms, a computer program was written which implemented the GCPD algorithms (Algorithm 6-1 and Algorithm 6-2). The computer program took as inputs the data relating to the variables required by the algorithms from the tables *Forum*-4 and *Forum*-5 and the values defined for the parameters (as discussed in Section 7.2.2). The output of the computer program consisted of two *lists of diagnosed values representing categories of problem existence* respectively for the two testing samples *Forum-4* and *Forum-5*.

### 7.2.4 Data Analysis

Through the experiment procedure, three types of data were collected for analysing the results of the designed experiments. They include classification tables [86], new estimation models which were developed by applying MLR [86] using the estimation samples, and two lists of diagnosed values representing categories of problem existence. Next, methods for analysing these data are presented.

As mentioned in Section 7.2.3, a classification table can cross-classify the observed response variable with a polytomous variable whose values were derived from the estimated multinomial logistic probabilities. According to such a classification table, the overall rate of correct classification for a predictive model can be calculated according to the following formula.

$$R = \frac{\sum_{i=1}^{q} p_i}{N} \times 100\% \quad (7.1)$$

where $R$ represents the overall rate of correct classification, $P_i$ corresponds to the number of cases for which the predicted response value matches the observed response value for the $i^{th}$ category of the response variable, $q$ stands for the overall number of categories of the response variable and $N$ represents the size of the data sample.

The developed new estimation models were applied to examine whether they produced the same set of predictors that were included in the original predictive models which were created on the full dataset. Moreover, the same set of statistical tests as adopted on the original predictive models was applied on the new estimation models. These encompass the likelihood ratio test [86] and the Pearson chi-square test [64]. The purpose of applying these tests on the estimation models was to ensure the validity of these models with regard to the significance of the estimation models, the significance of the predictors in the models and the goodness-of-fit of the models.

In terms of the last type of data obtained from the experiment procedure, each list of the diagnosed values representing categories of problem existence was compared with the list of the observed values in the corresponding testing sample (i.e. *Forum-4* or *Forum-5*). Based on this comparison, a *correct rate*—the rate of the problems that were correctly identified by a diagnosis algorithm to the size of the data sample was calculated for each of the diagnosis algorithms.

In the following section, the results of the designed experiments by applying the mentioned data analysis methods are presented.

## 7.3 Experiment Results

### 7.3.1 Apparent Validation for the Predictive Models I, II and III

The classification table that was created for examining the performance of the GCPD predictive model I with the full dataset is presented in Table 7.1. The GCPD predictive model I describes the relationship between the existence of the problem CP-1 and the variables indicating the existence of the problem. Therefore, the presented classification table cross-classifies the observed values with the predicted values of the response variable corresponding to the existence of the problem CP-1. In such a classification table, a row represents the observed values for one category of the response variable (i.e. 'yes', 'maybe' or 'no'); a column corresponds to the predicted values for one category of the response variable; and the last row and the last column contain some basic calculations on the table data.

Table 7.1 Classification table for the predictive model I (*N*=87)

| | Predicted | | | |
|---|---|---|---|---|
| Observed | Yes | Maybe | No | Percent Correct |
| Yes | 38 | 2 | 2 | 90.5% |
| Maybe | 5 | 10 | 3 | 55.6% |
| No | 9 | 1 | 17 | 63.0% |
| Overall Percentage | 59.8% | 14.9% | 25.3% | 74.7% |

Table 7.1 shows that 59.8%, 14.9% and 25.3% of the students in the data set (*N*=87) were ascertained by the GCPD predictive model I to belong to the category of 'Yes', 'Maybe' and 'No' respectively. The correct rate of problem

prediction under each response category was shown in the ‘percent correct’ column in Table 8.1. As can be seen from this table, the predictive model I predicted most accurately for the response category ‘Yes’ (90.5%), followed by the category ‘No’ (63.0%) and the category ‘Maybe’ (55.6%).

Furthermore, the overall rate of correct classification for the GCPD predictive model I on the full dataset (*N*=87) as calculated following the formula (7.1) is 65/87(i.e. 74.7%), which is relatively satisfied.

Concerning the GCPD predictive model II, the created classification table is presented in Table 7.2. The GCPD predictive model II describes the relationship between the existence of the problem CP-2 and the variables indicating the existence of the problem. Correspondingly, the presented classification table cross-classifies the observed values with the predicted values of the response variable representing the existence of the problem CP-2. Similar to Table 7.1, a row of the presented table represents the observed values for one category of the response variable (i.e. ‘yes’, ‘maybe’ or ‘no’); a column stands for the predicted values for one category of the response variable; and the last row and the last column contain some basic calculations on the table data.

Table 7.2 Classification table for the predictive model II (*N*=87)

| | Predicted | | | |
|---|---|---|---|---|
| Observed | Yes | Maybe | No | Percent Correct |
| Yes | 46 | 3 | 0 | 93.9% |
| Maybe | 10 | 3 | 2 | 20.0% |
| No | 3 | 0 | 20 | 87.0% |
| Overall Percentage | 67.8% | 6.9% | 25.3% | 79.3% |

As illustrated in Table 8.2, 67.8%, 6.9% and 25.3% of the students in the data set ($N$=87) were ascertained by the GCPD predictive model II to the category of 'Yes', 'Maybe' and 'No' respectively. The column 'percent correct' lists the correct rate of problem prediction under each response category. As can be seen from Table 7.2, the predictive model II predicted most accurately for the category of 'Yes' (93.9%), followed by the category 'No' (87.0%) and the category 'Maybe' (20.0%).

The overall rate of correct classification for the GCPD predictive model II which was calculated according to formula (7.1) (69/87) is relatively satisfied (i.e. 79.3%).

In terms of the GCPD predictive model III, the classification table that was created on the full dataset is presented in Table 7.3. As the GCPD predictive model III describes the relationship between the existence of the problem CP-3 and the variables indicating the existence of the problem, this classification table cross-classifies the observed values with the predicted values of the response variable for the problem CP-3.

Table 7.3 Classification table for the predictive model III ($N$=87)

| | Predicted | | | |
|---|---|---|---|---|
| Observed | Yes | Maybe | No | Percent Correct |
| Yes | 46 | 5 | 0 | 90.2% |
| Maybe | 6 | 7 | 1 | 50.0% |
| No | 1 | 1 | 20 | 90.9% |
| Overall Percentage | 60.9% | 14.9% | 24.1% | 83.9% |

Table 7.3 demonstrates that 60.9%, 14.9% and 24.1% of the students in the data set (*N*=87) were ascertained by the GCPD predictive model III as the category of 'Yes', 'Maybe' and 'No' respectively. It also shows that the predictive model III predicted most accurately for the category 'No' (90.9%), followed by the category 'Yes' (90.2%) and the category 'Maybe' (50.0%).

Compared with the other two predictive models, the overall rate of correct classification of the GCPD predictive model III is the highest (i.e. 83.9%). This indicates that the GCPD predictive model III performed well on the full dataset.

In the following subsection, the results of the split-sample validation for the three GCPD predictive models are presented.

### 7.3.2 Split-sample Validation for the Predictive Models I, II and III

**Results of the Estimation Model $I'$**

The estimation model $I'$ contains the same set of predictors that was identified by the predictive model I on the full dataset. These indicators include 'thread_view', 'post_reply' and 'post_create'. The estimation model $I'$ was statistically significant [-2 Log likelihood=30.000; $\chi^2(6)$ =58.384; P=0.000] (more information about the log-likelihood statistic can be found in [64]). The Pearson chi-square test [$\chi^2(66)$ =34.489, P=1.000] was not statistically significant, indicating that the estimation model $I'$ was a good fit.

Moreover, the significance of the predictors in the model was measured with the Likelihood ratio tests — 'thread_view' [-2 Log likelihood=50.604; $\chi^2(2)$

=20.604; P=0.000], ‘post_reply’ [-2 Log likelihood=63.616; $\chi^2$ (2) =33.616; P=0.000], and ‘post_create’ [-2 Log likelihood=55.900; $\chi^2$(2) =25.900; P=0.000].

The results of these statistical tests indicate the estimation model $I'$ is valid in terms of the model significance, the goodness-of-fit of the model and the significance of the predictors in the model.

The classification table that was created for examining the performance of the estimation model $I'$ on the validation sample VS-1 is presented in Table 7.4.

Table 7.4 Classification table for the estimation model $I'$ that was applied on the validation sample VS-1 (*N*=43)

| | Predicted | | | |
|---|---|---|---|---|
| Observed | Yes | Maybe | No | Percent Correct |
| Yes | 20 | 1 | 2 | 87.0% |
| Maybe | 2 | 3 | 2 | 42.9% |
| No | 4 | 0 | 9 | 69.2% |
| Overall Percentage | 60.5% | 9.3% | 30.2% | 74.4% |

Table 7.4 shows that 60.5%, 9.3% and 30.2% of the students in the validation sample (*N*=43) were classified by the estimation model $I'$ as the category of ‘Yes’, ‘Maybe’ and ‘No’ for the problem CP-1 correspondingly. The estimation model $I'$ predicted most accurately for the category of ‘Yes’ (87.0%), followed by the category ‘No’ (69.2%) and the category ‘Maybe’ (42.9%), which is consistent with the results shown in Table 8.1.

Furthermore, the overall rate of correct classification for the estimation model $I'$ on the validation sample VS-1 was calculated according to the formula

(7.1) and is relatively satisfied (12/43, i.e. 74.4%). This finding indicates that the estimation model $I'$ performed well on the validation sample VS-1.

**Results of the Estimation Model $II'$**

The estimation model $II'$ contains the same set of predictors that was identified by the predictive model II on the full dataset. They contain 'post_reply' and 'post_create'. The estimation model $II'$ was statistically significant [-2 Log likelihood=35.487; $\chi^2(4)$ =48.388; P=0.000]. The Pearson chi-square test [$\chi^2(68)$ =61.457, P=0.699] was not statistically significant, indicating that the estimation model $II'$ was a good fit.

In addition, the significance of the predictors in the model was measured with the Likelihood ratio tests—'post_reply' [-2 Log likelihood=51.085; $\chi^2(2)$ =15.598; P=0.000], and 'post_create' [-2 Log likelihood=50.355; $\chi^2(2)$ =14.868; P=0.001].

The results of these statistical tests reveal that the estimation model $II'$ is valid regarding the model significance, the goodness-of-fit of the model and the significance of the predictors contained in the model.

Table 7.5 represents the classification table that was created for examining the performance of the estimation model $II'$ on the validation sample VS-2. As can be seen from this table 53.5%, 30.2% and 18.6% of the students in the validation sample (*N*=43) were classified by the estimation model $II'$ as the category of 'Yes', 'Maybe' and 'No' for the problem CP-2 correspondingly.

Table 7.5 Classification table for the estimation model $II'$ that was applied on the validation sample VS-2 (*N*=43)

| Observed | Predicted | | | |
|---|---|---|---|---|
| | Yes | Maybe | No | Percent Correct |
| Yes | 20 | 4 | 0 | 83.3% |
| Maybe | 2 | 6 | 1 | 66.7% |
| No | 1 | 3 | 7 | 63.6% |
| Overall Percentage | 53.5% | 30.2% | 18.6% | 76.7% |

It is also illustrated in Table 7.5 that the estimation model $II'$ predicted most accurately for the category of 'Yes' (83.3%), followed by the category 'Maybe' (66.7%) and the category 'No' (63.6%).

The overall rate of correct classification for the estimation model $II'$ on the validation sample VS-2 is 76.7% (33/43) indicating that the estimation model $II'$ performed well on the validation sample VS-2.

**Results of the Estimation Model $III'$**

The estimation model $III'$ that was created from the estimation sample ES-3 identified the same set of predictors as the predictive model III with the full dataset. The identified indicators refer to 'post_reply' and 'post_create'. The estimation model $III'$ was statistically significant [-2 Log likelihood=23.074; $\chi^2(4)$ =54.483; P=0.000]. The Pearson chi-square test [$\chi^2(68)$ =37.831, P=0.999] was not statistically significant, indicating that the estimation model $III'$ was a good fit.

The significance of the predictors in the model was measured with the Likelihood ratio tests—‘post_reply’ [-2 Log likelihood=36.434; $\chi^2(2)$ =13.360; P=0.001], and ‘post_create’ [-2 Log likelihood=40.076; $\chi^2(2)$ =17.002; P=0.000].

The results of these statistical tests indicate that the estimation model $III'$ is valid with regard to the model significance, the goodness-of-fit of the model and the significance of the predictors in the model.

The classification table that was created for examining the performance of the estimation model $III'$ on the validation sample VS-3 is presented in Table 7.6.

Table 7.6 Classification table for the estimation model $III'$ that was applied on the validation sample VS-3 (*N*=43)

| | Predicted | | | |
|---|---|---|---|---|
| Observed | Yes | Maybe | No | Percent Correct |
| Yes | 19 | 4 | 0 | 82.6% |
| Maybe | 1 | 8 | 0 | 88.9% |
| No | 1 | 2 | 8 | 72.7% |
| Overall Percentage | 48.8% | 32.6% | 18.6% | 81.4% |

As can be seen from Table 7.6, different percentages of students in the validation sample VS-3 (*N*=43) were classified as the three response categories: 48.8%, 32.6% and 18.6% for ‘Yes’, ‘Maybe’ and ‘No’ respectively. The column ‘percent correct’ lists the correct rate of problem prediction under each response category. It reveals that the estimation model $III'$ predicted most accurately for the category of ‘Maybe’ (88.9%), followed by the category ‘Yes’ (82.6%) and the category ‘No’ (72.7%).

The overall rate of correct classification for the estimation model $III'$ on the validation sample VS-3 is 81.4% (35/43) indicating the estimation model $III'$ performed well on the validation sample VS-3.

### 7.3.3 Diagnostic Accuracy of the GCPD Algorithms

As mentioned in Section 7.2.1, a comparison-based approach was applied to measure the diagnostic accuracy of the proposed GCPD algorithms (i.e. the CP-5 diagnosis algorithm and the CP-6 diagnosis algorithm). The comparison between the observed values of the variable representing categories of problem existence judged by assessors and the diagnostic results provided by one of the GCPD algorithms can be demonstrated via a table. Based on this comparison table, correct rate of diagnosis (as defined in Section 7.2.4) for an individual algorithm can be calculated.

Table 7.7 illustrates the comparison that was applied for the CP-5 diagnosis algorithm. This comparison checked the differences between the observed values and the diagnosed values of the variable 'result' corresponding to the categories of problem existence for the problem CP-5 with the testing sample (i.e. *Forum*-4, *N*=18). As discussed in Algorithm 6-1, the variable 'result' was defined as a polytomous variable which includes a category of 'yes' (coded as '1') which means the group has the problem; a category of 'maybe' (coded as '2') which means the group may have the problem; and a category of 'no' (coded as '3') which means the group does not have the problem.

In Table 7.7, if the diagnostic value of the variable 'result' was equal to the observed value of this variable, a tick was assigned to the group that was examined;

otherwise, a cross was given. As can be seen from the results, the CP-5 diagnosis algorithm correctly diagnosed the problem CP-5 for all the groups except Group 9 with the testing sample ($N$=18). The correct rate of diagnosis by the CP-5 diagnosis algorithm is 94.4% (17/18) indicating the proposed CP-5 performed well on the testing sample (i.e. *Forum-4*).

Table 7.7 Comparison applied for the CP-5 diagnosis algorithm on the testing sample ($N$=18)

| Group ID | The observed value of the variable 'result' | The diagnosed value of the variable 'result' | Correct or not |
|---|---|---|---|
| 1 | 1 | 1 | ✓ |
| 2 | 1 | 1 | ✓ |
| 3 | 1 | 1 | ✓ |
| 4 | 3 | 3 | ✓ |
| 5 | 2 | 2 | ✓ |
| 6 | 1 | 1 | ✓ |
| 7 | 1 | 1 | ✓ |
| 8 | 1 | 1 | ✓ |
| 9 | 2 | 1 | × |
| 10 | 3 | 3 | ✓ |
| 11 | 3 | 3 | ✓ |
| 12 | 1 | 1 | ✓ |
| 13 | 1 | 1 | ✓ |
| 14 | 1 | 1 | ✓ |
| 16 | 1 | 1 | ✓ |
| 17 | 1 | 1 | ✓ |
| 18 | 1 | 1 | ✓ |
| 19 | 1 | 1 | ✓ |
| | | Correct rate | 94.4% |

Table 7.8 Comparison applied for the CP-6 diagnosis algorithm on the testing sample ($N$=18)

| Group ID | The observed value for the variable 'result' | The diagnosed value for the variable 'result' | Correct or not |
|---|---|---|---|
| 1 | 3 | 3 | ✓ |
| 2 | 1 | 1 | ✓ |
| 3 | 1 | 1 | ✓ |
| 4 | 1 | 1 | ✓ |
| 5 | 3 | 3 | ✓ |
| 6 | 3 | 3 | ✓ |
| 7 | 1 | 1 | ✓ |
| 8 | 3 | 3 | ✓ |
| 9 | 2 | 1 | × |
| 10 | 3 | 3 | ✓ |
| 11 | 3 | 3 | ✓ |
| 12 | 2 | 2 | ✓ |
| 13 | 3 | 3 | ✓ |
| 14 | 1 | 2 | × |
| 16 | 3 | 3 | ✓ |
| 17 | 1 | 3 | × |
| 18 | 3 | 3 | ✓ |
| 19 | 3 | 3 | ✓ |
| | | Correct rate | 83.3% |

Table 7.8 presents the comparison that was applied for the CP-6 diagnosis algorithm. The differences between the observed values and the diagnosed values of the variable 'result' corresponding to the categories of problem existence for the problem CP-6 with the testing sample (i.e. *Forum*-5, $N$=18) were compared in this table. As discussed in Algorithm 6-2, the variable 'result' was defined as a polytomous variable with three categories. The first category is 'yes' (coded as '1')

which means the group has the problem. The second category is ‘maybe’ (coded as ‘2’) which means the group may have the problem. Moreover, the last category ‘no’ (coded as ‘3’) which means the group does not have the problem.

As can be seen from Table 7.8, there are three groups (i.e. Group 9, 14 and17) whose diagnostic results provided by the CP-6 diagnosis algorithm do not match the observed values. The correct rate of problem diagnosis by the CP-6 diagnosis algorithm is 83.3% (15/18), which indicates that the proposed CP-6 algorithm performed well on the testing sample (i.e. *Forum-5*, *N*=18).

## 7.4 Discussion

The present experiments attempted to examine different aspects of the reproducibility of the established predictive models, and the diagnostic accuracy of the proposed diagnosis algorithms.

In order to give an overarching reflection on the GCPD predictive models, the findings from the initial assessment (as mentioned in Section 7.1) are also discussed. It is revealed that each of the established predictive models has identified and prioritized (in terms of relative impact on the final model) the types of student interactions with a collaborative learning forum that contribute to the prediction of the existence of the collaboration problem that is examined.

Regarding the GCPD predictive model I, the findings reveal that students who have created and replied to more posts in their group forums are less likely to have the problem CP-1. The positive relationship between the number of posts that a student has created or replied to and the level of contribution that the student has made in online discussions is consistent with the results of Talavera and Gaudioso [164] regarding student interactions with forum systems and their contributions to online discussions. Moreover, the finding that students who have viewed the threads in a forum many times were more likely to present the problem CP-1 was unexpected since it was believed that students with much contribution to online discussions should have viewed the threads in their group forums frequently. A possible explanation for this unexpected relationship can be that these students tended to observe the written discourse occurring online between other students but did not actively participate in the group discussion. This type of student is the so-called 'witness learner' or 'lurker'. According to Beaudoin's study [23], the 'witness learners' or 'lurkers' can still learn and benefit from simply reading the posts to their online studies.

Concerning the GCPD predictive model II, the findings indicate that students who have created and replied to more posts in their group forums are less likely to have the problem CP-2 (i.e. 'not actively meeting the deadlines'). These findings agree with Dimitracopoulou [55] with regard to the result that the number of posts made by a student can help identify the participation peak of the student in online discussions. However, the finding that the hypothetical indicator 'timeperiod_post_pattern' (i.e. the pattern of posting that a student made during a particular time period) did not significantly affect the prediction of the problem CP-2 and was not included in the final model was somewhat surprising. A further analysis of the data relating to the variable 'timeperiod_post_pattern' which were used to generate the predictive model II reveals that the observed data relating to one of the pattern of the variable ‘timeperiod_post_pattern’ (i.e. a student made few posts at the beginning of the group work but created many posts while the deadline was approaching) dispersed evenly in all the categories of the response variable. This indicates that the variable ‘timeperiod_post_pattern’ is not sufficient to classify the existence of the examined collaboration problem.

In terms of the GCPD predictive model III, the findings suggest that students who have created and replied to many posts in their group forums are less likely to have the problem CP-3 (i.e. ‘not actively completing the assigned work’). This is consistent with the results of studies [30,33] which revealed that the number of messages was an indication of activity for individual students or groups. Moreover, the finding that the hypothetical indicator ‘ratio_stupost_grpost’ did not significantly affect the prediction of the problem CP-3 was unexpected. This is because Bratitsis and Dimitracopoulou’s study [33] on usage interaction analysis in asynchronous discussions suggested that the proportion of the number of posts made by an individual student to the overall number of posts made by the group that the student participated in can reveal the contribution status of the student for the group activity. A further analysis of the development data reveals a special case in the data sample which can lead to this unexpected relationship. There was a student who contributed 8% of the overall group posts but was assessed not having the problem CP-3. However, this case should not be excluded from the data sample, because even though the student made relatively small number of posts (compared with those in other groups), he or she contributed the second largest number of posts while the remaining students had no contribution to the overall posts. Thus, the student was believed to be active enough to complete the assigned work in the group.

Next, reflections on the methods and results of the experiments reported in this chapter were provided. In terms of evaluating the performance of a predictive model, the rate of correct classification of problem existence was adopted. This is because it is a standard method to measure the overall performance of a logistic regression model regarding the classification of a response variable [86]. In addition, the method of calculating the rate of correct classification has already been adopted in several studies such as [157,171].

The findings from the apparent validation procedure that the average rate of correct classification by the three GCPD predictive models was approximately 80%, which indicates that the GCPD predictive models performed well on the full dataset. The GCPD predictive model III demonstrated the highest rate of correct classification (i.e. 83.9%) while the GCPD predictive model I displayed the lowest rate of correct classification (i.e. 74.7%). A possible explanation on why the predictive model III has received a better rate of correct classification than the other two models is that it achieved a satisfied rate of correct classification for each category of the response variable (as shown in the column ‘percent correct’ of Table 7.3).

Moreover, the split-sample validation was believed to be suitable for examining the validity of the predictive models on independent data which are similar to the data where the models originated from. There are several reasons for this. First, the split-sample validation technique is an intuitive and common technique for testing the reproducibility of a multinomial logistic regression model

[64]. Second, considering the size of the data sample available (*N*=87), other complex techniques such as bootstrap validation [45] were not considered suitable for examining the reproducibility of the established predictive models. This is because those complex validation techniques usually require for an extraordinary large data set where *N* can be thousands [51]. Third, the settings where the examined predictive models are targeted for are undergraduate modules which involve a piece of group work with a collaborative learning forum. The number of students who take part in such a module is usually not very big (under 300). Therefore, the split-sample technique is considered to enable a reliable assessment of the developed predictive models for future predictions in such settings. Finally, the split-sample validation technique has become popular for examining the reproducibility of predictive models in educational research. Examples of this include [39,90,167].

The findings from the split-sample validation reveal that the estimation models were able to produce the same sets of predictors as identified by the original predictive models and to show a good performance on the validation samples. These findings suggest that the GCPD predictive models are reproducible on independent data that are similar to the data where the original predictive models were established from. It is also noted from the results of the split-sample validation that none of the three estimation models achieved higher overall rate of correct classification than the original predictive models. However, there is no statistically significant difference between the two groups of rate of correct classification: $t(4) = 0.536$, $p = 0.621 > 0.05$.

Furthermore, regarding how to evaluate the GCPD algorithms, two options are available. One is to apply the GCPD algorithms on a virtual data set. The other is to adopt a comparison-based approach which examines the differences between the diagnostic results provided by the proposed algorithms and the results provided by assessors of the collaboration problems. The latter approach was chosen because the former one attempts only to examine the feasibility but not the effectiveness of the proposed algorithms. The findings from the comparison-based experiment reveal that a satisfying rate of correct classification was obtained for both of the GCPD algorithms. This indicates that the GCPD algorithms performed well on the testing samples. However, the final results can be variable as different values can be given to the parameters of the examined algorithms. Since the primary researcher was the organizer of the group work (who has the closest overview of it), it is believed that the values of parameters defined by the researcher fit into the setting where the testing samples originated from. Moreover, for future applications of the proposed algorithms, the teacher or moderator, who is checking the progress of the group work that is examined, is suggested to provide the definition of the required parameters. This can ensure the validity of the diagnostic results provided by the GCPD algorithms (as discussed in Section 6.2.4).

## 7.5 Summary

The chapter presented the methods and results of evaluating the GCPD predictive models and the GCPD algorithms which constitute the diagnostic mechanism that was discussed in the previous chapter. In this evaluation, the reproducibility of the GCPD predictive models and the diagnostic accuracy of the GCPD algorithms have been focused on. Correspondingly, apparent validation and split-sample validation techniques were carried out for the former evaluation objective, and a comparison-based approach was applied for the latter one. The findings from the experiments reveal that the overall performance of the GCPD predictive models on the full development data is satisfied and these models are reproducible on independent data which are similar to the data where the models originated from. Moreover, the findings also indicate that the GCPD algorithms performed effectively on the testing samples.

Having presented in the previous chapters the approaches for group formation and collaboration problem diagnosis in CLEs and the results of the relevant evaluations, the next chapter will explore an overarching architecture which is based on the proposed approaches for supporting group formation and collaboration problem diagnosis in CLEs.

# Chapter 8
# Exploring A Multi-Agent Architecture for Online Collaborative Learning

Chapter 3 and Chapter 6 respectively propose a set of components providing the solutions to the detailed issues faced for the main topics. In particular, the two chapters focus on construction of the algorithms and mechanisms that make the proposed components functional (i.e. how these components are realised). This chapter explores an architecture which can encompass all the components into a single system for managing online collaborative learning. This suggests an overarching framework which provides context for all the research proposals involved.

## 8.1 Introduction

As mentioned in Chapter 1, it is very time-consuming and labour-intensive for teachers to manage online collaborative learning in current CLEs. To check students' progress of collaboration, for example, a teacher has to visit many web pages regularly, examine the course activity log frequently to monitor students' collaborative activities, and compare manually the student activity records to identify students and groups with collaboration problems.

Considering this, the aim of this chapter is to explore an architecture which can intelligently manage online collaborative learning in terms of organizing effective groups and assessing collaboration problems. It targets to unify the components that constitute the proposed approaches for group formation (Chapter 3) and for group collaboration problem diagnosis (Chapter 6).

Software agents are considered to be a useful tool for modelling the desired architecture. An explanation of what software agents are is provided by Griffiths and Chao in [73]: "software programs with a degree of intelligence or autonomy to perform functions on behalf of person, organization or other software system."

The benefits of adopting agents for constructing the desired architecture particularly pertain to the increased degree of flexibility and autonomy of the system to be developed. The properties of agents including reactivity, pro-activeness and social ability allow the development of a system with enhanced flexibility. The property of reactivity enables an agent to sense and react to the events that occur in its environments. An agent is also capable of exhibiting goal-directed behaviours by taking the initiative (pro-activeness). That is, it can constantly monitor the environment where it is situated and pro-actively take action in pursuit of its goals as environment conditions change. Furthermore, an agent is able to interact and communicate with other agents (social ability). There is an increasing number of research studies that utilize software agents for developing pedagogical systems to support online collaborative learning such as MASCE [122], SACA [99], ELMS [116], I-MINDS [159] and CITS [147].

In order to achieve the aim of this chapter, the following objectives will be addressed. First, this chapter describes the pedagogical tasks that the architecture aims to address. Second, it attempts to explain what methodology was used to develop the multi-agent architecture and why this methodology was chosen. Third, it presents how the multi-agent architecture was analysed and designed using the adopted methodology. Furthermore, this chapter presents a high-level view of the developed multi-agent architecture for online collaborative learning.

The structure of the remaining sections is described as follows. Section 8.2 presents the scope of the pedagogical process that is addressed by the developed architecture regarding the aspects of group formation and collaboration problem diagnosis for online collaborative learning. An explanation of the Gaia methodology that was adopted and the reasons for it are provided in Section 8.3.

Section 8.4 reports the process of analysing and designing the desired architecture by applying the Gaia methodology, and the results of the development process which include several models capturing the features of the system from abstract to concrete levels. Exhaustive reporting on the models was omitted because the focus of this section is the research methodology it embodies.

Following that, Section 8.5 gives an overview of the developed multi-agent architecture including the types of agents that constitute the overall system, and the interrelationships between these agents and between agents and their environment. Finally, Section 8.6 provides a summary of this chapter.

## 8.2 Scope of the Pedagogical Process Supported

The following teaching and learning scenario illustrates a typical setting for the online collaborative learning process concerned in this chapter. A course is delivered through a collaborative learning environment (CLE) and contains a piece of collaborative group work for the participating students to complete. Students who join the course are assigned into different collaborative groups and expected to carry out all the activities relating to the group work through the CLE. Moreover, the CLE is capable of recording and maintaining the logs of student interactions with the system including those interactions for accomplishing the group activities.

The general process of collaborative learning involved in this scenario consists of building and arranging collaborative groups, establishing learning goals and plans, individual learning, group learning, and evaluating learning process and outcomes. The phase of group learning refers to students completing the designed group activities to achieve the group learning goal, which can include sharing individual learning results, collecting and analysing information, discussing issues and solving problems, and producing group results.

The developed architecture focuses on two aspects of the above process, i.e. to form collaborative groups and to diagnose collaboration problems. Since the architecture incorporates the components that constitute the approaches proposed for group formation and collaboration problem diagnosis, these two approaches are assumed to be applied by the constructed agents for accomplishing corresponding tasks. Next, the pedagogical tasks relating to the two aspects are presented below.

Concerning the formation of collaborative groups, a number of tasks are involved. In brief, these tasks mainly include obtaining students' learning styles and the value of the grouping parameter, and applying these values for forming collaborative groups (Chapter 3). In terms of the diagnosis of group collaboration problems, there are also a series of tasks to be accomplished. In general, these mainly include gathering student interaction data from a CLE and the values of the diagnosis parameters, ascertaining the existence of the group collaboration problems, and presenting the diagnostic products to teachers and students.

The developed architecture comprises four types of agents for carrying out the above tasks, which include the Profiler agent, the Grouper agent, the Monitor agent and the Diagnoser agent (details in Section 8.4 and 8.5). As stated in the previous section, agents are used as a tool to construct the desired architecture mainly because they provide increased degree of flexibility and autonomy of the system to be developed, and the properties of agents including reactivity, pro-activeness and social ability allow the development of a system with enhanced flexibility. To further explain this, the main characteristics of each agent in the developed architecture are described below.

**Profiler Agent**

- *Pro-activeness*: It does not only act in response to the environment, but also take the initiative to discover students who are expected to but do not complete the learning style questionnaire before the submission deadline expires. The Profiler agent can periodically check submissions of the questionnaire before the deadline, and remind students who do not submit their responses. This intends to ensure all the students can complete the questionnaire in time.

- *Autonomy*: At the beginning, the Profiler agent interacts with the system administrator, configuring data sources for obtaining student information. After the initial setting up phase, The Profiler agent is an independent entity, and it controls over its internal states and actions.

- *Social ability*: The agent is able to interact and communicate with the other agents in the multi-agent system.

**Grouper Agent**

- *Reactivity*: The Grouper Agent can react to various grouping requirements for different collaborative learning processes and the requests from the Monitor agent for providing information about formed groups.

- *Autonomy*: Initially, the Grouper agent works with the teacher, defining value of the grouping parameter. After this, The Grouper agent controls itself to perform functions and actions. It is an independent entity.

- *Social ability*: The agent is able to interact and communicate with the other agents in the multi-agent system.

**Monitor Agent**

- *Pro-activeness*: The Monitor agent is more than simply a database: it is able to process the student interaction data which it collects and maintains, and to respond to requirements for providing student interaction data to the Diagnoser agent. In addition, it can proactively verify the configurations of the data source where the student interaction data originate from. If it infers that there are changes in the relevant structures of the data source which may lead to the failure of collecting the desired student interaction data, the Monitor agent will notify the system administrator who maintains the data source to update the configuration of the data source. This is to ensure the data collection process can be successfully completed.

- *Autonomy*: At an initial stage, the Monitor agent works together with the system administrator, configuring data sources for gathering student interaction data. It also interacts with the teacher to define the value of the diagnosis parameters for the data collection process. Except these interventions, the Monitor agent controls itself to perform functions and actions. It is then an independent entity and do not need direct intervention from humans.

- *Social ability*: The agent is able to interact and communicate with the other agents in the multi-agent system.

**Diagnoser Agent**

- *Reactivity*: The Diagnoser Agent is able to react to requests for performing diagnostic tasks for different group work and presenting the diagnostic products to teachers and students.

- *Autonomy*: When the Diagnoser agent obtains a request for diagnosing the collaboration problems for the group work examined, it interacts with the teacher, defining the values of the diagnosis parameters. Except for this intervention, the Diagnoser agent controls itself to perform functions and actions. It is then an independent entity and does not need direct intervention from humans.

- *Social ability*: The agent is able to interact and communicate with the other agents in the multi-agent system.

The following section presents the methodology that was applied for modelling the multi-agent architecture.

## 8.3 Development Methodology

The Gaia methodology [172] was adopted for analysing and designing the desired multi-agent architecture. Gaia is an agent-oriented modelling methodology which can capture the macro (societal) level and micro (agent) level aspects of agent-based systems. It provides an agent-specific set of concepts through which an analyst can model a complex system.

The development process using Gaia was iterative which can help modelling the system appropriately. The whole process consisted of two phases: analysis and design phases. Regarding the analysis phase, Gaia aims to specify the structure of the system to be created from the requirement statements. By the notion of structure, the meaning that the key roles that agents play in the system and the interactions between these roles to achieve the goal of the system are referred to. The analysis phase produces a comprehensive role and interaction model which elaborates the permissions and responsibilities of the key roles identified, together with the protocols and activities they participate in.

In the design phase, the aim is to transform the abstract models obtained from the analysis phase into concrete models that can be easily implemented. The outcome of the design phase includes three models: an agent model which identifies a set of agent types via grouping closely related roles together; a service model that specifies the services (functions) of each agent role and the properties (inputs, outputs, pre-conditions and post-conditions) of these services; and an acquaintance model which defines the communication links between agent types. The output of the Gaia process is a specification of the agent system that is suitable for implementation.

Gaia was preferred to other methodologies such as the KGR approach [94] which is based on the Belief-Desire-Intention (BDI) paradigm [146] because Gaia provides a diverse set of generic models, which does not pertain to any particular agent technology, to capture the features of the system to be constructed. This can avoid premature commitment to the detailed design and implementation process [172]. The KGR approach, by contrast, depending on a particular agent technology (BDI), will make more commitment for resolving issues arising from the lower-level design process.

There are other agent-oriented methodologies such as TROPOS [34], AUML [22], and ADELFE [25]. A diagram that shows the relative coverage of these methodologies for software development is provided in Figure 8.1. TROPOS is a framework that spans the overall software development process, ranging from early requirements analysis to implementation [34]. TROPOS is surplus to requirements for modelling the intended architecture since the early requirements analysis (which states questions of the *why*, *what* and *how* of the system functionality) has already been addressed and the detailed design (which can be mapped directly to code) is out of the focus of this chapter (i.e. architectural design without commitment to detailed implementation issues). AUML is an extension of UML which adapts to agent-oriented software development [22]. As indicated in Figure 8.1, AUML mainly focuses on the detailed design phase, which is not appropriate for modelling the intended architecture. ADELFE is a softwre engineering methodology that is specific to the modelling of adaptive multi-agent systems [25]. Like TROPOS, ADELFE is also surplus to requirements for modelling the intended architecture because it covers the whole process of software development. Moreover, the intended architecture does not attempt to offer adaptive properties, so a specific methodology such as ADELFE for designing adaptive multi-agent systems is not suitable.

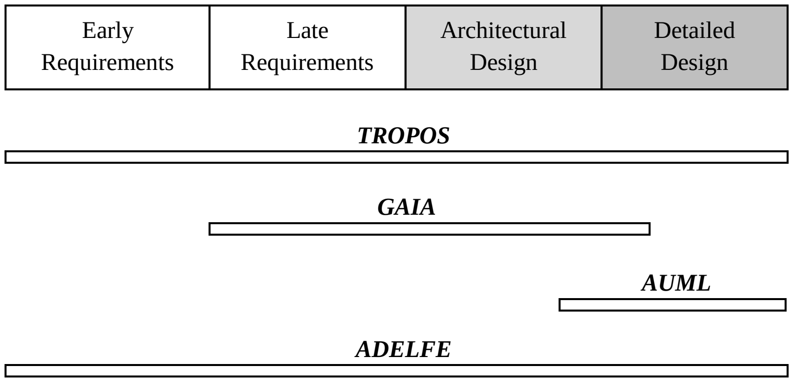


Figure 8.1. Agent-oriented software development methodologies (adapted from [34])

Furthermore, although object-oriented analysis and design (OOAD) is considered to develop software systems with attributes of high maintainability, reusability and scalability [70], it was not chosen for modelling the multi-agent architecture. This is because the literature [172,174] suggests not using object-oriented methodologies for modelling agent systems. There are two reasons for this. First, the representation of an object (as a set of attributes and methods) operates at an inappropriate level of abstraction for agents, since it does not capture much valuable information about an agent (such as autonomy and its internal state). Second, an object model can not adequately capture the relationships held between agents in a multi-agent system. An agent model needs to capture the dynamic interactions between agents, and the relationships between agents and non-agent elements of the system such as resources. However, an object model only captures static dependences between classes.

By following the Gaia methodology, we can make full use of an agent-oriented approach in terms of system development, for example by facilitating use of existing components (for tackling the problems of group formation and collaboration problem diagnosis), and in system use, providing characteristics such as reactivity, pro-activeness and social ability.

Next, the process and results of modelling the desired architecture by applying the Gaia methodology are presented.

## 8.4 Analyzing and Designing the Architecture Using Gaia Methodology

Following the Gaia methodology, the process of analysis and design produced a detailed analysis and design specification of the multi-agent architecture. The key models that were created from this process include: a role model which elaborates the key roles that agents play in online collaborative learning and the attributes of these roles including responsibilities, permissions, activities and protocols; an interaction model which defines the protocols for each type of inter-role interaction; an agent model that details the types of agents and the number of instances of each agent type in the actual system; a service model which describes the services (functions) associated with each agent type; and an acquaintance model that defines the communication pathways between the identified agent types.

The following subsections present how each of these models was constructed concerning the pedagogical process presented (Section 8.2). Since the focus of this chapter is not on presenting a critically evaluated system but exploring an overarching framework that provides context for other parts of this thesis, comprehensive reporting on the models was avoided. Therefore, the analysis and design process applying Gaia for constructing the desired architecture is presented.

### 8.4.1 The Role Model

In Gaia, an agent-based system is viewed as an artificial organization. Like a human organization, a set of roles can be defined for the agent-based system. An analysis of the pedagogical process presented (Section 8.2) was carried out to identify the roles. The principles for identifying these roles included: a role should be a position in the artificial organization that performs an individual function, and different roles interact with each other to achieve the goal of the organization. To model students' learning styles, for example, two separate roles were identified. One is named as profiling which is responsible for creating and distributing online leaning style questionnaire, collecting responses to the questionnaire and analysing students' learning style scores from these responses. The other is a profiling assistant that is in charge of obtaining the list of students who join a course and notifying them about the learning style questionnaire prepared and the deadline to submit it, reminding the students about the deadline, and notifying the teacher about the students who did not complete the online questionnaire.

The analysis phase is an iterative process, which means the concepts developed initially may be refined through a repetition of the analysis steps. As an output of the analysis phase, the role model was refined through several iterations of the analysis steps. In the final role model, a total of ten roles were identified for managing the collaborative learning process in terms of forming collaborative groups and assessing collaboration problems. A brief description of each role identified is presented below.

- *Profiling*: obtains students' learning style scores from learning style questionnaire.

- *Profiling assistant*: discovers new students who should complete the learning style questionnaire and maintains contact with students and teachers for accomplishing the task of learning styles modelling.

- *Grouping*: assigns given students into heterogeneous groups according to Algorithm 3-1 (the iGLS grouping algorithm) based on their learning style scores and the defined grouping parameter.

- *Grouping assistant*: identifies the value of the grouping parameter to use for forming collaborative groups and notifies the students about the grouping results.

- *Data gathering*: collects student interaction data from a CLE according to the predefined configurations (SQL statements defined corresponding to the data collection guidance, Section 6.3).

- *Data processing*: processes the collected student interaction data to obtain data for analysing the collaboration problems CP-5 and CP-6.

- *Data collection assistant*: defines the configurations and specifies the value of the parameter p4[1] (as defined in Algorithm 6-2) for gathering student interaction data.

- *Diagnosing*: judges the existence of the six types of collaboration problems (Section 5.4) for the students and groups participating in the group work examined based on the developed diagnostic mechanism and data obtained from the data collection process.

- *Diagnosing assistant*: configures the parameters that are needed for the diagnosis procedure (Section 6.2.4).

[1] The parameter p4 represents the percentage of the overall number of posts made by a group for defining relative majority.

- *Reporting*: produces basic statistics on the diagnosis results and reports the diagnostic products to teachers and students respectively.

Each of the roles identified above was defined by four attributes: responsibilities, permissions, activities, and protocols. *Responsibilities* decide the functionality of a role, which can be divided into two categories: liveness and safety responsibilities. A liveness responsibility defines some action (activities and/or protocols) that will be done by a role during the "life-cycle" of that role. A safety responsibility determines certain invariants (safety conditions) while executing a role. *Permissions* refer to the information resources that are available to a role to achieve its responsibilities. *Activities* are the "private" actions that are carried out by a role without interacting with other roles. *Protocols* define the way that a role can interact with other roles.

A role schema was drawn for each role identified which puts its various attributes into a single place. Thus, the role model constructed consists of a set of schemata, one specifying the attributes for each role in the agent system. The following discussion illustrates the schema defined for the Grouping role (Figure 8.2). This shows how a role schema was specified.

As shown in Figure 8.2, a liveness responsibility was specified for the Grouping role using Gaia liveness expression. On the left of the equation, the name of the role is specified (Grouping). The expression on the right defines the liveness properties of the role. The atomic components of the expression are either protocols or activities associated with the role. The responsibility defined for the Grouping role in this schema stands for it consists of executing the protocol GetLearningStyles and the protocol GetGroupingParameter, followed by the activity FormGroups and the protocol GetGroups. The symbol '.' represents the sequential execution of these protocols and the symbol '+' defines that all the protocols and activities are repeated for one or more times. More information about Gaia liveness expressions can be found in [172].

Role Schema: Grouping

---

Description:

This role involves requesting the Profiling role for students' learning style scores and the Grouping Assistant role for value of the grouping parameter required. It formulates groups based on the obtained learning style scores and the value of the grouping parameter, and responds to requirements for the groups formed from the Data Gathering role.

---

Protocols and Activities:

GetLearningStyles (Initiator), GetGroupingParameter (Initiator), FormGroups, GetGroups (Responder)

---

Permissions:

| | |
|---|---|
| reads | *learning style scores* |
| | *grouping parameter* |
| generates | *collaborative groups* |

---

Responsibilities

liveness:

Grouping = (GetLearningStyles. GetGroupingParameter . FormGroups . GetGroups)+

Figure 8.2. Schema for role Grouping

Other roles were specified using the same template schema as illustrated in Figure 8.2.

### 8.4.2 The Interaction Model

The interaction model is used to clarify the relationships between roles and to link the interactive agents. These relationships were initially identified in the role model (as protocols in the role schemata) and further specified in the interaction model. Thus, the interaction model is comprised of a set of protocol definitions. Each protocol defines one type of inter-role interaction. The definitions of the protocols focus on the nature and purpose of the interaction rather than any particular ordering of message exchanges. However, such an individual protocol definition will typically lead to many message interchanges in the run time system.

A protocol definition consists of six attributes: *protocol name*, *initiator*, *responder*, *inputs*, *outputs*, and *processing*. The name of a protocol gives a brief textual description capturing the nature of the interaction. Initiator addresses the role(s) responsible for starting the interaction. Responder presents the role(s) with which the initiator interacts. The inputs of a protocol define the information used by the protocol initiator while enacting the protocol. The outputs of a protocol define information supplied by/to the protocol responder during interactions. Additionally, “processing” gives a brief textual description of the processing activities involved in this interaction. As an illustration, Figure 8.3 shows the protocols defined for the ‘Grouping’ role.

(a)

| Protocol Name: **GetLearningStyles** | | |
|---|---|---|
| Initiator: **Grouping** | Responder: **Profiling** | Inputs: **The identifiers of students** |
| Processing: The Grouping role will start a protocol to interact with the Profiling role for requesting students' learning style scores when there is a grouping need. The request will be processed by sending the required learning style scores to the initiator. | | Outputs: **Learning style scores** |

(b)

| Protocol Name: **GetGroupingParameter** | | |
|---|---|---|
| Initiator: **Grouping** | Responder: **Grouping assistant** | Inputs: **The identifier of the activity which the grouping process is required for** |
| Processing: The Grouping role will start a protocol to interact with the Grouping assistant role for requesting the value of the desired grouping parameter. This request will be processed by sending the value of the parameter that is needed. | | Outputs: **The value of the required grouping parameter** |

(c)

| Protocol Name: **GetGroups** | | |
|---|---|---|
| Initiator: **Data gathering** | Responder: **Grouping** | Inputs: **The identifier of the collaborative group activity examined** |
| Processing: When the data collection process starts, the Data Gathering role has to request the Grouping role about the formed groups for the collaborative group activity examined. This request will be processed by sending the formed groups that are needed. | | Outputs: **Formed groups** |

Figure 8.3. Definition of protocols associated with the Grouping role: (a) GetLearningStyles, (b) GetGroupingParameter, and (c) GetGroups.

As can be seen from Figure 8.3, the Grouping role interacts with the 'Profiling' role to obtain the learning style scores of the students who will complete a piece of group work (GetLearningStyles protocol, Figure 8.3a) and with the ‘Grouping assistant’ role to obtain the value of the grouping parameter for forming the collaborative groups (GetGroupingParameter protocol, Figure 8.3b). In addition, the Grouping role will respond to the requirements from the Data Gathering role for providing formed groups for the grouping activity examined so that the Data Gathering role is able to collect relevant student interaction data from a CLE (GetGroups protocol, Figure 8.3c).

The protocol template as shown in Figure 8.3 was applied for defining the other protocols that constitute the interaction model.

### 8.4.3 The Agent Model

The agent model is used to specify the types of agents and the number of instances of each agent type in the actual system. In the Gaia context, an agent is a software entity playing a set of roles. Thus, the definition of the agent model amounts to identifying the specific roles associated with an agent type and how many instances of each agent type have to be instantiated. For identifying the agent types, there was a trade-off between the coherence of an agent type (i.e. how easily its functionality can be understood) and the efficiency of the design. In the agent model, an agent type was defined by packaging several closely related roles together. This is because it is more efficient to deliver a number of roles in a single agent than to deliver a number of agents each playing a single role. In addition, one instance of each agent type is defined for the actual system. The reasons for this include a Profiler agent can target the total set of students within a CLE, a Grouper agent can provide grouping services for every request sent from a CLE, a Monitor agent is able to gather interaction data from the central database of a CLE and a

Diagnoser agent can process every request for diagnosing problems from different users within a CLE.

The agent model was documented using a simple *agent type tree*. In such an agent type tree, the leaf nodes stand for the roles (as defined in the role model) and the other nodes represent agent types. The final agent model is illustrated in Figure 8.4. As can be seen from this figure, it is composed of four agent types: the Profiler, the Grouper, the Monitor and the Diagnoser. Each of the agent types was assigned two or three roles. For example, the Profiler agent type was associated with the Profiling role and the Profiling Assistant role (Figure 8.4a), and the Monitor agent type was assigned three roles: Data Gathering, Data Processing and Data Collection Assistant (Figure 8.4c).

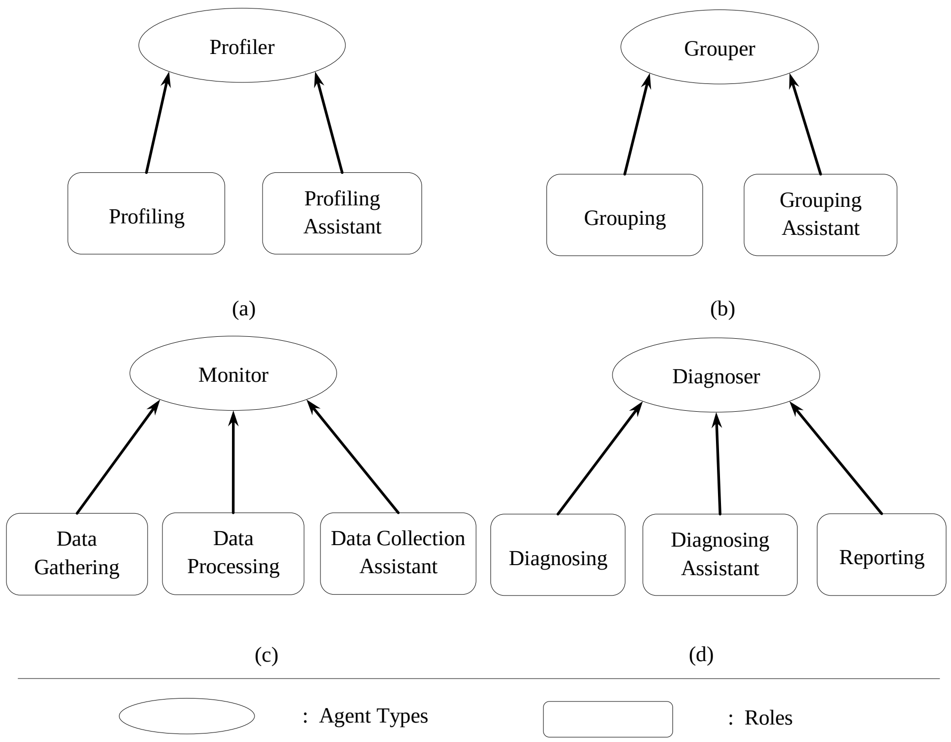


Figure 8.4. The agent model

Regarding each agent type shown in Figure 8.4, the associated roles were grouped together due to their high degree of interdependence. As an illustration, consider the Profiler agent (Figure 8.4a), the Profiling role can only know which students to send the learning style questionnaire after the Profiling Assistant role provides it for the information about the students. The Profiling Assistant can be informed about the students who have not completed the questionnaire by the Profiling role and thus contact them for completing the questionnaire. Take the Diagnoser agent as another example. The Diagnosing role has to interact with the Diagnosing assistant role for obtaining the diagnosis parameters so as to ascertain the existence of the collaboration problems in question. The Reporting role has to request the Diagnosing role for the diagnosis results of the group work examined so that it can produce relevant reports to teachers and students.

### 8.4.4 The Service Model

The service model further identified the services associated with individual agent roles and specified the key properties of these services. In Gaia, the notion of service means a single, coherent block of activity in which an agent will engage. This is different from what it may mean in OO terms (i.e. a method), because an agent has control over its services while an object's methods are available for other objects to invoke. Moreover, the concept of service in a Gaia service model is distinguished from the web services in Service-Oriented Architecture. The latter defines a service as an abstract notion that represents the resource characterised by an abstract set of functionality that is provided [28].

The services that each agent will perform were derived from the list of protocols, activities, responsibilities of the roles that it implements. Every activity identified in the role model corresponds to a service. There is at least one service associated with each protocol. A safety responsibility as defined in the role model can also represent a service property. The services defined for each agent type in the agent model are presented below.

- *Profiler agent*: discover new students, distribute learning style questionnaire, monitor students, notify teachers, extract learning style scores from responses to questionnaire, and respond to requirements for learning style scores.
- *Grouper agent*: identify grouping parameter, obtain students' learning style scores, form groups, store groups, notify students, and respond to requirements for formed groups.
- *Monitor agent*: define configuration of data source, specify parameters for data gathering, obtain formed groups, collect student interaction data, process the collected data, respond to requirements for data relating to student interactions, verify configuration of data source, and notify system administrator.
- *Diagnoser agent*: configure the diagnosis parameters, obtain student interaction data, make judgements on the problem existence, produce the diagnosis reports, report the diagnosis results to teachers, and inform students.

For each service identified above, the properties of the inputs, outputs, pre-conditions and post-conditions were defined. Inputs and outputs to services were derived in an obvious way from both the interaction model (for services involving the elaboration of message exchange between agent roles) and the role model (for services involving the evaluation and modification of information resources). Pre- and post-conditions represent constraints and states on the execution and completion of services. They were derived from the safety responsibilities of a role.

As an illustration, the services defined for the Profiler agent is concentrated on (Table 8.1). The service "discover new students" was derived from the GetNewStudent activity of the Profiling Assistant role. It is in charge of identifying the details of students who are expected to complete the learning style questionnaire. It takes "the identifier of a new grouping activity" as input and returns "details of students who need to complete the questionnaire" as output. This service has a pre-condition that the configuration of the CLE database is available, which was derived from the safety responsibility of the Profiling Assistant role. There is no associated post-condition for this service (represented as "true" in Table 8.1).

The service associated with the GetStudentDetails protocol and the DistributeQuestionnaire activity of the Profiling role is denoted as "distribute learning style questionnaire". It handles the delivery of the invitation emails and the questionnaire to the students who are expected to complete the questionnaire.

The third service ("monitor students") involves checking students who haven't completed the questionnaire before the submission deadline expires. If there are students identified to have not completed the questionnaire, this service will send out email reminders to these students.

The next service "notify teachers" is responsible for checking students who haven't submitted the questionnaire after the submission deadline expires and notifying the teacher these students through emails. It has a pre-condition that the deadline for submission expires, which was derived from the safety responsibility of the Profiling Assistant role.

Table 8.1 The services defined for the Profiler agent

| Service | Inputs | Outputs | Pre-condition | Post-condition |
|---|---|---|---|---|
| discover new students | the identifier of a new grouping activity | details of students who need to complete the questionnaire | configuration of CLE database is available | **true** |
| distribute learning style questionnaire | details of students who need to complete the questionnaire, the deadline of completion | email invitation to the students for the online questionnaire (include URL and deadline) | URL of the online questionnaire is available and the deadline for completion is set up | **true** |
| monitor students | two lists of students: total and who have submitted the questionnaire, the deadline of completion | emails to notify the students who haven't yet completed the questionnaire | the deadline for submission of the questionnaire does not expire | the Profiler agent regularly checks students who haven't completed the questionnaire |
| notify teachers | list of students who haven't completed the questionnaire | email to notify the teacher the list of students who haven't yet finished the questionnaire | the deadline for submission of the questionnaire expires | postpones the responds to the requirements for learning style scores and waits for the teacher's decision |
| extract learning style scores from responses to questionnaire | responses to the questionnaire | learning style scores | all questions in the questionnaire are answered | learning style scores are stored in the database |
| respond to requirements for learning style scores | the identifiers of students | the learning style scores for the required students | all required scores are available | the requestor obtains the learning style scores required |

The service "extract learning style scores from responses to questionnaire" was derived from the ExtractLSScore activity of the Profiling role. It involves collecting student responses to the questionnaire, calculating scores based on the responses, and storing the obtained scores in database.

The final service involves responding to requirements for obtaining learning style scores. This was derived from the GetLearningStyles (Responder) protocol of the Profiling role (Figure 8.3a).

### 8.4.5 The Acquaintance Model

The final model that was created from the design phase is the acquaintance model. This model simply defines the communication links between agent types, but does not define the concrete messages to send and when to send the messages. This was to avoid premature commitment to detailed design. The acquaintance model provides a basis for revisiting the system design so that problems such as communication bottlenecks can be removed.

The acquaintance model was developed from the interaction and agent model, which is illustrated using a directed graph (Figure 8.5). A node in the graph represents an agent type and an arc stands for a communication pathway. An arc $a \rightarrow b$ indicates that $a$ will send messages to $b$, but $b$ will not necessarily send messages to $a$.

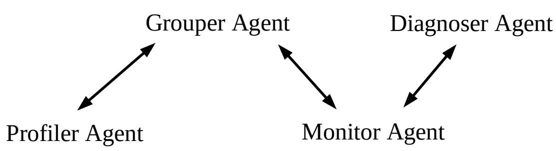


Figure 8.5. The acquaintance model

## 8.5 Overview of the Multi-Agent Architecture

This section presents an overview of the multi-agent architecture that was developed from the analysis and design process described in Section 8.4. Figure 8.6 illustrates the developed multi-agent architecture, which consists of four agents: the Profiler agent, the Grouper agent, the Monitor agent and the Diagnoser agent. This figure also illustrates the environment that these agents are situated in. The environment refers to the human users, other computer systems and information resources that a multi-agent system interacts with or makes use of. In particular, the human users that the agents interact with include teachers and students who participate in the online collaborative learning process, and the system administrator who maintains a CLE. The computer system that these agents interact with corresponds to the CLE where the collaborative group process is undertaken. In addition, the information resources that the agents make use of include student information and student interaction data that are stored in the data centre of a CLE.

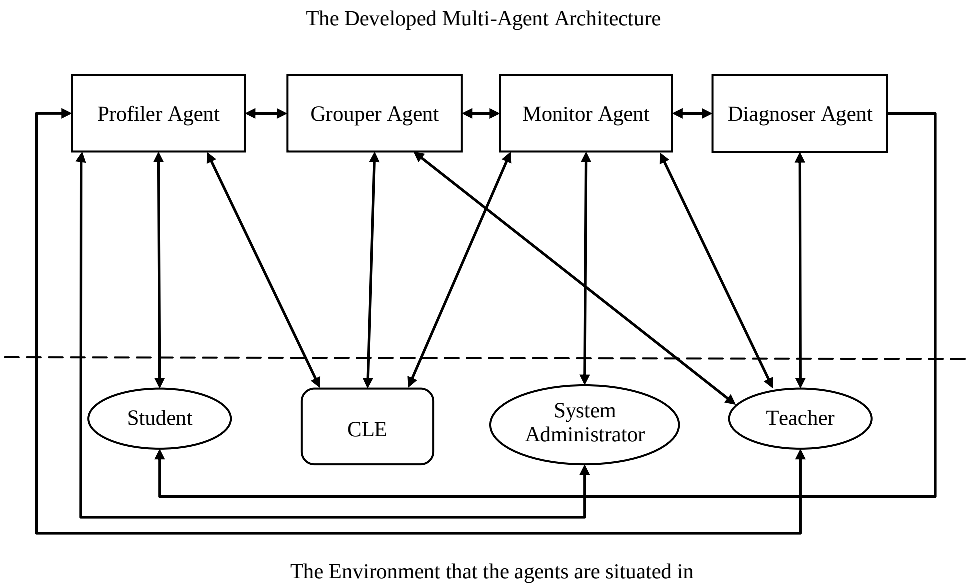


Figure 8.6. Overview of the multi-agent architecture

In the above figure, the interactions between the agents and between the agents and the environment are demonstrated. A brief explanation of the key interactions illustrated is provided below.

When a request for learning styles modelling is received from the teacher who organizes a piece of group work, the Profiler agent will interact with the supporting CLE to obtain details of the students who need to complete the learning style questionnaire. After the students submit their answers to the questionnaire, the Profiler agent will extract their learning style scores from their responses and store them in its database. When the Grouper agent receives a request for forming collaborative groups from the teacher, it will request the Profiler agent for providing the students' learning style scores. With the obtained learning style scores, the Grouper agent will form heterogeneous groups and return the grouping results to the CLE so that the CLE can place the students into corresponding group working areas (e.g. forums, wikis) based on this grouping results when the students execute the group activities.

Moreover, when the Diagnoser agent obtains a request for diagnosing the collaboration problems for the group work examined from the teacher, it will request the Monitor agent for providing relevant student interaction data. Then, the Monitor agent will ask the Grouper agent for information about the formed groups for the group work examined. After receiving information about the formed groups from the Grouper agent, the Monitor agent will collect and process student interaction data for these groups from the data centre of a CLE and send the processed data to the Diagnoser agent for further analyzing. Then, the Diagnoser agent will analyse the obtained data to identify the existence of the collaboration problems and present these diagnostic products to the teacher and the students.

Furthermore, at an initial stage, the Profiler agent and the Monitor agent need to interact with the system administrator for configuring the data source. The Diagnoser agent is desired to interact with the teacher for defining the value of the diagnosis parameters.

The goal of this chapter is to explore an architecture to encompass all the components derived from the approaches proposed for group formation and collaboration problem diagnosis. Since this chapter is exploratory, no evaluation has been carried out. The Gaia methodology focuses on modelling concrete concepts, and it does not address the issue of implementation. To implement a multi-agent system adopting the developed architecture, an appropriate development platform should be determined. Some of the popular platforms for developing multi-agent systems include JADE [24] and JADEX [144]. JADE is a Java based platform which complies with the FIPA standards for realizing agent management, communication language and protocols, but it does not support agent reasoning. JADEX is a software framework that can explicitly represent the mental attitudes of agents following the belief-desire-intention (BDI) model. It provides a reasoning engine which can automatically deliberate about the agents' goals and then subsequently achieve these goals by applying appropriate plans. JADEX also complies with the FIPA standards for agent communications. Detailed issues regarding the implementation of the designed multi-agent system are out of the scope of the thesis and are desired to be addressed for future work.

The importance of such an agent architecture not only lies in providing an overarching framework, but also supporting the development of intelligent collaborative learning environments, which has been noted as a significant direction of research in the e-learning field [5,50,75]. An intelligent collaborative learning environment (iCLE) provides an online learning community with an interactive and multi-functional work area with intelligent support for the whole cycle of collaborative education, including organizing teams, monitoring and assessing individual contributions, advising on group work and communication, and tutoring. An agent-based approach lends itself to developing iCLE systems since many of the desired properties and requirements of iCLE systems coincide with those provided by the use of agents, such as autonomy, reactivity and proactiveness (goal-oriented).

Existing agent-based architectures for online collaborative learning such as MASCE [121] and ELMS [116] identify the agent types and the system requirements and functionalities, but lack certain design specifications. In particular, there is a lack of precision with respect to areas such including: the key roles that intelligent agents can play in online collaborative learning management; the computational resources consumed and generated by a role for performing a pedagogical task; the protocols adopted for the interactions between different roles; the agent types with mapped roles and the number of instances of each type in an actual system; the services that the agents provide. Fully specifying these aspects will enable the system to fully exploit the strengths of agents (including pro-activeness, reactivity, autonomy and social ability). The presented agent architecture addresses the above issues by providing a detailed analysis and design specification, which comprises several models of a multi-agent system for managing online collaborative learning.

## 8.6 Summary

In this chapter, a multi-agent architecture for online collaborative learning was presented. This architecture aims to support the pedagogical tasks involved in the processes of group formation and collaboration problem diagnosis for online collaborative learning. A description of the methodology for analyzing and designing the architecture was provided including the essential concepts to be constructed for the architecture, the development process, the reasons and benefits for adopting the methodology. Then the detailed analysis and design process following the Gaia methodology was discussed, which produced a set of models being able to capture the features of the system from abstract to concrete levels. Based on the analysis and design results, an overview of the multi-agent architecture was presented. As the architecture incorporates the components proposed in previous chapters (Chapter 3 and Chapter 6), it provides an overarching framework for all the research proposals involved.

The next chapter concludes this thesis and presents the research contributions. Some suggestions are made for future work, which covers the topics that are unaddressed as a result of the resources constraints and the extensions that could be made for future study.

# Chapter 9
# Conclusions and Future Work

Forming effective groups and assessing group collaboration problems have been identified, based on literature, as two important aspects to enhance collaborative group work. This thesis has investigated the main topic of how to provide intelligent support for teachers to cope with the tasks of group formation and collaboration problem diagnosis in a collaborative learning environment. The previous chapters have successfully achieved this goal, and this chapter summarizes the findings from this research, the main contributions to the research field and possible directions for future work.

## 9.1 Conclusions

As defined in Chapter 1, this research aimed to explore solutions for improving the delivery of support for group work in collaborative learning environments, which could provide an enhanced and efficient way for teachers to cope with the tasks of constructing collaborative groups and diagnosing group collaboration problems.

This aim was successfully achieved through accomplishing the research objectives as listed in Section 1.2. This research started with the first objective by carrying out a comprehensive literature review in the fields of collaborative learning environments and group collaboration (Chapter 2). This review identified gaps in current research relating to a lack of support for group formation that tailors to individual students' characteristics and for diagnosing major student-induced group collaboration problems automatically and efficiently in a collaborative learning environment. Theories and practice relating to the topics of interest were also examined, which included learning style theories, empirical studies on the effects of learning styles for group formation, interaction analysis and predictive modelling methodologies.

The next phase of this research centred on accomplishing the objectives aimed towards the proposal and development of an approach for group formation based on students' learning styles and an add-on tool that implemented the proposed approach for a LAMS system (Chapter 3). The successful implementation of the proposed approach on top of LAMS suggests that this approach fits well into contemporary collaborative learning environments and a real world scenario demonstrates the developed tool can support teachers to cope with the process of group formation efficiently.

With affirming the feasibility of the proposed approach for group formation, this research then focused on the evaluation of the grouping algorithm proposed. This evaluation emphasised on investigating the effectiveness of the grouping algorithm for forming groups to conduct collaborative group work (Chapter 4). Therefore, an experiment was carried out which examined the question of whether the diverse learning style groups formed by the proposed algorithm perform more effectively and efficiently than the similar learning style groups formed by a comparison grouping algorithm. A sample of 20 undergraduate students completed the experiment. Multiple types of data were collected including group record forms, audio recordings, post-study questionnaire, and expert questionnaire (Section 4.2.3). Both quantitative and qualitative data analysis methods were applied for analysing the experiment results. This allowed a thorough investigation of the learning achievements, collaboration processes and student feedback for the diverse and the similar learning style groups examined, particularly with respect to the quality of group interactions.

The findings from the above experiment suggest that the proposed grouping algorithm tends to form collaborative groups which seem to demonstrate better learning achievements and more effective group collaboration processes, and possess a greater student enjoyment. Reflecting on the multi-faceted findings in detail, several differences between the diverse learning styles groups (DLS groups) and the similar learning style groups (SLS groups) were identified (Section 4.3). First, the DLS groups had achieved better average group and average individual student achievements. Second, the DLS groups spent significantly more time on meaningful interactions with significantly fewer negative social-emotional reactions to showing disagreements. Third, members of the DLS groups tend to be more enthusiastic about giving feedback on each other's thoughts, whereas this was a common problem for the SLS groups. Furthermore, the DLS groups produced more constructive arguments and seem to more actively face the conflicts occurring in the group process. Finally, more students preferred to participate in the DLS groups, and several advantages were reported.

The above results of the experiment agree with literature which advocate heterogeneous groups and believe that heterogeneous groups are more effective than homogeneous groups. Moreover, this evaluation provides inside views of the advantages of heterogeneous groups over homogeneous groups which have not been revealed by previous studies.

The next goal focused on identifying major student-induced group collaboration problems and their causes. This goal was successfully accomplished via conducting an online survey (Chapter 5). This survey mainly gathered three aspects of information: demographic information about the participants, the participants' perceptions of group collaboration problems and their causes, and information about the types of tools that they had previously used when working on collaborative group work. A total of 173 students responded, most of whom (i.e. 87% of the total) were students from 18 universities in the UK. The responses to the survey were analysed by quantitative analysis methods (Section 5.2.4).

Summarising the results obtained from the above survey, six major group collaboration problems were identified and each had several potential causes. The majority of the respondents had experienced most of the problems addressed to them. This provided a level of confidence that the problems were significant and they have been correctly identified. It was also found that there were no statistically significant association between the participants' background and their perceptions on the factors resulting in the problems addressed, and forums was the most frequently used type of asynchronous collaboration tools that was utilised by the respondents for completing online group work.

Based on the survey results, an XML-based representation of the linkages between the major collaboration problems and their causes identified was created (Section 5.5.1). The potential applications of this representation are two-fold (Section 5.5.2). The first is in supporting student self-reflection. The second is in facilitating the collaborative process.

The next two objectives focused on the proposal and development of an approach for diagnosing group collaboration problems based on student interactions with a collaborative learning environment and a supporting tool (Chapter 6). The main research question targeted for this part is how to be ascertained of the existence of different collaboration problems based on student interactions with a collaborative learning forum (Section 6.1). A dataset was successfully created based on the data collected from a web-based computer science group project (Section 6.2.2). This provided the data for accomplishing the predictive modelling process and the evaluation experiments. A diagnostic mechanism was constructed for addressing the main research question mentioned above, which comprised a set of developed (mathematical) models, algorithms and a chosen tool (Section 6.2). Other two subsidiary components were also developed which are complements to achieve the overall goal (Section 6.3 and 6.4).

A web-based tool was developed for the above approach, which mainly implemented the core diagnostic mechanism and the presentation of the diagnostic products for teachers. This tool enabled teachers to cope with the whole process of a diagnosis task with a set of prepared student interaction data. This implementation provides a proof-of-concept of the core research ideas that constitute the proposed approach.

This research continued with evaluating the performance of the core diagnostic mechanism developed on a test dataset (Chapter 7). The emphasis of this evaluation was laid on the validity of the predictive models and the diagnostic accuracy of the diagnostic algorithms established. Several experiments were performed and a mixture of methods was applied to conduct the experiments including apparent validation, split-sample validation, and a comparison-based method (Section 7.2). Quantitative methods were adopted for analyzing the results of the experiments (Section 7.2.4).

The findings from the above experiments showed that the predictive models constructed were statistically significant and they fit the development data well. The findings also revealed that the overall performance of the predictive models on the full development data was satisfied and these models were reproducible on independent data which were similar to the data where the models originated from. Moreover, the diagnostic algorithms obtained a satisfying rate of correct classification which indicated they performed effectively on the test dataset.

Having identified a set of components from the proposed approaches, the next goal focused on exploring a multi-agent architecture that could unify all the components into a single system for managing online collaborative learning (Chapter 8). Gaia methodology was adopted for analyzing and designing the agent-based architecture (Section 8.3). There were three reasons for this. The first was that Gaia could provide a diverse set of generic models which could avoid premature commitment to the detailed design and implementation process. The second reason lied in the fact that other agent-oriented methodologies were surplus to requirements such as TROPOS or not suitable for the modelling task such as ADELFE (which is for designing adaptive multi-agent systems). Finally, Gaia is a modelling methodology which could provide a set of agent-oriented concepts for modelling the features of agent-based systems while some other modelling methodologies such as OOAD could not. The detailed analysis and design process was presented in Section 8.4. This final architecture consisted of four types of agents and each agent played two or three key roles in managing online group work (Section 8.5). Since Chapter 8 was exploratory, no evaluation was carried out.

## 9.2 Research Contributions

There are three main contributions of this thesis.

The first contribution is a novel approach for group formation, which applies students' learning styles to form heterogeneous groups. Current research fails to suggest such an approach that can automatically and efficiently form learning style groups in web-based collaborative learning environments. As shown in Chapter 2, there currently exist few methods and software tools for forming learning style groups such as [124,140]. The problems with these methods lie in that they adopt either a manually-assigned or a complex process to form learning style groups which can be very time-consuming, and they are not originally targeted for collaborative learning environments. The novelty of the proposed approach is the provision of an automated grouping method that can tailor to individual students' learning styles and fit well into the existing collaborative learning environments. The evaluation not only indicates the feasibility of incorporating this approach into contemporary collaborative learning environments to support group formation, but also suggests the strength of this approach which is being capable of forming diverse groups that tend to perform more effectively and efficiently than similar groups for conducting group discussion tasks.

The second contribution relates to identifying major student-induced group collaboration problems and their causes from the perspectives of students, and providing a machine-readable form of the linkages between the problems and their causes identified. Current literature fails to adequately address this issue. The review of literature in Chapter 2 shows a number of empirical studies including but not limited to [8,71,81,93,118,142,143] which have revealed that there still exist a variety of problems in group collaboration, and student-induced problems are the most serious. These studies, however, based on individual empirical practice with a small sample size, do not identify the major student-induced problems for a wide population, and systematically address the factors that may cause such problems. The novelty and importance of the survey-based study presented in this thesis is the provision of a student perspective on the major student-induced group collaboration problems and their causes, and a unique perspective on the linkages between the problems and causes identified. This study supplements current literature, and can be used with other related research for providing a comprehensive view on what constitute group collaboration problems and their causes.

The third contribution is a novel approach for diagnosing the major student-induced group collaboration problems identified. This approach was developed to address the outstanding need for an automated and efficient approach that can ascertain the existence of the major collaboration problems for individual students and groups in a collaborative learning environment. As shown in Chapter 2, current research suggest the types of data that indicate the existence of the collaboration problems identified [9,30,33,91,164,166], and the general methods to obtain the data from a learning system or environment [21,33,125]. However, no research has addressed the issue of how to determine the existence of various collaboration problems identified based on student interactions with a collaborative learning environment. The originality and significance of this approach lies in the provision of various methods for ascertaining the existence of different student-induced group collaboration problems based on student interaction data that result from the group work examined. The overall positive evaluation results obtained strengthen this approach as a contribution to research and specifically, the collaborative learning environments and group collaboration field.

Besides the above main contributions, a multi-agent architecture was developed which unifies the components derived from the approaches proposed into a single system for managing online collaborative learning. This is viewed as a contribution to the thesis itself since it suggests an overarching framework providing context for other parts of the research and an interesting area that needs to be investigated further to progress the intelligent collaborative learning environments field.

## 9.3 Future Work

This section brings together the interesting topics for future research. These include the areas that can be strengthened for improving current work and the new questions for future study.

In terms of the evaluation of the proposed grouping algorithm, a wide generalisation was not the goal of this evaluation (Chapter 4). The conducted evaluation was based on a relatively small sample ($N$=20 students), however, it provided multi-dimension and in-depth information of the group collaborative processes examined. As discussed in Chapter 4, the findings from this evaluation can be generalised to a set of situations where similar group discussion tasks are performed. However, a more thorough evaluation of the grouping algorithm's effectiveness is needed if a wide generalisation is required. Two kinds of activities can be carried out for achieving this goal. First, conduct experiments on large samples. This can increase the possibility of gaining statistically significant results. Second, carry out experiments for various types of group work.

Regarding the evaluation of the proposed predictive models and diagnostic algorithms, the split-sample validation and the comparison-based diagnostic accurracy evaluation was based on relatively small smaples, respectively $N$=43 and $N$=18 (Chapter 7). This is because it was difficult to obtain larger samples for this evaluation due to the limited resouces available to this doctoral project. The difficulties of obtaining the required test data mainly lied in finding undergraduate modules which could provide the complete set of data for creating the test data set.

A wide generalisation could be achieved if an evaluation based on larger data samples could be conducted.

The next area to improve current work would be developing a prototype system that implements the defined multi-agent architecture for managing online collaborative learning. As discussed in Section 8.5, the analysis and design process following the Gaia methodology focused on modelling concrete concepts of the system to be built, but it did not refer to the implementation issues. However, this feature enables the implementation of the developed multi-agent architecture to be not limited to specific development languages and platforms. Two important issues should be decided for implementing the prototype system. First, an appropriate development platform should be selected. Possible platforms include JADE [24] and JADEX [144]. Second, the question of what process can be followed to implement the prototype system with the selected platform is needed to be addressed. The word “process” here refers to the procedure of converting the defined Gaia models to platform-specific codes. This kind of process has been defined for some current multi-agent development platforms such as the GAIA2JADE process for JADE [129]. If the prototype system could be developed, it would affirm the feasibility of adopting agents for constructing the overarching architecture for managing online collaborative learning.

There are a few new questions that arose from this research and can be investigated for future work. Chapter 5 developed an XML-based representation of the linkages between the major collaboration problems and their causes identified from the survey results. It was also noted that one potential application of this representation is in facilitating the collaborative process in online collaborative learning. As discussed in Section 5.5.2, a possible way of facilitation is suggesting appropriate learning advice to students that are identified to possess different collaboration problems. This leads to several questions which should be answered.

- What types of learning advice can be defined referring to the causes of individual collaboration problems defined in the XML?
- How to select appropriate learning advice to moderate different collaboration problems based on the linkages defined in the XML?
- How the learning advice should be presented to the students?
- How effective this learning advice-based facilitation approach?

The second area for extensions include establishing diagnostic mechanisms that are specific to Web 2.0 tools. One of the findings from the survey conducted for this thesis (Chapter 5) reveals that Web 2.0 tools such as wikis and blogs are widely used for supporting online group work (wikis with the second largest number of responses and blogs with the third largest responses as shown in Figure 5.2). The proposed diagnostic mechanism focuses only on forums, because forums was identified as the most frequently used tool for supporting web-based collaborative group work from the described survey (Figure 5.2). It is interesting to propose corresponding mechanisms for ascertaining the existence of student-induced group collaboration problems that arise from group work taken via Web 2.0 tools. This leads to the following quesitons:

- Whether do current Web 2.0 tools track student interactions with the systems? What kinds of students interactions data are available from these tools for revealing the existence of group collaboration problems?

- What methods can be proposed for determining the collaboration problems in question?
- How effective of the methods for diagnosing the collaboration problems?

Furthermore, the multi-agent architecture constructed in this thesis unifies the proposed components for group formation and collaboration problem diagnosis (Chapter 8). One interesting question has arised from this architecture, whether the results from diagnosing the group collaboration problems can be used to improve the grouping component so that the constructed student groups tend to possess less collaboration problems? The results of collaboration problem diagnosis include student and/or group collaboration problems. For answering the above question, the following sub-questions should be researched:

- Are there associations between the learning styles of students who own the group collaboration problem(s) and the types of problem(s) that they possess?
- What are the links between students' learning styles and the problems that are identified for them?
- How to improve the grouping component based on the links between learning styles and the collaboration problems that are identified?

# Bibliography


[1] Claroline: Open source collaborative e-learning and e-working platform. [Online]. Available: http://www.claroline.net/

[2] Ilias: Open source e-learning. [Online]. Available: http://www.ilias.de/docu/

[3] P. Adey, “Learning styles and strategies: A review of research,” London, UK: King's College London, School of Education, 1999.

[4] J. Ahn, “Personality of learners and group collaboration developments in e-learning,” in *Proceedings of the World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education*, 2003, pp. 1455-1458.

[5] R. M. Aiken, M.-N. Bessagnet and J. Israel, “Interaction and collaboration using an intelligent collaborative learning environment,” *Education and Information Technologies*, vol.10, no.1, pp. 67-82, 2005.

[6] O. N. Al-Shalchi, “The effectiveness and development of online discussions,” *Journal of Online Learning and Teaching*, vol.5, no.1, pp. 104-108, 2009.

[7] E. Alfonseca, R. M. Carro, E. Mart ń, A. Ortigosa and P. Paredes, “The impact of learning styles on student grouping for collaborative learning: A case study,” *User Modeling and User-Adapted Interaction*, vol.16, no.3-4, pp. 377-401, 2006.

[8] H. An, S. Kim and B. Kim, “Teacher perspectives on online collaborative learning: Factors perceived as facilitating and impeding successful online group work,” *Contemporary Issues in Technology and Teacher Education*, vol.8, no.1, pp. 65-83, 2008.

[9] A. R. Anaya and J. G. Boticario, “Application of machine learning techniques to analyse student interactions and improve the collaboration process,” *Expert Systems with Applications*, vol.38, no.2, pp. 1171-1181, 2011.

[10] A. Anderson, W. Cheyne, H. Foot, C. Howe, J. Low and A. Tolmie, “Computer support for peer-based methodology tutorials,” *Journal of Computer Assisted Learning*, vol.16, no.1, pp. 41-53, 2000.

[11] T. Anderson, R. Liam, D. R. Garrison and W. Archer, “Assessing teaching presence in a computer conferencing context,” *Journal of Asynchronous Learning Networks*, vol.5, no.2, 2001.

[12] Apache Software Foundation. Apache struts web framework. [Online]. Available: http://struts.apache.org/

[13] Apache Software Foundation. Apache tomcat. [Online]. Available: http://tomcat.apache.org/

[14] Applied Linguistics LLC. Grammarly: An automated proofreader. [Online]. Available: http://www.grammarly.com/

[15] K. Atkinson. Gnu aspell: A free and open source spell checker. [Online]. Available: http://aspell.net/

[16] Automattic Inc. After the deadline: A software service for language checking. [Online]. Available: http://afterthedeadline.com/

[17] M. S. Balaji and D. Chakrabarti, “Student interactions in online discussion forum: Empirical research from ‘media richness theory’ perspective,” *Journal of Interactive Online Learning*, vol.9, no.1, pp. 1-22, 2010.

[18] R. F. Bales, “Interaction process analysis: A method for the study of small groups,” Cambridge, MA: Addison Wesley, 1950.

[19] R. F. Bales, “A set of categories for the analysis of small group interaction,” *American Sociological Review*, vol.15, no.2, pp. 257-263, 1950.

[20] B. O. Barefoot, Second national survey of first-year academic practices, Technical Report, Gardner Institute, 2002.

[21] B. Barros and M. F. Verdejo, “Analysing student interaction processes in order to improve collaboration. The degree approach,” *International Journal of Artificial Intelligence in Education*, vol.11, no.3, pp. 221-241, 2000.

[22] B. Bauer, J. P. Muller and J. Odell, “Agent uml: A formalism for specifying multiagent software systems,” *International Journal of Software Engineering and Knowledge Engineering*, vol.11, no.3, pp. 1-24, 2001.

[23] M. F. Beaudoin, “Learning or lurking? Tracking the ‘invisible’ online student,” *Internet and Higher Education*, vol.5, no.2, pp. 147-55, 2002.

[24] F. Bellifemine, A. Poggi and G. Rimassa, “Jade - a fipa-compliant agent framework,” in *Proceedings of the 4th International Conference on the Practical Applications of Agents and MultiAgent Systems (PAAM99)*, 1999, pp. 97-108.

[25] C. Bernon, M. P. Gleizes, S. Peyruqueou and G. Picard, “ADELFE: A methodology for adaptive multi-agent systems engineering,” *Lecture Notes in Computer Science.*, no.2577, pp. 156-169, 2003.

[26] Blackboard Inc. Blackboard learn platform: Online learning tools for a better education experience. [Online]. Available: http://www.blackboard.com/Platforms/Learn/Overview.aspx

[27] T. Bohannon, “Predictive modelling in higher education,” in *SAS Global Forum*, 2007.

[28] D. Booth, H. Haas, F. McCabe, E. Newcomer, M. Champion, C. Ferris and D. Orchard, Web services architecture, Technical Report, http://www.w3.org/TR/ws-arch/, 2005.

[29] J. Borges, T. G. Dias and J. F. e. Cunha, “A new group-formation method for student projects,” *European Journal of Engineering Education*, vol.34, no.6, pp. 573-585, 2009.

[30] T. Bratitsis and A. Dimitracopoulou, “Indicators for measuring quality in asynchronous discussion forums,” in *Proceedings of International Conference on Cognition and Exploratory Learning in Digital Era (CELDA 2006)*, 2006, pp. 8-10.

[31] T. Bratitsis and A. Dimitracopoulou, “Interaction analysis as a multi-support approach of social computing for learning, in the ‘collaborative era’: Lessons learned by using the dias system,” in *Proceedings of the 8th IEEE International Conference on Advanced Learning Technologies (ICALT 2008)*, 2008, pp. 536-538.

[32] T. Bratitsis and A. Dimitracopoulou, “Monitoring and analysing group interactions in asynchronous discussions with the dias system,” in *Proceedings of the 12th International Workshop on Groupware (GRIWG 2006)*, 2006, pp. 54-61.

[33] T. Bratitsis and A. Dimitrkopoulou, “Data recording and usage interaction analysis in asynchronous discussions: The d.I.A.S. System,” in *Proceedings of the Workshop on Usage Analysis in Learning Systems*, 2005.

[34] P. Bresciani, A. Perini, P. Giorgini, F. Giunchiglia and J. Mylopoulos, “Tropos: An agent-oriented software development methodology,” *Autonomous Agents and Multi-Agent Systems*, vol.8, no.3, pp. 203-236, 2004.

[35] J. E. Brindley, C. Walti and L. M. Blaschke, “Creating effective collaborative learning groups in an online environment,” *The International Review of Research in Open and Distance Learning*, vol.10, no.3, 2009.

[36] S. Britain, A review of learning design: Concept, specifications and tools: A report for the jisc e-learning pedagogy programme, Technical Report, www.jisc.ac.uk/uploaded_documents/ACF1ABB.doc, 2004.

[37] J. Burdett, “Making groups work: University students' perceptions,” *International Educaiton Journal*, vol.4, no.3, pp. 177-191, 2003.

[38] M. A. Campion, G. J. Medsker and A. C. Higgs, “Relations between work group characteristics and effectiveness: Implications for designing effective work groups,” *Personnel Psychology*, vol.46, pp. 823-850, 1993.

[39] F. Cano and A. B. G. Berben, “University students’ achievement goals and approaches to learning in mathematics,” *British Journal of Educational Psychology*, vol.79, no.1, pp. 131-153, 2009.

[40] E. Caropreso and S.-J. Chen, “The impact of personality on collaborative online learning,” in *Proceedings of the International Conference Society for Information Technology & Teacher Education*, 2003, pp. 2371-2375.

[41] C. A. Carver, Jr., R. A. Howard and W. D. Lane, “Enhancing student learning through hypermedia courseware and incorporation of student learning styles,” *IEEE transactions on education*, vol.42, no.1, pp. 33, 1999.

[42] S. L. Chang, “Using online concept mapping with peer learning to enhance concept application,” *The Quarterly Review of Distance Education*, vol.9, no.1, pp. 17-27, 2008.

[43] S. Chatterjee and A. S. Hadi, “Regression analysis by example,” Hoboken, N.J.: Wiley-Interscience, 2006.

[44] K. W. Cheng, “The effect of web-based collaborative learning methods to the accounting courses in technical education,” *College Student Journal*, vol.43, no.3, pp. 2009.

[45] M. R. Chernick, “Bootstrap methods : A guide for practitioners and researchers,” Hoboken, N.J.: Wiley-Interscience, 2008.

[46] F. Coffield, D. Moseley, E. Hall and K. Ecclestone, “Should we be using learning styles? What research has to say to practice,” London: Learning and Skills Research Centre, 2004.

[47] E. G. Cohen, “Restructuring the classroom: Conditions for productive small groups,” *Review of Educational Research*, vol.64, no.1, pp. 1-35, 1994.

[48] S. G. Cohen and D. E. Bailey, “What makes teams work: Group effectiveness research from the shop floor to the executive suite,” *Journal of Management*, vol.23, no.3, pp. 239-290, 1997.

[49] J. Dalziel, “Implementing learning design: The learning activity management system (LAMS),” in *Proceedings of the 20th Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education*, 2003, pp. 593-596.

[50] T. Daradoumis, S. Caballé, J. M. Marquès and F. Xhafa, “Intelligent collaborative e-learning systems and applications,” Berlin: Springer, 2009.

[51] A. C. Davison and D. V. Hinkley, “Bootstrap methods and their application,” Cambridge; New York, NY, USA: Cambridge University Press, 1997.

[52] B. De Wever, T. Schellens, M. Valcke and H. Van Keer, “Content analysis schemes to analyze transcripts of online asynchronous discussion groups: A review,” *Computers & Education*, vol.46, no.1, pp. 6-28, 2006.

[53] K. Deibel, “Team formation methods for increasing interaction during in-class group work,” *SIGCSE BULLETIN*, vol.37, no.3, pp. 291-295, 2005.

[54] P. Dillenbourg and D. Schneider, “Collaborative learning and the internet,” in *Proceedings of the International Conference Computer Assisted Instruction*, 1995, pp. 6-13.

[55] A. Dimitracopoulou, “Computer based interaction analysis supporting self-regulation: Achievements and prospects of an emerging research direction,” *Technology, Instruction, Cognition and Learning*, vol.6, no.4, pp. 291-314, 2009.

[56] L. Dykes and E. Tittel, “XML for dummies,” Hoboken, N.J.: Wiley, 2005.

[57] Eclipse Foundation. Eclipse IDE for Java EE developers. [Online]. Available: http://eclipse.org/downloads/moreinfo/jee.php

[58] A. P. Ellis, J. R. Hollenbeck, D. R. Ilgen, C. O. Porter, B. J. West and H. Moon, “Team learning: Collectively connecting the dots,” *Journal of Applied Psychology*, vol.88, no.5, pp. 821-835, 2003.

[59] E. S. J. d. Faria, J. M. Adan-Coello and K. Yamanaka, “Forming groups for collaborative learning in introductory computer programming courses based on students' programming styles: An empirical study,” in *Proceedings of 36th Annual Conference on Frontiers in Education*, 2006, pp. 6-11.

[60] R. M. Felder, “Reaching the second tier--learning and teaching styles in college science education,” *Journal of College Science Teaching*, vol.22, no.5, pp. 286-290, 1993.

[61] R. M. Felder and L. K. Silverman, “Learning styles and teaching styles in engineering education,” *Engineering Education*, vol.78, no.7, pp. 674-681, 1988.

[62] R. M. Felder and B. A. Soloman. Index of learning styles questionnaire. [Online]. Available: http://www.engr.ncsu.edu/learningstyles/ilsweb.html

[63] R. M. Felder and J. Spurlin, “Applications, reliability and validity of the index of learning styles,” *International Journal of Engineering Education*, vol.21, no.1, pp. 103-112, 2005.

[64] A. P. Field, “Discovering statistics using spss,” Los Angeles; London: SAGE Publications, 2009.

[65] N. D. Fleming and C. Bonwell. Vark learning styles inventory. [Online]. Available: http://www.vark-learn.com/english/page.asp?p=questionnaire

[66] N. D. Fleming and C. Mills, “Not another inventory, rather a catalyst for reflection,” *To Improve the Academy*, vol.11, pp. 137, 1992.

[67] D. R. Forsyth, “Group dynamics,” Belmont, California: Wadsworth Cengage Learning, 2009.

[68] FSF.hu Foundation. Hunspell: A open source spell checker. [Online]. Available: http://hunspell.sourceforge.net/index.html

[69] J. P. Gee, “An introduction to discourse analysis : Theory and method,” New York: Routledge, 2005.

[70] R. G. Gibson, “Object oriented technologies : Opportunities and challenges,” Hershey, PA: Idea Group, 1999.

[71] P. K. Gilbert and N. Dabbagh, “How to structure online discussions for meaningful discourse: A case study,” *British Journal of Educational Technology*, vol.36, no.1, pp. 5-18, 2005.

[72] P. M. Griffin, S. O. Griffin and D. C. Llewellyn, “The impact of group size and project duration on capstone design,” *Journal of engineering education*, vol.93, no.3, pp. 185-194, 2004.

[73] N. Griffiths and K. M. Chao, “Agent-based service-oriented computing,” London; New York: Springer, 2010.

[74] M. Grigoriadou, K. Papanikolaou and E. Gouli, “Investigating how to group students based on their learning styles,” in *Proceedings of the IEEE International Conference on Advanced Learning Technologies*, 2006, pp. 1139-1140.

[75] M. S. Hamdi, “Masacad: A multi-agent approach to information customization for the purpose of academic advising of students,” *Applied Soft Computing*, vol.7, no.3, pp. 746-771, 2007.

[76] J. D. Hamilton, “Time series analysis,” Princeton, N.J.: Princeton University Press, 1994.

[77] S. Hans, M. Anne, R. Nikol and H. Sabine, “A new method to assess the quality of collaborative process in CSCL,” in *Proceedings of the 2005 Conference on Computer Supported collaborative learning: The next 10 years!*, 2005, pp. 622-631.

[78] E. R. Harold and W. S. Means, “XML in a nutshell,” Sebastopol, CA: O'Reilly, 2004.

[79] F. E. Harrell, “Regression modeling strategies : With applications to linear models, logistic regression, and survival analysis,” New York: Springer, 2001.

[80] A. Hassanien, “A qualitative student evaluation of group learning in higher education,” *Higher Education in Europe*, vol.32, no.2-3, pp. 135-150, 2007.

[81] M. Herrick, M.-F. G. Lin and C. Huei-Wen, “Online discussions: The effect of having two deadlines,” in *Proceedings of Society for Information Technology & Teacher Education International Conference 2011*, 2011, pp. 344-351.

[82] K. F. Hew and W. S. Cheung, “Attracting student participation in asynchronous online discussions: A case study of peer facilitation,” *Computers & Education*, vol.51, no.3, pp. 1111-1124, 2008.

[83] S. R. Hiltz and M. Turoff, “What makes learning networks effective?,” in *Communications of the ACM*, 2002, vol.45, no.4, pp. 56-59.

[84] M. Hishina, R. Okada and K. Suzuki, “Group formation for web-based collaborative learning with personality information,” *International Journal on E-Learning*, vol.4, no.3, pp. 351-364, 2005.

[85] P. Honey and A. Mumford, “The manual of learning styles,” Maidenhead: Peter Honey Publications, 1982.

[86] D. W. Hosmer and S. Lemeshow, “Applied logistic regression,” New York: Wiley, 2000.

[87] A. Hron and H. F. Friedrich, “A review of web-based collaborative learning: Factors beyond technology,” *Journal of Computer Assisted Learning*, vol.19, no.1, pp. 70-79, 2003.

[88] M. Idzelis. Jazzy: The Java open source spell checker. [Online]. Available: http://jazzy.sourceforge.net/

[89] D. W. Johnson and R. T. Johnson, “Cooperation and the use of technology,” in *Handbook of research on educational communications and technology, 2nd ed.*, Mahwah, NJ: Lawrence Erlbaum Associates, 2004, pp. 785-811.

[90] M. Jones, J. Humphreys and D. Prideaux, “Predicting medical students intentions to take up rural practice after graduation,” *Medical Education*, vol.43, no.10, pp. 1001-1009, 2009.

[91] N. Jun, H. Shinichi, Y. Kazaru and Y. Yuhei, “Itree: Does the mobile phone encourage learners to be more involved in collaborative learning?,” in *Proceedings of the 2005 Conference on Computer Supported Collaborative Learning: The next 10 years!*, 2005, pp. 470-478.

[92] A. Khamesan and N. Hammond, “Synchronous collaborative concept mapping via ICT: Learning effectiveness and personal and interpersonal awareness,” in *Proceedings of the 1st International Conference on Concept Mapping*, 2004.

[93] N. Khandaker and L. K. Soh, “Assessing individual contributions to groupwork by a summary of tracked computer-supported collaborative activities,” in *Proceeding of Frontiers in Education Conference (FIE)*, 2010, pp. 1-6.

[94] D. Kinny, M. Georgeff and A. Rao, “A methodology and modelling technique for systems of bdi agents,” in *Proceedings of the 7th European Workshop on Modelling Autonomous Agents in a Multi-Agent World*, 1996, pp. 56-71.

[95] J. P. Klein and M. L. Moeschberger, “Survival analysis : Techniques for censored and truncated data,” New York: Springer, 1997.

[96] D. A. Kolb, Hay Resources Direct and Hay Group, “The kolb learning style inventory,” Boston, Mass.: Hay Resources Direct, 2007.

[97] V. Kollias, N. Mamalougos, X. Vamvakoussi, M. Lakkala and S. Vosniadou, “Teachers’ attitudes to and beliefs about web-based collaborative learning environments in the context of an international implementation,” *Computers & Education*, vol.45, no.3, pp. 295-315, 2005.

[98] J. Kuljis and F. Liu, “A comparison of learning style theories on the suitability for elearning,” in *Proceedings of the IASTED Conference on Web Technologies, Applications, and Services*, 2005, pp. 191-197.

[99] Y. Lafifi and T. Bensebaa, “Learners' assessment in a collaborative learning system,” *Asian Journal of Information Technology*, vol.6, no.2, pp. 145-153, 2007.

[100] F.-Q. Lai, K. Snapp and C. Burk, “Online peer evaluation as an assessment and collaborative learning approach: Perspectives from two students,” in

*Proceedings of Society for Information Technology & Teacher Education International Conference 2011*, 2011, pp. 437-441.

[101] M. S. Lambert, T. T. Miriam and F. M. Susan, "Predictive modelling," Betascript Publishing, 2010.

[102] LAMS Foundation Limited. Lams: Learning activity management system. [Online]. Available: http://lamsfoundation.org/index.htm

[103] W. Lan, Z. Wei-Wei and L. Yu-Fen, "An empirical study on the prediction model of postgraduate education in hebei province," in *Proceedings of the 2010 International Conference on Machine Learning and Cybernetics (ICMLC 2010)*, 2010, pp. 1327-1331.

[104] Y. Li, M. Dong and R. Huang, "Toward a semantic forum for active collaborative learning," *Educational Technology & Society*, vol.12, no.4, pp. 71-86, 2009.

[105] Y. Li and R. Huang, "Analyzing peer interactions in computer-supported collaborative learning: Model, method and tool," in *Proceedings of the 1st International Conference on Hybrid Learning and Education (ICHL 2008)*, 2008, pp. 125-136.

[106] Y. Li, J. Wang, J. Liao, D. Zhao and R. Huang, "Assessing collaborative process in cscl with an intelligent content analysis toolkit," in *Proceedings of 7th IEEE International Conference on Advanced Learning Technologies (ICALT 2007)*, 2007, pp. 257-261.

[107] M. B. Ligorio and M. Veermans, "Perspectives and patterns in developing and implementing international web-based collaborative learning environments," *Computers & Education*, vol.45, no.3, pp. 271-275, 2005.

[108] T. A. Litzinger, S. H. Lee, J. C. Wise and R. M. Felder, "A psychometric study of the index of learning styles," *Journal of Engineering Education*, vol.96, no.4, pp. 309-320, 2007.

[109] S. Liu and M. Joy, "A diagnostic mechanism and tool for analyzing group collaboration problems with online group work," in *Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education (ELEARN 2011)*, 2011, pp. 2613-2618.

[110] S. Liu and M. Joy, "Discovering student interactions with a collaborative learning forum that predict group collaboration problems," in *Proceedings*

*of International Conference of Education, Research and Innovation (ICERI 2011)*, 2011.

[111] S. Liu, M. Joy and N. Griffiths, "The effects of learning styles on group formation for undergraduate students' group work: An exploratory empirical study," *Effective Education, Under Revision*, 2012.

[112] S. Liu, M. Joy and N. Griffiths, "Gaoole: A gaia design of agent-based online collaborative learning environment," in *Proceedings of the 8th European Conference on eLearning (ECEL 2009)*, 2009, pp. 339-350.

[113] S. Liu, M. Joy and N. Griffiths, "iGLS: Intelligent grouping for online collaborative learning," in *Proceedings of the 9th IEEE International Conference on Advanced Learning Technologies (ICALT 2009),* 2009, pp. 364-368.

[114] S. Liu, M. Joy and N. Griffiths, "Incorporating learning styles in a computer-supported collaborative learning model," in *Proceedings of the International Workshop on Cognitive Aspects in Intelligent and Adaptive Web-based Education Systems (CIAWES 2008)*, 2008, pp. 3-10.

[115] S. Liu, M. Joy and N. Griffiths, "Students' perceptions of the factors leading to unsuccessful group collaboration," in *Proceedings of the 10th IEEE International Conference on Advanced Learning Technologies (ICALT 2010)*, 2010, pp. 565-569.

[116] Z. Liu, H. Jin and Z. Fang, "Collaborative learning in e-learning based on multi-agent systems," in *Proceedings of the 10th IEEE International Conference on Computer Supported Cooperative Work in Design (CSCWD 2006)*, 2006, pp. 1-5.

[117] Z. F. Liu and S. S. Cheng, "The student satisfaction and effect of group discussion on networked cooperative learning with the portfolio assessment system," *International Journal of Education and Information Technologies*, vol.1, no.3, pp. 161-166, 2007.

[118] J. Loh and R. Smyth, "Understanding students' online learning experiences in virtual teams," *Journal of Online Learning and Teaching*, vol.6, no.2, pp. 335-342, 2010.

[119] P. Lowry, T. Roberts, N. Romano, P. Cheney and R. Hightower, “The impact of group size and social presence on small-group communication,” *Small Group Research*, vol.37, no.6, pp. 631-661, 2006.

[120] R. J. Magjuka and T. T. Baldwin, “Team-based employee involvement programs: Effects of design and administration,” *Personnel Psychology*, vol.44, pp. 793-812, 1991.

[121] H. Mahdi and S. S. Attia, “Masce: A multi-agent system for collaborative e-learning,” in *Proceedings of IEEE/ACS International Conference on Computer Systems and Applications (AICCSA 2008)*, 2008, pp. 925-926.

[122] H. Mahdi and S. A. Sally, “Developing and implementing a multi-agent system for collaborative e-learning,” in *E-learning*, InTech, 2010, ch. 2, pp. 19-42.

[123] S. Mahenthiran and P. J. Rouse, “The impact of group selection on student performance and satisfaction,” *International Journal of Educational Management*, vol.14, no.6, pp. 255-264, 2000.

[124] Maria Kyprianidou, Stavros Demetriadis, Andreas Pombortsis and G. Karatasios, “Pegasus: Designing a system for supporting group activity,” *Multicultural Education & Technology Journal*, vol.3, no.1, pp. 47-60, 2009.

[125] M. May, S. George and P. Prevot, “Travis to enhance students’ self-monitoring in online learning supported by computer-mediated communication tools,” *International Journal of Computer Information Systems and Industrial Management Applications*, vol.3, pp. 623-634, 2011.

[126] S. Mencke and R. Dumke, “A framework for agent-supported e-learning,” in *Proceedings of the International Conference on Interactive Computer Aided Learning (ICL 2007)*, 2007.

[127] B. Millis. Managing—and motivating!—distance learning group activities. [Online]. Available: http://www.tltgroup.org/gilbert/millis.htm

[128] Moodle.org. Moodle: Open-source community-based tools for learning. [Online]. Available: http://moodle.org/

[129] P. Moraitis and N. Spanoudakis, "The gaia2jade process for multi-agent systems development," *Applied Artificial Intelligence*, vol.20, no.2-4, pp. 251-273, 2006.

[130] J. Moreno, D. A. Ovalle and R. M. Vicari, "A genetic algorithm approach for group formation in collaborative learning considering multiple student characteristics," *Computers & Education*, vol.58, no.1, pp. 560-569, 2012.

[131] R. Mudge, "The design of a proofreading software service," in *Proceedings of the NAACL HLT 2010 Workshop on Computational Linguistics and Writing*, 2010, pp. 24-32.

[132] I. B. Myers and M. H. McCaulley, "Manual: A guide to the development and use of the myers-briggs type indicator," Palo Alto, CA: Consulting Psychologists Press, 1985.

[133] D. Naber, "A rule-based style and grammar checker," Diplomarbeit Technis Fakultät, Universität Bielefeld, Germany, 2003.

[134] T. Nielsen, "Inventory and manual for the danish self-assessment learning styles inventory," unpublished work, 2005.

[135] T. Nielsen, A. E. Hvas and A. Kjaergaard, "Student team formation based on learning styles at university start: Does it make a difference to the students?," *Reflecting Education*, vol.5, no.2, pp. 85-103, 2009.

[136] R. Nisbet, J. F. Elder and G. Miner, "Handbook of statistical analysis and data mining applications," Amsterdam; Boston: Academic Press/Elsevier, 2009.

[137] A. C. North, P. A. Linley and D. J. Hargreaves, "Social loafing in a co-operative classroom task," *Educational Psychology*, vol.20, no.4, pp. 389-392, 2000.

[138] A. Ounnas, H. Davis and D. Millard, "A framework for semantic group formation," in *Proceedings of the 8th IEEE International Conference on Advanced Learning Technologies (ICALT 2008)*, 2008, pp. 34-38.

[139] K. Papanikolaou, E. Gouli and M. Grigoriadou, "Accommodating individual differences in group formation for collaborative concept mapping," in *Proceedings of the 2nd International Conference on Concept Mapping*, 2006, pp. 16-23.

[140] P. Paredes, A. Ortigosa and P. Rodriguez, “A method for supporting heterogeneous-group formation through heuristics and visualization,” *Journal of Universal Computer Science*, vol.16, no.19, pp. 2882-2901, 2010.

[141] M. Pattie, “Agents that reduce work and information overload,” *Communications of the ACM*, vol.37, no.7, pp. 30-40, 1994.

[142] T. Paulus, “Online but off-topic: Negotiating common ground in small learning groups,” *Instructional Science*, vol.37, no.3, pp. 227-245, 2009.

[143] S. L. Piezon and W. D. Ferree, “Perceptions of social loafing in online learning groups: A study of public university and u.S. Naval war college students,” *The International Review of Research in Open and Distance Learning*, vol.9, no.2, 2008.

[144] A. Pokahr, L. Braubach and W. Lamersdorf, “Jadex: Implementing a bdi-infrastructure for jade agents,” in *EXP*, 2003, vol.3, no.3, pp. 76-85.

[145] S. Puntambekar, G. Erkens and C. E. Hmelo-Silver, “Analyzing interactions in cscl: Methods, approaches and issues,” New York: Springer, 2011.

[146] M. Rao and P. Georgeff, “Bdi-agents: From theory to practice,” in *Proceedings of the 1st International Conference on Multiagent Systems (ICMAS 95)*, 1995, pp. 312-319.

[147] M. A. Razek, C. Frasson and M. Kaltenbach, “Toward more cooperative intelligent distance learning environments,” in *Proceedings of the Workshop on Software Agents - Co-operation - Human Activity (SACHA 2002) - ITS Conference*, 2002.

[148] M. A. Redmond, “A computer program to aid assignment of student project groups,” in *Proceedings of SIGCSE'01*, 2001, pp. 134-138.

[149] P. Reimann, “How to support groups in learning: More than problem solving,” in *Supplementary Proceedings of the 11th International Conference on Artificial Intelligence in Education (AIED 2003)*, 2003, pp. 3-16.

[150] R. Riding and I. Cheema, “Cognitive styles-an overview and integration,” *Educational Psychology*, vol.11, no.3, pp. 193 - 215, 1991.

[151] T. S. Roberts and J. M. McInnerney, “Seven problems of online group learning (and their solutions),” *Educational Technology & Society*, vol.10, no.4, pp. 257-268, 2007.

[152] E. J. Robertson, “The effects of learning styles on group development in an online learning environment,” Master of Science Thesis, Department of Education, University of North Carolina Wilmington, Wilmington, N.C., 2005.

[153] W. Rubens, B. Emans, T. Leinonen, A. G. Skarmeta and R.-J. Simons, “Design of web-based collaborative learning environments. Translating the pedagogical learning principles to human computer interface,” *Computers & Education*, vol.45, no.3, pp. 276-294, 2005.

[154] R. H. Rutherfoord, “Using personality inventories to form teams for class projects: A case study,” in *Proceedings of the 7th Conference on Information Technology Education (SIGITE 2006)*, 2006, pp. 9-14.

[155] D. A. Sandmire and P. F. Boyce, “Pairing of opposite learning styles among allied health students: Effects on collaborative performance,” *Journal of Allied Health*, vol.33, no.2, pp. 156-163, 2004.

[156] J. A. Schellenberg, “Group size as a factor in success of academic discussion groups,” *The Journal of Educational Sociology*, vol.33, no.2, pp. 73-79, 1959.

[157] P. Sentas, L. Angelis and I. Stamelos, “Multinominal logistic regression applied on software productivity prediction,” in *Proceedings of the 9th Panhellenic conference in informatics*, 2003.

[158] G. G. Smith, C. Sorensen, A. Gump, A. J. Heindel, M. Caris and C. D. Martinez, “Overcoming student resistance to group work: Online versus face-to-face,” *The Internet and Higher Education*, vol.14, no.2, pp. 121-128, 2011.

[159] L.-K. Soh, N. Khandaker, X. Liu and H. Jiang, “A computer-supported cooperative learning system with multiagent intelligence,” in *Proceedings of the 5th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2006)*, 2006, pp. 1556 - 1563.

[160] SPSS Inc., “Ibm spss statistics 19 algorithms,” U.S. Patent 7023453, 2010.

[161] D. S. Stein and C. E. Wanstreet, “Role of social presence, choice of online or face-to-face group format, and satisfaction with perceived knowledge gained in a distance learning environment,” in *Midwest Research-to-Practice Conference in Adult, Continuing, and Community Education*, 2003.

[162] I. Steiner, “Group process and productivity,” Academic Press, 1972.

[163] N. Stoyanova and P. Kommers, “Concept mapping as a medium of shared cognition in computer supported collaborative problem solving,” *Journal of Interactive Learning Research*, vol.13, no.1-2, pp. 111-133, 2002.

[164] L. Talavera and E. Caudioso, “Mining student data to characterize similar behaviour groups in unstructured collaboration spaces,” in *Proceedings of the Workshop on AI in CSCL*, 2004, pp. 17-23.

[165] R. Taylor, “The effects of using learning styles inventories to create more effective groups in project based learning activities,” *The Divergent Learning Journal, Fall 2010 Edition*, pp. 31-36, 2010.

[166] M. Toshio, K. Hiroshi, Y. Kazaru, N. Tomoko, N. Toshihisa, H. Shin-ichi, F. Satoru, N. Jun and S. Mariko, “Promotion of self-assessment for learners in online discussion using the visualization software,” in *Proceedings of the 2005 conference on Computer support for collaborative learning: learning 2005: the next 10 years!*, 2005.

[167] A. J. S. F. Visschers-Pleijers, D. H. J. M. Dolmans, I. H. A. P. Wolfhagen and C. P. M. van der Vleuten, “Development and validation of a questionnaire to identify learning-oriented group interactions in PBL,” *Medical Teacher*, vol.27, no.4, pp. 375-381, 2005.

[168] D.-Y. Wang, S. S. J. Lin and C.-T. Sun, “Diana: A computer-supported heterogeneous grouping system for teachers to conduct successful small learning groups,” *Computers in Human Behavior*, vol.23, no.4, pp. 1997-2010, 2007.

[169] M. E. Warkentin, L. Sayeed and R. Hightower, “Virtual teams versus face-to-face teams: An exploratory study of a web-based conference system,” *Decision Sciences*, vol.28, no.4, pp. 975-994, 1997.

[170] M. Wessner and H. R. Pfister, “Group formation in computer-supported collaborative learning,” in *Proceedings of the 2001 International ACM*

*SIGGROUP Conference on Supporting Group Work (GROUP 2001)*, 2001, pp. 24-31.

[171] S. Williams van Rooij, “Open-source learning management systems: A predictive model for higher education,” *Journal of Computer Assisted Learning*, to appear, 2011.

[172] M. Wooldridge, N. R. Jennings and D. Kinny, “The gaia methodology for agent-oriented analysis and design ” *Journal of Autonomous Agents and Multi-Agent Systems*, vol.3, no.3, pp. 285-312, 2000.

[173] J. Yeo, Y.-J. Lee, A.-L. Tan, S.-C. Tan and S. Lum, “Analyzing cscl-mediated science argumentation: How different methods matter,” in *Proceedings of the 9th International Conference on Computer-Supported Collaborative Learning (CSCL 2009)*, 2009, pp. 113-117.

[174] F. Zambonelli, N. R. Jennings and M. Wooldridge, “Developing multiagent systems: The gaia methodology,” *ACM Transactions on Software Engineering and Methodology*, vol.12, no.3, pp. 317-370, 2003.

[175] H. Zhuge, Y. Li, J. Bi and T. y. Cheung, “Kgcl: A knowledge-grid-based cooperative learning environment,” *Lecture Notes in Computer Science.*, no.2436, pp. 192-202, 2002.