智慧型電腦分組系統之設計與評估

研究生：王岱伊　　　　　　　　　　　　　指導教授：孫春在 博士
林珊如 博士

國立交通大學資訊科學與工程研究所

摘要

好的開始是成功的一半！所以設計出良好的小組是相當重要的。但由於各領域其影響小組成效的因素有所不同，因此本論文將研究範圍限定在教育上，探討如何將一個班級的學生組成許多良好的合作學習小組。

合作學習廣泛地被各級學校所採用，但課堂教師最常採用的分組方式是隨機抽籤或由學生自行組隊，很難可以如教育理論所建議的—採用學生的心理特質進行異質分組，以提供合作學習的成功機率。因此本論文提出一套嶄新的異質分組系統，希望基於教育理論、以資訊技術爲工具，協助教師得以進行更精緻化的合作學習。

本系統中，提供兩種異質分組法—DIANA、FUTS。DIANA 分組法基於教育公平性，以基因演算法尋找較佳的分組可能，提供組內異質、組間同質的分組建議。FUTS 分組法基於心理學大師 Sternberg 的建議，以反覆改善演算法，企圖組合出各小組風格皆相當顯著的組合。

本論文中，以合作設計教學實驗(475 人)來驗證這兩種分組法的效能，發現其在成績與學生滿意度上皆顯著優於隨機分組，且學生年級及樣本密度此二權變因素與分組法有顯著的交互作用。實驗結果建議國小教師可採用 DIANA 平衡分組法，國中教師可採用 DIANA 與 FUTS 分組法。

Computer-Supported Grouping Systems Based on AI Technologies: Design and Evaluation

Student: Dai-Yi Wang

Advisors: Dr. Chuen-Tsai Sun
Dr. Sunny San Ju Lin

Institute of Computer Science and Engineering
National Chiao Tung Univesity

Abstract

Many Computer-Supported Collaborative Learning (CSCL) systems emphasize the use of technical tools to support effective/productive social interaction, social knowledge construction, and reflection. Only a handful of CSCL mediating tools provide help for the task of composing groups with good chances of success in task achievement and learning, and even fewer offer algorithm-based recommendations for establishing groups from a large pool of students with various characteristics and/or learning capacities. The author describes her work with other designers to create two computer-supported grouping systems. The first, named Differences In And Non-differences Among groups (DIANA), uses genetic algorithms to achieve fairness, equity, flexibility, and balance. The other, named Full Thinking Styles groups (FTS), uses iterative improvement algorithms to ensure the representation of all possible thinking styles in each team. DIANA and FTS were tested with 475 students assigned to groups of three, either randomly (63 groups), using DIANA (52), or using FTS (43). The results indicate that a) DIANA and FTS groups outperformed random groups overall, b) DIANA groups outperformed FTS and random groups in elementary school settings, and c) DIANA and FTS groups outperformed random groups in junior high school settings. Suggestions for applying computer-supported group composition systems are offered.

誌　　謝

本論文能夠順利地完成，不是單單只倚靠個人的辛苦以及努力，而是要歸功於許多人的指導、協助。在此，希望以我最誠摯的心意，向你們說聲「謝謝」。

首先感謝我的指導教授孫春在教授，由於他不吝於分享其豐富的經驗與知識，讓我學會以更寬廣的視野去看事情、做研究。感謝共同指導教授林珊如教授，給予我論文上認真地指導與細心地協助、耐心地傾聽我的想法、關心我的狀況，讓我的博士生涯注入了許多溫暖與陽光。其次，感謝曾憲雄教授與袁賢銘教授對本論文的指導與建議，使本論文得以更為完整。第三，要感謝口試委員陳國棟教授、王淑玲博士、游寶達教授、張隆紋教授對於本論文之指正與建議。

我亦非常感謝研究室的許多伙伴們：佩嵐的鼓勵與討論；宗元、偉民在口試時所給予的協助；政隆、文力、金村、森德辛苦幫忙做實驗；還有許多學長、同學、學弟妹們的關心，謝謝你們！

感謝我的好朋友們：謝謝體貼細心的學妹圈圈總是陪我吃飯聊天，排解苦悶；謝謝育瑋聽我抱怨，幫我解決問題；謝謝小婷讓我的娛樂不匱乏；謝謝貼心的小愷總是陪我熬夜；謝謝親愛的高中同學龜龜、JUJU、阿豆、阿奶、雅雅、小花、阿瓜、大胖，因為有你們的友情支柱，我不怕困難！

最後，最最最感謝的就是我的家人，爸爸、媽媽、大姐、二姐、小妹在我這二十年的求學生涯中，不斷地對我付出、關懷，以及那份永無止盡的愛，讓我可以無後顧之憂地、恣意地享受自己所選擇的生活。

王岱伊　　謹於

交通大學

中華民國九十五年六月

Contents

List of Figures

List of Tables

Chapter 1
Introduction

1.1 Benefits of cooperative learning and computer supported cooperative learning

Cooperative learning is recognized as an effective teaching approach that benefits students in terms of achievement, motivation, and social skills (Cohen, 1994a; Johnson & Johnson, 1989; Sharan, 1999; Slavin, 1995). Research results have shown that cooperative learning benefits students in terms of cognition (e.g., gaining higher achievement), affect (e.g., positive motivation), and behavior (e.g., social skills). Numerous studies have been conducted on factors that influence cooperative learning success, including intra-group interdependence, group development, task demands, resources, group process, and issues of race and ethnicity (Abrami, Chambers, Poulsen, De Simone, d'Apollonia & Howden, 1995; Cohen, 1994b; Johnson & Johnson, 1994; Kagan, 1994; Sharan & Sharan, 1992; Slavin, 1995). The literature contains a great deal of evidence and examples to serve as guides for teachers.

Computer-supported cooperative learning (CSCL) (especially in conjunction with information technologies) also promises a number of innovations to improve teaching and learning (Scardamalia & Bereiter, 1994; Suthers & Jones, 1997; Vosniadou, Corte, Glaser& Mandl, 1996). Many researchers have demonstrated how the sophisticated use of technical applications such as e-mail, electronic bulletin boards, conferencing systems, and specialized groupware can facilitate cooperative learning (Coleman, 1997). Most emphasize the use of technical tools to support effective/productive social interaction, social knowledge construction, and reflection.

1.2 Theory versus the reality of the classroom

Managing cooperative or small group learning efforts poses challenges for teachers, who often must deal with students who lack the requisite social skills, have problems with social loafing, or problems with time management (Johnson & Johnson, 1991). Experienced teachers know that simply putting students together to perform a task does not ensure quality cooperative learning. As Johnson and Johnson (1990) and Slavin (1995) have observed, successful cooperative learning requires positive interdependence, meaningful interaction, individual accountability, collaborative skills training, and appropriate rewards.

Although many CSCL systems are well-designed according to established principles for the construction of cooperative learning environments (Strijbos, Martens & Jochems, 2004), many teachers face major problems at the very beginning of a project due to a lack of knowledge of how to form groups that have better chances to execute successful teamwork. In this area, few studies offer helpful advice about the effects of various grouping methods. The result: many teachers allow students to form their own groups or create groups via random assignment or according to seat arrangement.

Teachers who are more accustomed to traditional learning techniques but who want to try cooperative learning must make two important efforts. First, they need to identify specific student characteristics for establishing groups—for example, race, gender, and ability (Cohen & Lotan, 1997; Cordero, DiTomaso & Farris, 1996; Savicki, Kelley & Lingenfelter, 1996), self-efficacy (Bandura, 1997), learning style

(Sternberg, 1998), and other factors that strongly affect group learning outcomes. Second, teachers must consider group type—heterogeneous or homogeneous. According to Dembo (1994), many cooperative and small-group learning researchers believe that heterogeneous groups are more likely to a) provide opportunities for students to learn how to interact with different types of classmates, and b) improve chances of academic success (Cohen, 1994a; Johnson & Johnson, 1994). However, there is evidence showing that extreme differences among group members can impair cooperation (Webb, 1989).

Currently there are very few CSCL mediating tools that provide help for composing groups and even fewer that offer recommendation algorithms for selecting team members from a large pool of students based on various characteristics and/or learning capacities. Thus, even though CSCL techniques are gaining popularity, using them correctly poses challenges for the majority of teachers.

1.3 Object—early success

To enhance cooperative learning potentiality, I created a framework to help teachers use elaborative group composition methods that can improve the odds of implementing successful cooperative learning projects. The framework employs powerful information computation techniques to create groups according to principles identified by educational researchers and theorists. The three primary design principles are

1. Taking into consideration psychological features that are relevant to learning outcomes. For example, Sternberg (1998) emphasizes thinking styles to promote effective cooperative learning. The framework described in this paper uses thinking

style as an exemplar that represents all possible psychological aspects of learners.

2. It was assumed that heterogeneity is a better goal than homogeneity because it promotes diversity in student characteristics and equips groups with tools for achieving multiple learning purposes (Johnson & Johnson, 1994). The reasons are described above.

3. In terms of educational equity, a goal was established to ensure that all students benefit from cooperative learning. This requires a strategy for accommodating all students by placing them in appropriate groups for successful cooperative learning. This means rejecting the idea of grouping the best students together and ignoring the weaker ones. The designers set out to find workable ways for grouping that consider all students at the same time, regardless of differences in talent or psychological features. In addition, grouping adequacy was taken into account for both individual and whole class levels to ensure that student distribution does not increase a sense of debt in some groups.

In summary, grouping is a fundamental step in cooperative leaning. To consider multiple psychological features for creating heterogeneous groups, teachers must deal with major computational requirements. With the goal in mind of assisting teachers, the design team created a framework to implement two computer-supported grouping systems: *DIANA (Differences In And Non-differences Among groups)* and *FUTS (Full Thinking Styles groups).*

1.4 Organization

The outline of this dissertation is as follows: in chapter 2, group studies in the fields of education and information technology (IT) are introduced. Chapter 3 presents an analysis of the difficulties of using psychological features for group composition. A two-phase grouping framework is described in Chapter 4, an implementation algorithm in Chapter 5, and the entire system in Chapter 6. Chapter 7 and 8 discuss evaluations of DIANA and FUTS. Finally, Chapter 9 contains a conclusion and potential future perspectives of computer-supported group composition.

Chapter 2
Literature Review & Study Fixed Position

2.1 Group formation: educational perspective

In their list of critical decisions to be made when grouping students for cooperative learning activities, Abrami et al. (1995) noted that teachers must consider group size, group activity duration, student characteristics, methods of group composition and organization, and the manner of assigning students to groups. These decisions are affected by student age and interpersonal skills, instructional goals, activity properties, the climate of class trust, and teacher beliefs.

2.1.1 Common grouping methods in current use

In his survey of the literature on cooperative learning, Abrami (1995) found that the majority of teachers use one of three methods to assemble small learning groups:

1. Teachers allow students to form their own groups. Unfortunately, students tend to form teams based on friendship or common interests in a topic, and friendship-based groups are generally homogeneous (Abrami et al., 1995). Although cooperation may be facilitated as a result of harmonious communication, it can also produce ineffective results due to a lack of multiple perspectives. Furthermore, shy students or students with less developed social skills are easily excluded by other members of homogeneous groups.

2. Teachers use simple methods such as putting together students who sit next to or near each other (Abrami et al., 1995). The main advantage of these methods is that individual students do not feel rejected or singled out. The main disadvantage is that some groups may consist of all low-ability students who are less successful at performing complex tasks. Another potential problem is the unintentional creation of groups that lack balance in terms of ethnic or socio-economic position, in which higher status students dominate their lower status classmates (Cohen, 1994b).

3. Teachers form groups according to student characteristics. The two most common alternatives are heterogeneous or homogeneous, with heterogeneous groups providing more opportunities for students to learn how to work cooperatively with different people. Cohen (1994b) and Johnson & Johnson (1994) are among many researchers who have presented evidence showing that heterogeneous grouping enables students to learn more in terms of academic knowledge and social skills. However, Webb (1989) warns that the range of member differences within a group should not be too extreme in order to prevent the construction of barriers to cooperation. Abrami et al. (1995), Cohen (1986, 1994a), and Webb (1985) have also examined how such characteristics as gender, ethnic status, socio-economic status, and personality type affect learning performance and cooperative interaction in group activities. A list of characteristics that are often used when constructing heterogeneous and homogeneous groups is presented as Table 1.

Table 1: Commonly used characteristics for constructing heterogeneous and homogeneous groups.

Heterogeneous groups	gender, race, ethnicity, language, status, learning style, thinking style, personality traits
Homogeneous groups	living location, first language other than English.

2.1.2 Ability-based groups

Abrami et al. (1995) note that creating heterogeneous groups based on ability has benefits for students at both ends of the ability spectrum, although there is a risk that high-ability students will complain about spending too much time teaching peers or that low-ability students will feel singled out for needing special attention. In contrast, homogeneous groups based on ability may encourage high-ability students to reach or exceed their potential, but they can also lead to classroom polarization, with low-ability students having fewer opportunities for improvement. A comparison of heterogeneous-ability and homogeneous-ability groups is presented in Table 2.

Table 2: Advantages and disadvantages of heterogeneous-ability and homogeneous-ability groups.

	Advantage	Disadvantage
Heterogeneous-ability group	This arrangement benefits high-ability and low-ability student learning.	High-ability students may complain of taking too much time to teach others and low-ability students may feel singled out for needing special attention.
Homogeneous-ability group	Judicious use of homogeneous groups can encourage high ability students to reach their potential.	Classroom polarization may occur.

Based on a review of studies on helping behaviors in cooperative groups, Webb (1989) reported that a) students in all-high or all-low ability homogeneous groups are more likely to ask for terminal help (e.g., the correct answer) or surface information due to a lack of sufficient motivation to explain their ideas or to discuss alternatives; and b) students in all-low ability groups are more hesitant to ask for help. He therefore concluded that cooperative learning groups perform best when they contain a mix of high- and low-ability members.

2.1.3 Gender-based groups

Savicki et al. (1996) studied three types of college-level groups that used computer-mediated communication (CMC) to discuss issues in a psychology class: female-only, male-only, and a heterogeneous mix. They reported that members of the all-female groups used more words in their CMC messages and expressed greater satisfaction with the process compared to members of the other two groups. In a separate study, Webb (1985) observed that girls in mixed groups tend to let boys deal with most problems, even when they outnumber boys.

2.1.4 Balanced groups

Huxham & Land (2000) studied heterogeneous student groups based on individual psychological features. They used questionnaire results to categorize group member roles as activists, reflectors, theorists, and/or pragmatists. Students were assigned to groups in a manner that emphasized intra-group and de-emphasized inter-group differences. According to their results, groups created by random selection and heterogeneous groups performed equally well.

Since the majority of researchers appear to agree with the idea that heterogeneous grouping promotes positive interdependence, better group performance, and effective interaction, heterogeneity was chosen as the grouping goal when designing the group composition framework described in this dissertation.

2.2 Using thinking styles to compose cooperative groups

In addition to the characteristics listed in Table 1, Sternberg (1998) suggests that teachers consider thinking styles to promote cooperative learning among individuals in small groups, with the term *thinking style* described as personal tendencies and attitudes associated with utilizing one's own skills. Thinking style is not the equivalent of talent or ability, but entails personal preferences for methods that determine the use of intelligence. Sternberg identified thirteen thinking styles, all of which affect all persons at the same time, but to different degrees. Hence, there is a need to simultaneously consider the degree of all thinking styles in individuals instead of simply classifying them in terms of a single thinking style.

Sternberg also established a *functionality dimension* consisting of three larger categories of thinking style: *legislative, executive, or judicial*. Individuals who follow a legislative style are innovative and do things according to their own rules. Executive thinkers are more likely to follow prescribed rules and to show a preference for ideas that they fully understand. Judicial thinkers don't pay much attention to rules, preferring instead to compare ideas and to make judgments based on their benefits and deficiencies.

Sternberg & Louise (1996) also suggests that teachers compose cooperative teams according to student thinking styles—specifically putting one member from each of the three thinking styles just mentioned to complement each other in task performance. He claims that positive effort occurs when an individual's thinking style matches environmental conditions and requirements. To improve the odds of finding or creating such a match, he advises teachers to establish cooperative teams that are balanced in terms of executive, legislative, and judicial thinking styles so that group members can both influence and challenge one another. Hence, the framework described in this dissertation uses thinking style as a heterogeneous grouping factor.

2.2 Group formation from a computing perspective

Although computer-supported cooperative learning facilitated cooperative learning, few CSCL mediating tools provided help in composing promising groups until a branch of intelligent application research on web-based learning devoted to form effective teams.

2.2.1 Intelligent system

Few CSCL mediating tools were created to help with small group composition until a branch of intelligent application research in web-based learning devoted to team formation was established. Currently there are several adaptive/intelligent educational systems that facilitate web-based learning (Brusilovsky, 1999). These systems not only project classroom-like learning conditions, but also offer students adaptive courseware, personalized assistance, and individual remediation that complements student efforts according to learning status. The application of adaptive/intelligent technologies protects students from feeling as though they are lost in an ocean of information, which is a common problem with web-based learning.

Intelligent agents in the form of tutors or peers can assist learning by guiding students in accordance with courseware requirements or known learning deficiencies. The power of intelligent agents is determined by the degree of artificial intelligence, sufficient information on the students using a system, and the accuracy of learning modeling. Agents can perform multiple complex roles to match diverse instructional needs and goals. Roles that are commonly played by agents in educational settings include tutor (Chan & Baskin, 1990; Chan & Chou, 1997), tutee (Biswas et al., 2001; Scott & Reif, 1999), collaborator (Hietala & Niemirepo, 1998; Ryokai, Vaucelle & Cassell, 2003), competitor (Chan & Baskin 1990; Ramirez & Uresti, 2000), and troublemaker (Aimeur & Frasson, 1996).

2.3.2 Adaptive grouping support

According to the technical literature, past intelligent technologies were mostly applcable to individual learning, but the centralized management of learning records stimulated some researchers to analyze and match models for many students at the same time (Brusilovsky, 1999). Some research effort was spent on adaptive collaboration support, which uses system knowledge about different students (stored in the form of student learning model) to form well-matched collaborative groups (Bishop, Greer & Cooke, 1997; Hoppe, 1995; Ikeda, Go & Mizoguchi, 1997; McCalla, Greer, Kumar et al., 1997). Brusilovsky(1998) considers that adaptive collaboration support is a particular technology, which is an important development.

In general, computer-supported group formation consists of the three phases, initiating collaborative situation, finding out suitable teammates, and negotiating for constructing a final work-team (Wessner & Pfister, 2001). I particularly introduce the former two phases, that have relations with this study.

Initiating collaborative situations

That is, deciding when to use cooperative learning techniques. The three parties involved in this decision are

- teachers, who are in charge of designing collaborative learning activities aimed at matching courseware needs—for instance, combining a cooperative project with problem solving.
- students, who often spontaneously ask for cooperation when they feel friendless, helpless, illiterate, or in some other manner caught in a predicament.
- intelligent systems that detect when students are mired in difficulties and who may therefore benefit from a cooperative environment to address learning disorder concerns. Examples include students who regularly fail quizzes, who repeatedly make the same or similar mistakes, who continually misunderstand certain concepts, or who are stuck at some point in the learning process. Systems occasionally put students in cooperative learning environments to help them review a lesson by teaching others.

Finding well-matched learning partners

Unfortunately, few technology researchers pay attention to this issue, until they have a chance to examine abundant information of students' learning in central storage that is collected during web-based learning, technologists realize that it can be used to group students. Some research grouped students via student models, and some via other information. At least three research teams have offered suggestions on finding a suitable learning partner. Following, I introduce some studies to explain how to find a suitable learning partner.

Concept complementation

Ikeda, Go and Mizoguchi (1997) proposed a novel system in which agents observe student learning progress. When the agent detects that a student is having difficulty, it asks the system to put that student into a cooperative group. The system is also programmed to find suitable partners and to create communications channels among group member agents. Students enter a group learning situation following agent negotiation. Learning goal ontology is the basis for Ikeda et al.'s proposed system. The ontology is used to assign roles to students (e.g., learner, helper, presenter, observer, participant, or debater) when they are placed into cooperative groups. The guiding purpose is to identify an individual's learning goals with those of the group. On the side, Bishop, Greer & Cooke (1997), McCalla et al. (1997) were also devoted to find out the most suitable partner to form problem-solving groups, which is based on students' knowledge of the domain.

Browsing behaviors similarity

Tang and Chan (2002) arranged students in terms of similar backgrounds in browsing behaviors and course knowledge. They argue that browsing activities are reliable indicators of students' knowledge skills, interests, and learning progress, and that simple monitoring techniques are sufficient for identifying students with similar learning characteristics. This approach resembles traditional homogeneous interest/ability grouping methods.

Intended points

Wessner and Pfister (2001) utilize knowledge about collaborative contexts to establish intended points of cooperation without any need for a detailed learning domain model. Their system provides an interface that allows course designers to easily integrate collaborative activities into learning environments. After setting group type and size in advance according to learner characteristics and course structure, the system can create corresponding groups. However, groups were formed by random assignment or by teacher decision via the interface provided by the system. The researchers did not go into detail about appropriate matches between or among learning partners.

Regardless of how group formation is initiated—by system detection or user requisition, according to the complementary concept (Ikeda et al., 1997), according to browsing behaviors (Tang & Chan, 2002), or randomly via intended points (Wessner & Pfister, 2001)—all of the approaches mentioned so far adopt dynamic grouping methods to shift students from individual to collaborative learning modes. However, sometimes teachers do not have access to relevant student learning information (e.g., when they enter a new learning environment or when teachers are unfamiliar with a class). Moreover, some project-oriented or problem-solving learning activities require group work, at least initially. Hence, a system that can quickly place learners in appropriate groups without having to build a complex, detailed learning model is worth investigating.

2.4 Study position, purposes, and goals

Cooperative learning requires careful design and planning. Success is less likely if groups are assembled arbitrarily. Educational researchers have established theories and in some cases given suggestions such as forming heterogeneous groups according to psychological features. But taking the time to create groups based on specific features is both difficult and time-consuming for teachers, who are already pressed for time. Most currently available grouping systems adopt some form of random assignment, with a few intelligent systems able to form complementary groups in terms of student learning models.

This dissertation is a description of my attempt to develop a computer-supported grouping system, based on educational theory, that simplifies the task of manipulating complex information for the purpose of creating successful cooperative learning groups. A primary goal is to make this task easy for busy teachers. The proposed system was designed to a) form heterogeneous groups based on the psychological features of students, and b) allow for the rapid introduction of students into a cooperative learning situation without having to construct individual student learning models.

The following principles guided the system design process:

1. Ensure that all students take part in cooperative learning. When researchers assign individuals into groups in laboratory settings, they often disregard students who are difficult to deal with or who express vague features. Educators in real-life classrooms cannot disregard anyone, thus it is necessary to ensure that every student benefits from cooperative learning rather than only a few capable students. The grouping system described in this dissertation was designed to aid teachers in group composition so that no student needs are ignored. The system was designed with the belief that everyone’s right to education and achieving excellence should be valued.

2. Adequate grouping should be a goal rather than forming “dream teams.” In conjunction with principle #1, the objective of group composition should not be to

merely produce refined teams, but to group an entire pool of students so that everyone benefits.

3. Ensure that every student benefits from cooperative learning. When grouping students, some teachers use the strategy of choosing the best students first and building groups around them—a strategy that inevitably creates a number of groups consisting primarily of less capable students. Hence, a grouping system should aim to maintain within-group heterogeneity and between-group balance.

4. Create groups, not clusters. Grouping for cooperative learning has at least two requirements that differentiate it from general clustering: teachers are often required to form groups of equal size, and all students should be taken care of and assigned to the most suitable group possible.

Based on these principles, the main purpose of the DIANA and FUTS grouping systems is to ensure fairness—that is, ensure that everyone assigned to a group starts on equal ground. The other primary purpose is to create a system that is flexible and easy to use in order to reduce teacher workloads in CSCL management.

Chapter 3
Problem Analysis

The educational literature encourages teachers to form groups according to psychological features that are not easily observed and that often consist of multiple continuous variables. These characteristics make the grouping problem more complex and perhaps open to the benefits of powerful computing capabilities. A computer programmer is more likely to view group formation as a question of mathematical combinations requiring careful design to ensure diversity within and among groups needs. In this chapter I will analyze the grouping problem mathematically, using psychological features as variables.

3.1 Problems encountered in the use of psychological features

Psychological features possess certain natural properties that make them difficult to use for purposes of grouping students. First, psychological variables are embedded and often not easy to observe—even if a teacher has plenty of time to make detailed observations, which most teachers don't. In contrast, demographic variables (e.g., gender, race, age) are easier to measure and therefore more convenient for making fast, short-term grouping decisions (Cohen, 1997; Cordero et al., 1996; Savicki et al., 1996). Addressing this challenge requires the use of a trustworthy, well-developed psychological inventory—for instance, Lin & Chao's (1999) Thinking Styles Questionnaire. In the present project the goal is to use psychological variables as grouping factors, thus requiring the creation of a questionnaire that can be easily distributed, completed, and collected online, and that allows for easy scoring so that the results can be used quickly with a group composition algorithm.

A second problem is the complex nature of psychological variables. Using thinking styles as an example, it is incorrect to state that individuals use one style only; a better approach is to view thinking styles as the way (or ways) that individuals prefer to use the abilities they have, with most people using multiple thinking style patterns. Teachers must consider all styles simultaneously, thus increasing the complexity of the composition problem.

For purposes of this dissertation, I will use the following definition of a student psychological profile:

Definition 1: The psychological profile of student *x* can be measured and represented as $F(x) = (f_1(x), f_2(x), \cdots f_n(x))$ when n psychological features are to be considered simultaneously.

Teachers who try to maintain simplicity by using the single most significant thinking style identified in a student will unfortunately remain ignorant of the effects of other thinking styles and thus artificially diminish student diversity. Normalizing scores to a range between 0 and 1, a student's combined pattern of executive, legislative, and judicial thinking styles may be measured as 0.1, 0.7, and 0.5, respectively. To choose legislative to represent this student's learning style would ignore the strong influence of judicial thinking style in this student's psychological character.

A third problem is the continuous nature of most psychological variables compared to categorical data (e.g., gender or some other demographic factor). In comparison, it is much more difficult to assign students according to self-efficacy scores that range from 15 to 55.

It is also tempting to create categories based on continuous data—for instance, dividing high, medium, and low executive thinking style scores into separate categories. The challenge here is identifying reasonable cut-off scores. Even if it were possible, the process would be time-consuming, ignore complexity within and diversity among students, and overlook valuable psychological information. For this reason, many researchers oppose the arbitrary division of continuous data, leaving teachers with no easy approach to grouping in the presence of multiple psychological features.

3.2 Problems encountered in composing groups

Forming heterogeneous groups requires calculations of group diversity. To address this issue, the design team tabulated student thinking style questionnaire scores and treated each score as a single point along three orthogonal vectors. By drawing each psychometric variable as a dimension, individual thinking styles can be positioned as a point in geometric space, and space vectors can be used to transform what is essentially an abstract problem into a structured, procedural problem—for instance, transforming the diversity of two individuals' thinking styles into a problem involving the geometric distance between two points. In other words, diversity can be defined in terms of Euclidean distance as follows:

Definition 2: Let $S = \{s_1, s_2, \ldots, s_m\}$ be a set of students waiting to be assigned to a group. Each student is represented as a dot in an n-dimensional feature space. The degree of diversity between any two students can be expressed in terms of

Euclidean distance:

$$D(s_i, s_j) = \sqrt{\sum_{k=1}^{n} (f_k(s_i) - f_k(s_j))^2}$$

Three students forming a triangular shape can be considered a single group, thus making the grouping goal one of putting together heterogeneous groups of individuals whose thinking style points create the largest possible triangles.

Defining intra-group differences in terms of distance makes it possible to find optimal solutions using exhaustive algorithms. The first step is to construct a distance matrix of all possible pairs, then aggregate pairs with the largest distances until three points are established. The process is to be repeated until no more triads can be found or formed. In light of the complexity of such an exhaustive algorithm, Lin & Sun (2000) adopted Random Mutation Hill Climbing (RMHC) for the purpose of finding optimal solutions as quickly as possible.

Although using a distance-based grouping algorithm appears to be intuitively reasonable, many of Lin and Sun’s RMHC-recommended groups were not very heterogeneous. The problem is illustrated in Fig. 1, in which a teacher wants to compose two groups of three students each based on two psychological characteristics. Each point along the two-dimensional space in the first sequence represents a student. In the second sequence, students A, B and C are assigned to a group that has the greatest potential for heterogeneity, therefore D, E and F must be placed in the second group. The placement of student C in group 1 increases the homogeneity of group 2, thus jeopardizing the heterogeneous grouping goal.

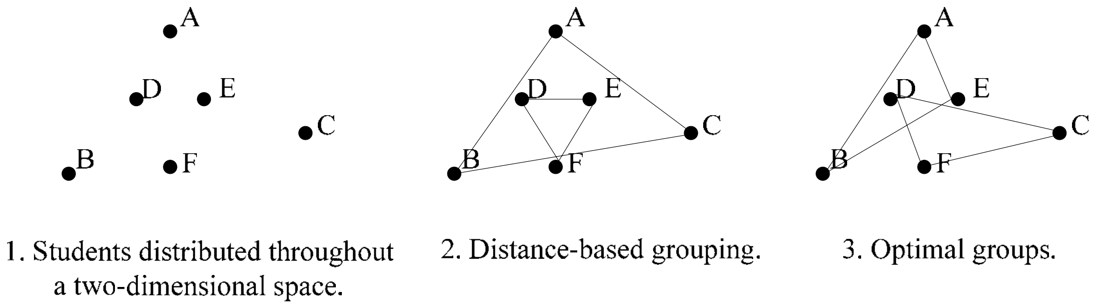


Fig. 1. A distance-based grouping algorithm example.

A second example, illustrated in Fig. 2, involves nine students that a teacher wants to separate into three optimum groups based on two learning characteristics. Each dot represents a student in a two-dimensional psychological space. The most heterogeneous group would consist of A, B and C and the second-most heterogeneous would consist of D, E, and F (Fig. 2b). However, those groupings would result in a third grouping of G, H and I—one with very low heterogeneity. As shown in Fig. 2c, the A-B-C, D-E-F, and G-H-I triangles become progressively smaller, indicating a steady decrease in intra-group diversity and a contradiction of the original goal of placing all students in the most heterogeneous groups possible. Stated in a different way, the problem requires a global optimal rather than local optimal solution to achieve educational equity.

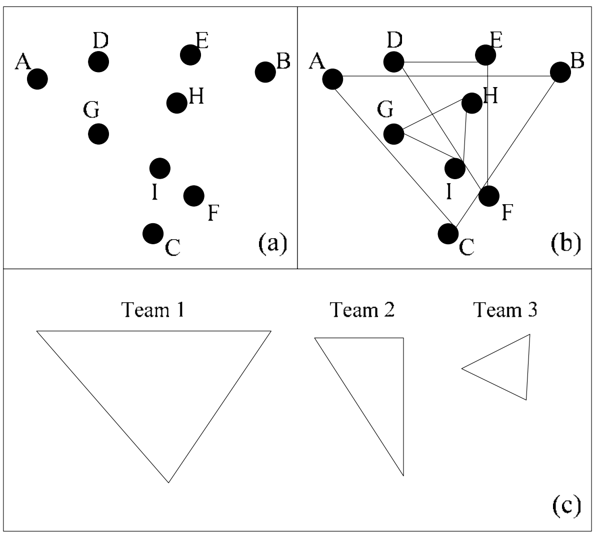


Fig. 2. A comparison of distance-based group composition.

Using a grouping algorithm based on distance produces triangles of various sizes. As size decreases, so does intra-group diversity. This type of greedy algorithm inevitably forms groups with extreme heterogeneity, groups with concurrently decreasing heterogeneity and increasing homogeneity, and groups with extreme homogeneity. Identifying an appropriate cut-off point between heterogeneous and homogeneous groups is problematic—a distance-based grouping algorithm produces heterogeneous groups that are prized by educators, but they also produce undesirable homogeneous groups that conflict with the educational equity goal of assigning all students to their most suitable groups.

An example of optimal groupings is shown in sequence 3 of Fig. 1, in which A, B, and E are assigned to group 1 and C, D, and F to group 2. The two groups have sufficient levels of intra-group diversity—that is, their triangles are similar in shape. Our proposed DIANA grouping method is based on shape instead of distance, in accordance with an assumption that similarities in shape represent similarities in terms of heterogeneity. The result will be in compliance with the stated goals of *fairness* (groups having the same size), *equity* (assigning all students to their most suitable group), *flexibility* (allowing teachers to address single or multiple psychological variables), and *heterogeneity* (guaranteeing individual diversity for promoting intra-group interactions).

3.3 Sternberg’s suggestion: Full thinking styles

Robert J. Sternberg, a cognitive psychologist, argues that the most effective teams in terms of task accomplishment require a strong balance of executive, legislative, and judicial thinking styles. Any group can benefit from a member who works industriously and who knows how to follow rules (executive style), but the group also needs the balancing effect of an innovative individual (legislative style) in order to achieve breakthroughs that are often based on rule-breaking insights. As a mediating force, the group can benefit from a member who keeps an eye on rules while comparing and evaluating their characteristics (judicial style). The second grouping method proposed in this dissertation, FUTS, was designed to implement Sternberg's theory. The guiding principle for this method is ensuring that each group has "substantial features" of chosen psychological factors.

Based on this background, the third definition is presented as follows:

Definition 3: In a team of three individuals whose thinking styles differ in a manner similar to those shown in Table 3, their thinking styles can be expressed as

$$G_1 \Rightarrow \begin{cases} A_1 = Max(A_{11}, A_{12}, A_{13}) \\ L_1 = Max(L_{11}, L_{12}, L_{13}) \\ J_1 = Max(J_{11}, J_{12}, J_{13}) \end{cases}$$

Table 3. Thinking styles of the three individuals used in Definition 3.

Thinking Style	Member 1	Member 2	Member 3
Executive	A11	A12	A13
Legislative	L11	L12	L13
Judicial	J11	J12	J13

Group members with different thinking style profiles are more likely express reciprocal influences and introduce working preference dynamics that may in turn lead to greater chances of success. The group compositional goal should be to ensure that there is a comprehensive and salient mix of executive, legislative, and judicial thinking styles on each team. A particular style may be contributed by more than one member or a single member may express more than one thinking style. While the ideal group will have thinking styles distributed equally among different members, such distribution cannot be predicted or controlled. The framework designers therefore adopted a priority mechanism, with highest priority given to combinations in which each group member expresses a single style. The least favorable scenario has one group member expressing all three thinking styles.

The names *Ai*, *Li* and *Ji* are used to represent characteristic values for members of team *i*. In a scenario consisting of n teams, their value set can be written as:

$$(G_1 \sim G_n) \Rightarrow \begin{cases} (A_1, A_2, A_3, \ldots\ldots,\ A_n) \\ (L_1, L_2, L_3, \ldots\ldots.,\ L_n) \\ (J_1, J_2, J_3, \ldots\ldots,\ J_n) \end{cases}$$

The design goal was to find combinations with the largest possible characteristic values for each team—in other words, to identify groups with maximum *A*, *L*, and *J* (the minimum characteristic values for all teams).

$$\begin{aligned} A &= Min(A_1, A_2, A_3, \ldots\ldots, A_n) \\ L &= Min(L_1, L_2, L_3, \ldots\ldots., L_n) \\ J &= Min(J_1, J_2, J_3, \ldots\ldots, J_n) \end{aligned}$$ →Find a combination that has maximum *A*, *L*, and *J*

Based on this analysis, the optimal grouping condition is to find

$\underset{p}{Max}\ A(p), L(p), J(p)$, where *p* represents a grouping result.

Chapter 4
Two-phase Grouping Framework

As stated in chapters 2 and 3, two issues need to be addressed regarding grouping as a fundamental cooperative learning issue. First, multiple psychological variables (as opposed to single demographic variables) must be measured and used as grouping factors, keeping in mind that these variables consist of continuous data and are strongly related to learning performance. Second, the guiding strategic goal is to assign students to the most suitable group so that all groups have similar capacities for success. The novel computer-assisted grouping framework described in this paper has been designed so as to address these two problems. It is hoped that the final product will help teachers use psychological features as grouping factors for assigning students to suitable groups, and help researchers find optimal combinations for cooperative learning.

Assume the formation of N triad teams. The flow of the two-phase grouping framework is shown as Fig. 3. The first phase of the proposed grouping framework entails categorizing individuals in terms of thinking style inclinations. The number of teammates will determine the number of categories—that is, choosing one person from each category to form heterogeneous groups. As a result, teammates' TSs are heterogeneous and can fit in with our grouping goals, DIANA and FUTS, according to different methodologies in the second phase.

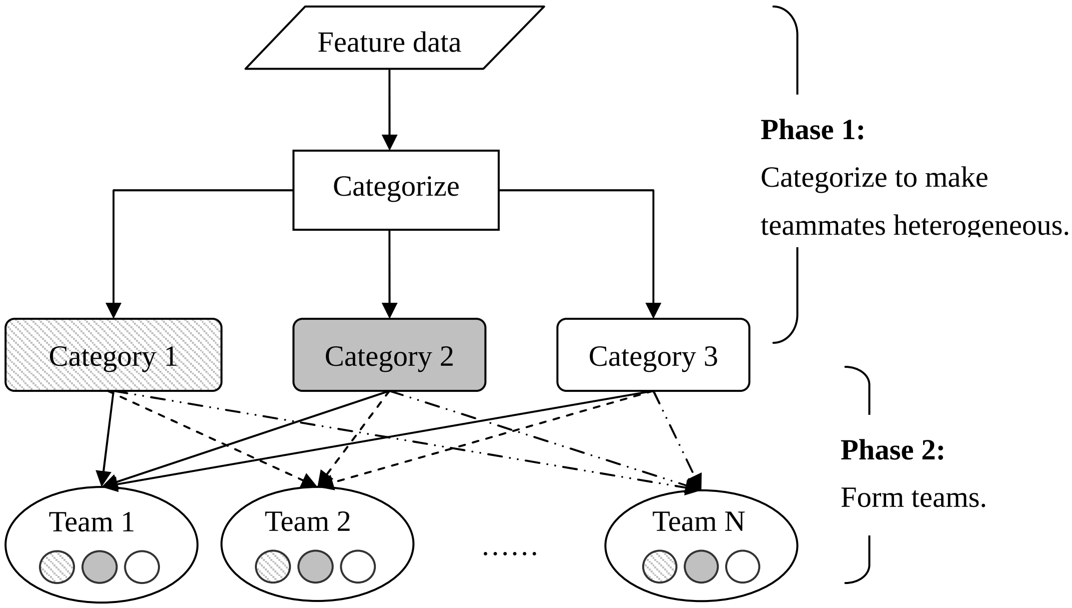


Fig. 3 A two-phase grouping framework.

4.1 First phase—categorization

In this phase, students are separated into several categories. The number of categories is decided by the number of group members. In this example the goal is to assign students to groups of three, therefore the sample pool requires three separate categories. The categories are formed naturally by recursion, thus leading to suitable categorization for the entire class. As part of the goal of creating heterogeneous teams, an important task for this stage is finding a prototypical group shape that reflects a certain degree of diversity within each group and maintains a certain degree of balance across all groups. An equal emphasis on individual and global performance helps to prevent the problem of having a high level of diversity in one group at the expense of other groups.

In this example, group members thinking styles are visualized as three points in a two-dimensional space. The key here is to find triangular shapes for all groups that are as similar as possible in order to maintain similarity in terms of within-group diversity. The proposed grouping system defines diversity in terms of shape within a geometric space. This requires defining a "typical" shape—a task that is dependent on the characteristics and diversity of the persons in a sample. A typical shape (or group) can be defined as follows:

Definition 4: Let $S = \{s_1, s_2, \ldots, s_m\}$ be a set of *m* students forming *c* categories in an n-dimensional feature space, with *ci* standing for the *i*th category containing *Ni* students with centroid *vi*. The typical group can be expressed as $V = (v_1, v_2, \ldots v_n)$, where $v_i = \frac{1}{N_i} \sum_{s_j \in c_i} F(s_j)$.

4.2 Second phase—grouping

The most important task in the second phase is to select suitable students for each group. Since they have different theoretical principles, the DIANA and FUTS grouping techniques have different ways of defining suitability. Forming DIANA groups requires categorical separation and a definition of a typical group shape (as described for the first phase), after which single students from each category can be selected to form groups whose shapes are similar to the defined typical shape. Inter-group diversity is eventually controlled by this shape. An illustration of the steps required to separate nine students into three groups of three members each according to two psychometric features is presented in Fig. 4.

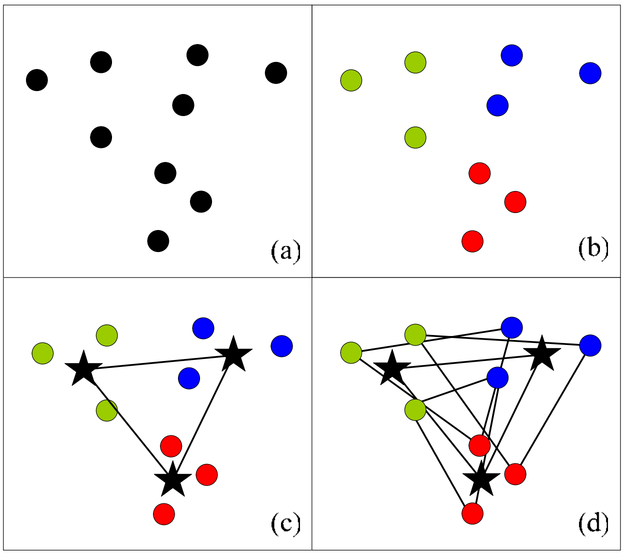


Fig. 4. An example of a two-phase grouping model. a, nine students as represented by nine dots in a two-dimensional space; b, splitting students into three categories (one color per category); c, connecting the centers (black stars) of each category to form a "typical" group; d, selecting one student from each category to form group shapes that resemble the typical group shape.

To form FUTS groups, teammates were selected based on the analysis discussed in section 3.3.

Chapter 5
Methodology

5.1 Categorization

As stated in the preceding chapter, the number of categories for any group is determined by group size and the requirements that no one should be left out and all category sizes should be the same. These requirements contradict the principle of traditional clustering, which maintains similarity within groups and differences between or among groups.

I therefore took the k-means algorithm (Duda & Hart, 1973) and added a reallotment function to the while-loop to identify static categories. This function can take some students from an oversized category and redistribute them to the next closest category.

The categorization algorithm is presented in Fig. 5. Its four steps are a) determining the initial locations of all category centers, b) allocating individual students to their nearest category, c) reapportioning students to maintain categories with equal numbers of members, and d) computing category centers and returning to step b whenever a category center changes (Fig. 6). This method organizes students around category centers. A small number of individuals are situated between categories, thus creating a high level of dispersal.

In this phase an algorithm was adopted for controlling teammate count, like the K-means algorithm being used to set a precise cluster number. Users who form teams of different sizes must adjust the K parameter accordingly. I also added a control

Algorithm reallot ()
begin
 for while category sizes are not equal **do**
  begin
  compute the distance between each student in the over-sized category and other categories
  reallot the student who's distance is shortest to his second nearest, unfilled category
  end

Algorithm categorization (features of students)
begin
 set the initial category center at the utmost of each dimension
 for while the new category centers aren't the same as the old ones **do**
  begin
  dispatch each student to his nearest category
  reallot()
  end
  compute new category centers
end

Fig. 5. The categorization algorithm.

mechanism to ensure equal numbers in each category, thus controlling heterogeneity. However, sample distribution cannot be controled. Since all individuals need to be assigned to teams of equal size, this phase runs continuously in an attempt to find better categorizations and uses the second phase to improve grouping solutions.

Teachers and researchers prefer categorization results that indicate optimum diversity. The most distinct types can be produced by setting the initial category center at the utmost value of each dimension. Also during this phase, teachers can consider more than one learning characteristic and assign them equal value.

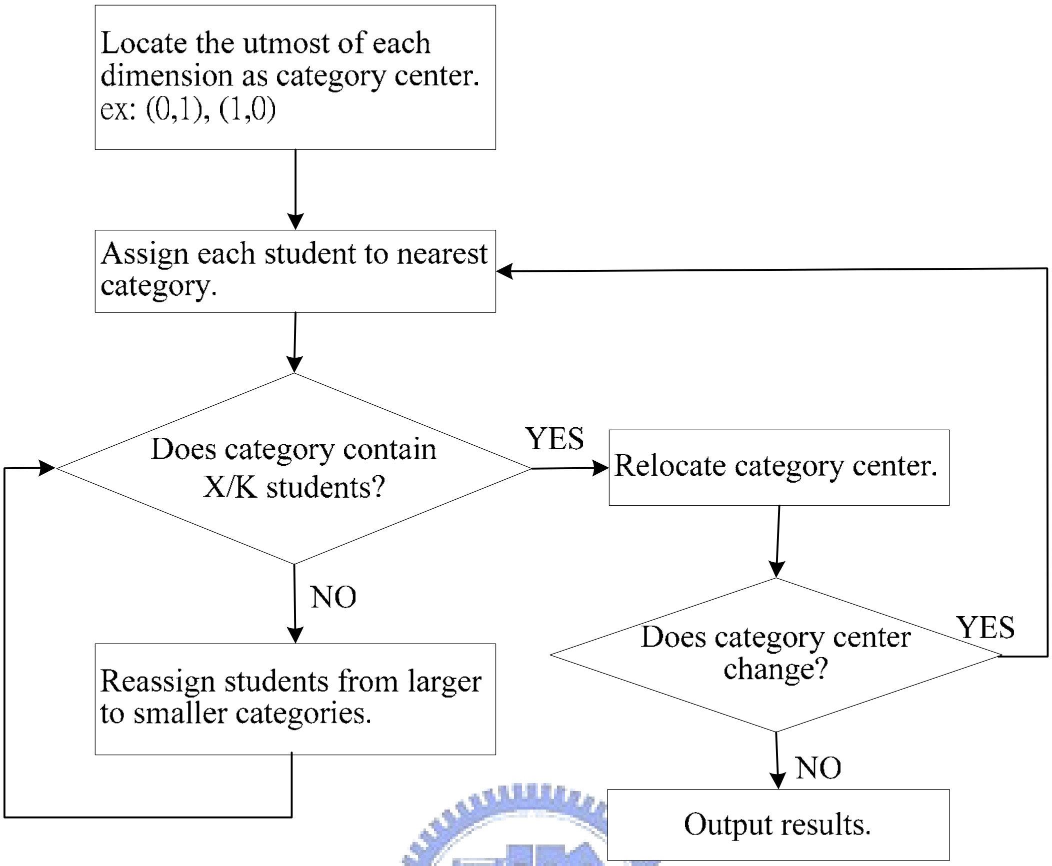


Fig. 6. Categorization stage flow chart for X students assigned to K groups.

5.2 Balanced grouping

After phase 1, the triangular shape of the final category centers is considered a prototype representing the desired structure of all heterogeneous groups. Once a group structure is defined, every effort is made to make all group shapes identical or very similar to the prototype. A genetic algorithm (Holland, 1975) was adopted for evolving an approximate solution for this combination problem. Geneticists use three operators (crossover, mutation, and inversion) to create new chromosome populations from existing populations, with individual solutions evaluated after a predetermined number of generations have evolved. The main components of the GA process are:

1. Chromosomes. In the present study, one chromosome represents one group and each gene within a chromosome represents a single student in each category.

Chromosome length equals category number (i.e., group size); population size equals the number of students divided by group size. An example is given in Fig. 7.

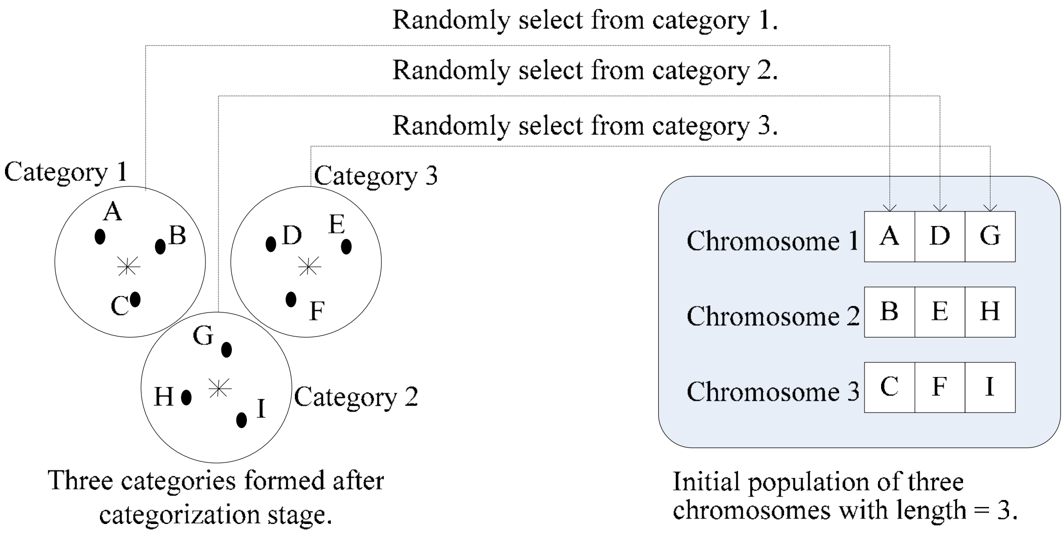


Fig. 7. Chromosome decoding and initial population.

2. Fitness. To avoid problems associated with the RMHC grouping principle, distance was not used to measure intra-group differences. Since only one student is selected from each category to form a group, the final category center shape is viewed as the prototype shape for all heterogeneous groups (Fig. 8). Differences between actual and targeted chromosome shapes are computed, with chromosome fitness equaling the inverse of the absolute value of the difference. The higher the fitness value, the better the performance. The fitness function is formulated as follows:

Definition 4: If a chromosome is composed of $(s_1, s_2, \cdots, s_c)$ students selected from c different categories to form a team, chromosome fitness can be expressed as $\dfrac{1}{\sqrt{[sort(D(v_i, v_j)) - sort(D(s_i, s_j))]^2}}$, where

$i, j = 1 \sim c,\ i \neq j, and\ sort\ is\ a\ sorting\ \ function$

3. Crossover. Two chromosomes randomly selected from a population can be crossed at a randomly chosen point to form two offspring. In this project, crossovers were performed only when the fitness of the offspring exceeded that of its parents.

d) Mutation. This operator allows for a crossover of two chromosomes even if doing so does not improve the fitness value. Again, the higher the fitness value, the better the performance.

DIANA's optimal formation stage consists of five GA steps:

1) Start with a randomly generated population based on classification stage results.

2) Calculate the fitness of each chromosome in the population.

3) Randomly select two chromosomes and check to see if fitness will increase following a crossover. If yes, perform the crossover; if no, perform a mutation with a probability of 0.001.

4) Replace the current population with the new population.

5) Return to step 2.

In the present study the iteration number was 1,000.

5.3 Full thinking style grouping

A stated goal is to find groupings with maximum *A*, *L* and *J* values; as discussed earlier, different groupings can affect those values. Fig. 9 presents an illustration of this problem in terms of the search concept, with computing complexity expressed as

O(n!)^m for forming n m-person teams. Therefore, Hill Climbing and Simulated Annealing (two iterative improvement algorithms that search for targets from an initial state) were used to find an optimal solution.

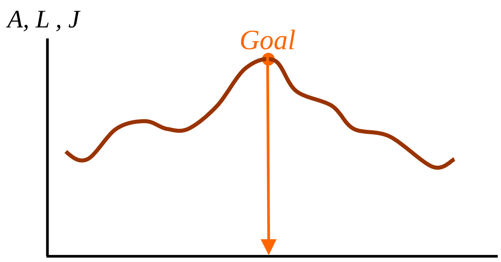


Fig. 9. Grouping problem search space.

Hill Climbing algorithms always move toward a state that exceeds the current state in some manner. A flow chart of the Hill Climbing algorithm used to find grouping targets is shown in Fig. 10.

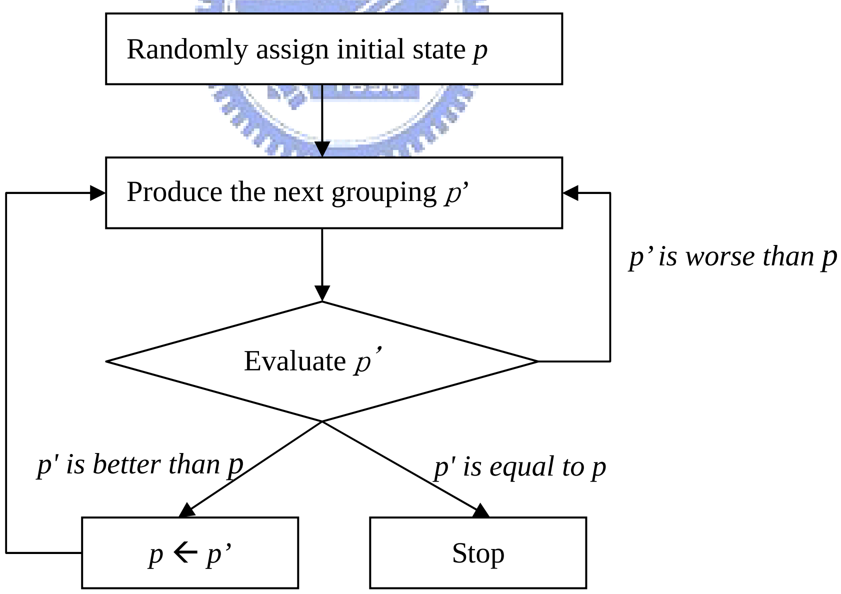


Fig. 10. Flow chart for the Hill Climbing algorithm used in this study.

To find the next best *p'*, current grouping was used to find a *near grouping* (defined as a single exchange of teammates). Exchanges only occur among members in the same category—a condition that ensures the maintenance of phase 1 heterogeneity. An exchange example is shown in Fig. 11. For N teams there are $3 \times C_2^N$ possibilities of near solutions, from which the best one is selected.

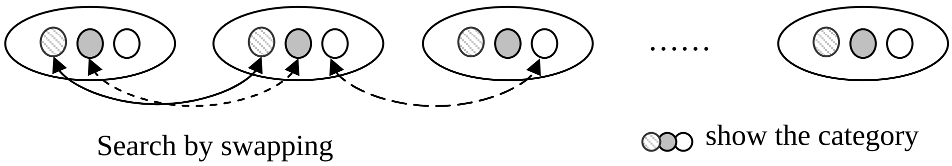


Fig. 11. Method used to find next grouping.

A comparison among the *A*, *L*, and *J* values (discussed in section 3.3) is performed to evaluate whether a near grouping is better than the current grouping.

If $\begin{cases} A_1 \geq A_2 \\ L_1 \geq L_2 \\ J_1 \geq J_2 \end{cases}$ and $(A_1 - A_2) + (L_1 - L_2) + (J_1 - J_2) > 0$, *p1* is better than *p2*.

A more complex comparison is required when the *A*, *L*, and *J* values are equal. Table 4 presents an example for two teams produced from two groupings with TS values listed.

Table 4. Thinking Style distributions for two teams.

	Team 1			Team 2		
	EXE	LEG	JUD	EXE	LEG	JUD
Member 1	28	15	17	28	15	17
Member 2	20	15	10	10	5	5
Member 3	20	15	17	5	10	5

Both teams have one member with the same TS values (28, 15, 17). However, when teammate diversity, the effect of entirety, and the potentiality of finding a better solution are considered, the formation of Team 2 is better than that of Team 1. For this reason, Evalgroup was introduced to the process for the purpose of forming teams with significant TS variation; larger Evalgroup values are desirable.

$$
\begin{aligned}
\textit{Evalgroup(Team i)} = {} & (|A_{i1} - A_{i2}| + |A_{i1} - A_{i3}| + |A_{i2} - A_{i3}|) + \\
& (|L_{i1} - L_{i2}| + |L_{i1} - L_{i3}| + |L_{i2} - L_{i3}|) + \\
& (|J_{i1} - J_{i2}| + |J_{i1} - J_{i3}| + |J_{i2} - J_{i3}|)
\end{aligned}
$$

Evalgroup (Team 1) = (8 + 0 + 0) + (0 + 0 + 0) + (7 + 7 + 0) = 30

Evalgroup (Team 2) = (18 + 23 + 5) + (10 + 5 + 5) + (12 + 0 + 12) = 90

Evalgroup (Team 2) = 90 > *Evalgroup* (Team 1) =30, therefore the Team 2 formation is considered better than that of Team 1.

Extended to n teams, the formula is defined as

$$
\textit{Eval2(p)} = \sum_{i=1}^{n} \begin{array}{l} [(|A_{i1} - A_{i2}| + |A_{i1} - A_{i3}| + |A_{i2} - A_{i3}|) \\ + (|L_{i1} - L_{i2}| + |L_{i1} - L_{i3}| + |L_{i2} - L_{i3}|) \\ + (|J_{i1} - J_{i2}| + |J_{i1} - J_{i3}| + |J_{i2} - J_{i3}|)] \end{array}
$$, where p is a grouping result.

If *Eval2(p')* > *Eval2(p)*, then *p'* is better than *p*, therefore, *Eval2(p)* becomes the second evaluation.

In this study, a Hill Climbing algorithm with a dual evaluation mechanism was repeatedly used to identify better grouping results. The algorithm stopped when it could not find a better solution, but there was potential for it to get stuck in local maxima. Simulated Annealing algorithms were incorporated to deal with this problem. These algorithms can accept less optimal solutions by jumping over local maxima, thus the probability of tolerating a worse solution decreases exponentially. A flow chart describing this Simulated Annealing method is shown in Fig. 12. As shown, the δ(Perturbation Rule) is designed to randomly select the next status (as opposed to selecting the next best status, as in Hill Climbing). Similar to the Hill Climbing method, teammates are exchanged to produce the next grouping, but the number of exchanges are limited: only two teams (out of the entire number of teams) can exchange single members, and only one time.

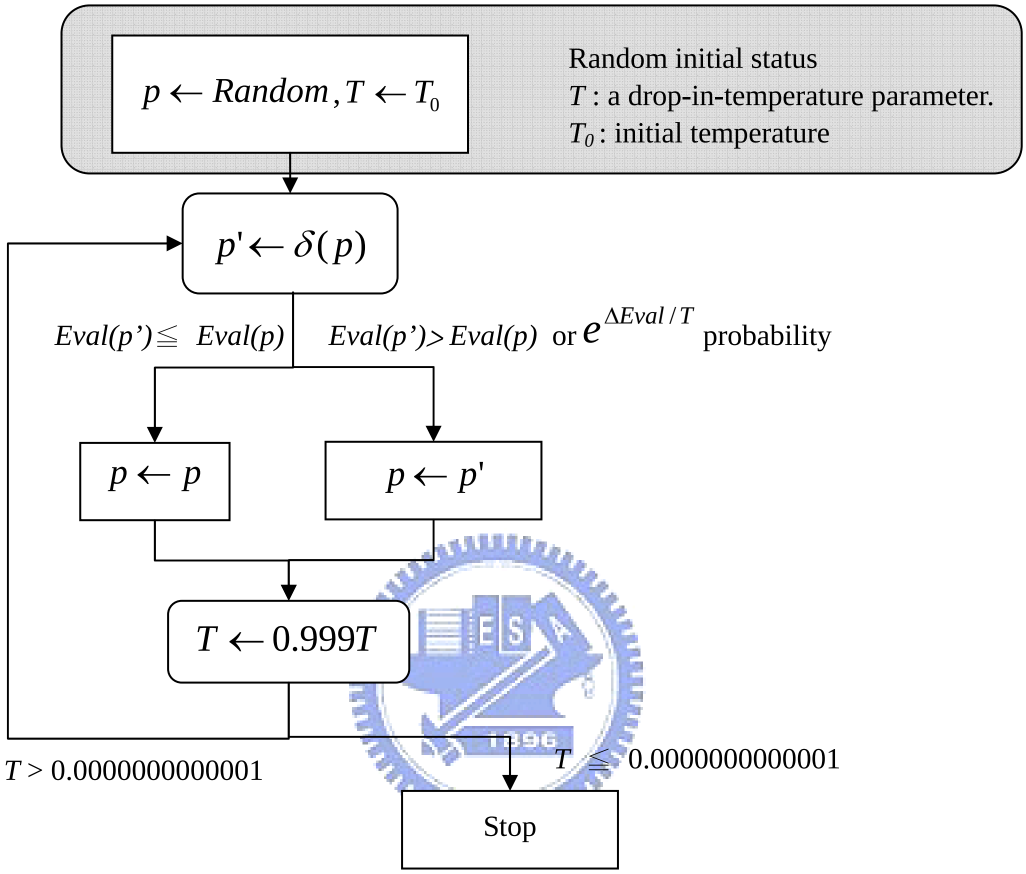


Fig. 12. A flow chart of the Simulated Annealing method.

The evaluation function in the Simulated Annealing algorithm is similar to that of the Hill Climbing algorithm (which combines two evaluation mechanisms). The Simulated Annealing algroithm evaluation function formula is defined as:

$$\begin{aligned}\Delta Eval &= [A(p') - A(p)] + [L(p') - L(p)] + [J(p') - J(p)] + \\ &\quad 0.1 \times [Eval\ 2(p') - Eval\ 2(p)]\end{aligned}$$

If $\Delta Eval > 0$, meaning *p'* is better than *p*, then p is replaced by *p'*, otherwise the current status will be kept. To avoid falling into a local optimal, *p'* was allowed to replace *p* with a probability of $e^{\Delta Eval/T}$ when $\Delta Eval \leqq 0$. T decreased gradually in tandem with increasing iterations, thus reducing the probability of accepting a worse solution. In this manner the searching problem is converged. A threshold of .0000000001 was set to stop this algorithm.

Two iterative improvement algorithms were integrated into the process described in this paper to achieve the stated grouping goals and to provide each team with strong thinking styles. Hill Climbing is used to find an approximate solution quickly, and Simulated Annealing is used to avoid falling into a local optimal.

Chapter 6
Implementation

An online questionnaire was designed to make it easier for teachers to identify and collect data on the psychological features of their students. The questionnaire system was connected to a heterogeneous grouping system that combined DIANA (*Differences In And Non-differences Among groups*) and FUTS (*Full Thinking Styles groups*) (Fig. 13).

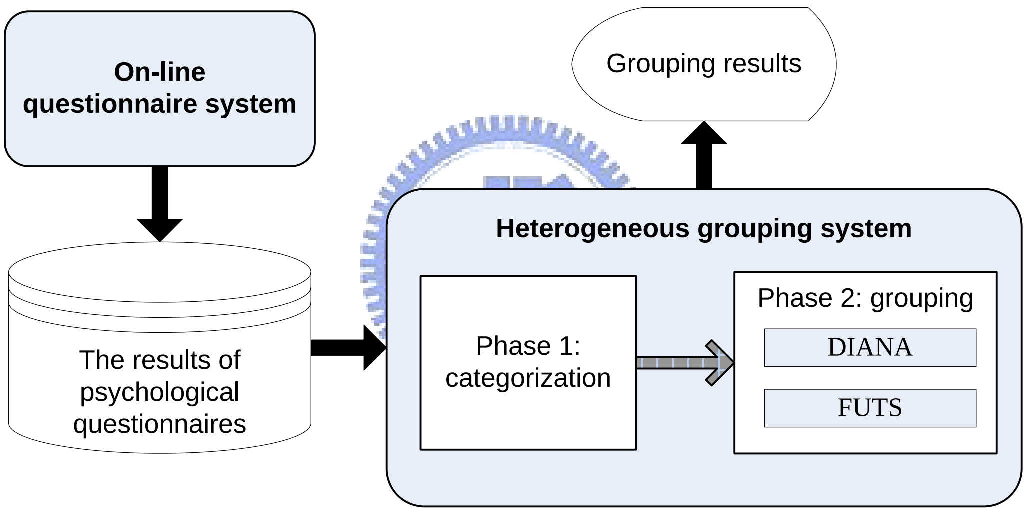


Fig. 13. The computer-supported grouping system.

6.1 On-line questionnaire system

The online questionnaire system interface is shown in Fig. 14. The system was designed to allow researchers or teachers to collect psychological data from any sample, and to store the information in a database. As previously discussed, student characteristics are often multiple and continuous in nature.

Fig. 14. Screen from the On-line Thinking Style Questionnaire used in this study. Lift frame shows guides and meaning of each point along a 5-point scale (A: not at all similar, B: a little similar, C: cannot judge, D: somewhat similar, D: all similar). Right frame shows the questionnaire content. Chinese version is for Taiwanese students.

6.2 Heterogeneous grouping systems

The interface for the heterogeneous grouping system is shown in Fig. 15. The first step entails loading data on student characteristics collected via the psychological questionnaire. Next, a teacher determines optimal group size according to instructional objectives, then chooses the DIANA or FUTS grouping method to generate a report listing student characteristic(s) and team numbers for heterogeneous group composition. The DIANA grouping method performs computations before recommending heterogeneous groups that meet the limitations discussed in Chapter 2; as stated, the purpose of DIANA is to allocate students to the most suitable group on both individual and whole class levels. In contrast, FUTS is used to generate groups with thinking styles that are conducive to brainstorming. Teachers can also load different psychological variables according to task requirements or instructional goals. In its present form, the proposed grouping system can consider a maximum of seven variables for composing groups consisting of 3-7 members; minor system modifications can increase both parameters.

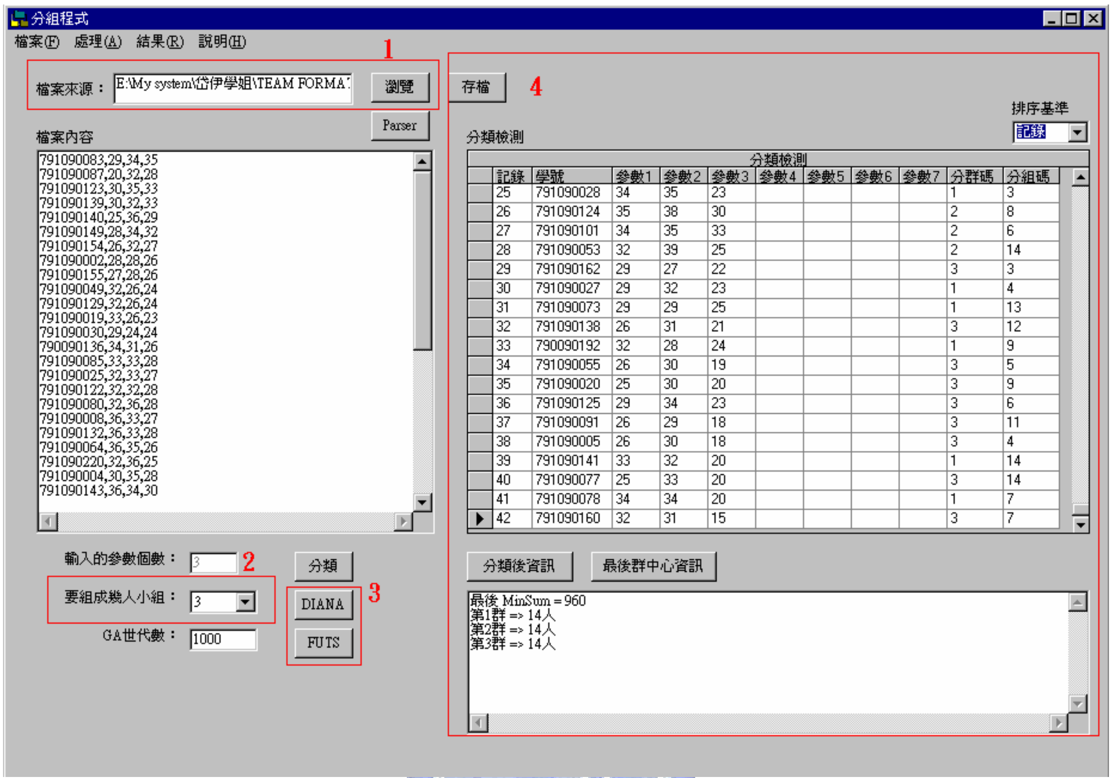


Fig. 15. Heterogeneous grouping system interface.

A test of DIANA's capabilities was performed using 46 freshmen participants enrolled in an introductory computer science class at a technical university in northern Taiwan. Mean, standard deviation, and correlation data on the students' thinking styles are presented in Table 5. A significant correlation was identified between the executive and judicial styles—that is, individuals with high executive style scores also had high judicial style scores. This made it difficult to identify exclusive legislative, judicial, or executive thinkers, and therefore impossible to compose heterogeneous groups with members representing one distinct thinking style.

Table 5. Descriptive Statistics and Correlation Matrix for Thinking Styles as Grouping Factors.

Thinking Style	Mean	SD	Executive	Legislative	Judicial
Executive	31.93	3.42	--		
Legislative	30.33	3.73	r = .247	--	
Judicial	25.33	4.56	r = .408**	r =.200	--

** p < .01

The proposed DIANA system was successfully used to address this problem. As shown in Fig. 16, DIANA classified students into three categories with centers of (0.82, 0.79, 0.59), (0.79, 0.87, 0.75) and (0.66, 0.74, 0.57). Category 1 groups consisted primarily of students with high legislative scores, category 2 with high executive and high judicial scores, and category 3 with the lowest scores in all three thinking styles.

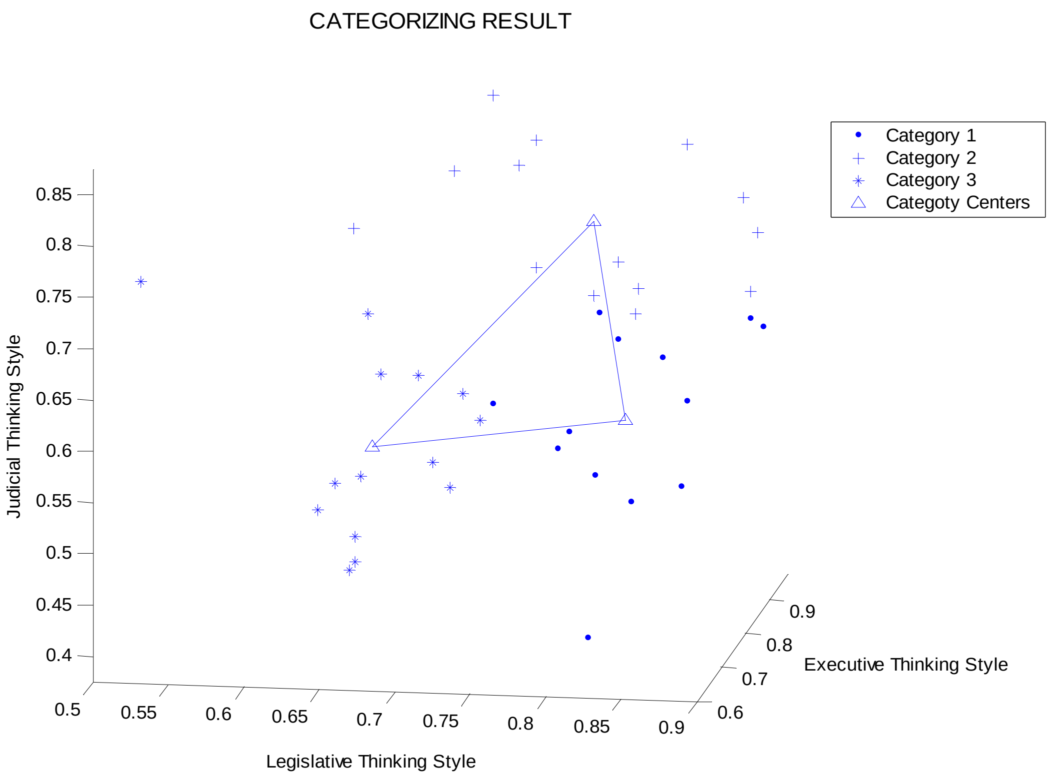


Fig. 16. Classification results for a sample of 36 students. The three category centers form a triangle.

In this project the mutation rate was set at 0.001. The average fitness during the evolutionary process is shown in Fig. 17. As indicated, the curve increases sharply for the first 28 generations, keeps rising, and remains steady after the 171st generation.

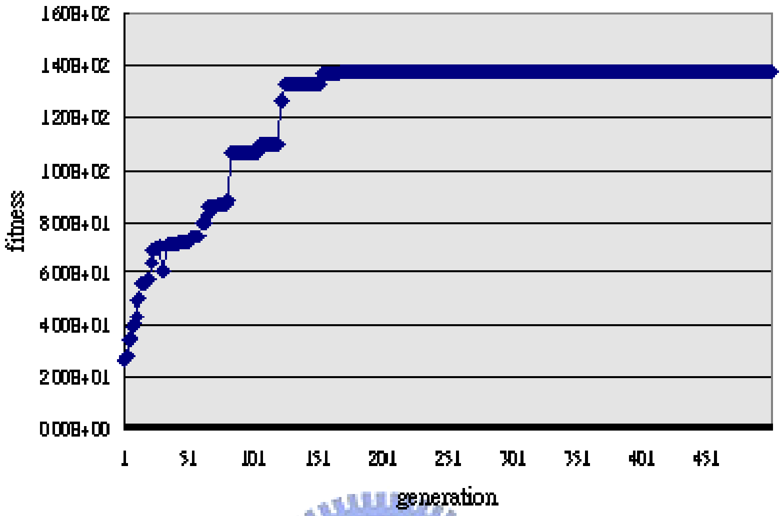


Fig. 17. Average fitness values during the evolutionary process.

Chapter 7
Experiment

An experiment was designed and conducted to evaluate the effectiveness of the grouping process described in the preceding chapters and the capabilities of DIANA and FUTS. The primary research questions were:

1. Which group type (DIANA, FUTS, or randomly assigned) performs best in a cooperative learning situation?

2. Which group type receives more positive subjective comments from its members concerning group partners and the cooperative learning process?

The treatment in this experiment was the grouping method (DIANA, FUTS, or random assignment); student participants attended an elementary or junior high school, thus calling for a 3 by 2 factorial design. Dependent variables were cooperative learning achievement and participant perceptions concerning member attitudes and the cooperative process. Based on the suggestions of a large number of researchers that heterogeneous grouping promotes positive interdependence, better group performance, and more effective interactions, heterogeneity was chosen as the grouping goal. A comparison was made among groups formed according to suggestions by DIANA (designed to form balanced groups based on educational equity), by FUTS (designed to form complete thinking style groups based on Sternberg's suggestions), and by random selection.

7.1 Participants and treatment

Participants were 269 fourth grade students in 8 classes taught by 2 teachers in 2 elementary schools and 229 eighth grade students in 7 classes taught by 2 teachers in 2 junior high schools—all in Taiwan. Details on the number of students in each class are presented in Table 6. All teachers volunteered to participate in the experiment. Every attempt was made to enhance the ecological validity and generalizability of the findings.

To eliminate interference from the use of different instructors, classes were randomly assigned to one of the three grouping methods; students in individual classes were grouped using only one of the three methods. Classes were viewed as individual units in which students were assigned to triads. The result was 55 groups created by the DIANA system, 45 by the FUTS system, and 70 by random composition. All groups were given the same cooperative design assignment during the same four-week period.

As shown in Table 6, significant correlations were observed in some (but not all) classes between legislative and executive styles, executive and judicial styles, and judicial and legislative styles. In other words, the classes showed different distribution patterns for the three thinking styles. A density of thinking style index was designed to test and verify whether the distribution pattern in each class affected DIANA or FUTS capability to perform its distributive task. The density index is defined as follows:

Table 6. Descriptive statistics of participants

Grade	Teacher	class	N	N of group	Method	Legislative TS (1)	Executive TS (2)	Judicial TS (3)	*r* of (1) (2)	*r* of (2) (3)	*r* of (1) (3)	Density	Label of density
Elementary students	Teacher A	408	32	11	FUTS	4.0188	3.8688	4.1938	0.358*	0.211	0.386*	9.107	Low
		409	29	10	DIANA	4.0069	3.331	3.9379	0.242	0.169	0.106	23.026	Low
		410	31	10	RANDOM	4.2194	3.7613	4.1161	0.128	-0.017	0.163	13.760	Low
		411	32	11	DIANA	4.025	3.5188	4.0063	0.135	0.107	0.258	14.369	Low
	Teacher B	401	37	13	RANDOM	3.9514	4.1243	3.7622	0.352*	-0.11	0.18	28.502	Meddle
		402	36	13	RANDOM	3.7833	3.6056	3.1111	0.2	0.529*	0.06	11.063	Low
		404	35	12	FUTS	3.92	3.6171	3.1657	0.308	0.472*	0.438*	19.497	Low
		405	37	13	DIANA	4.0162	4.027	3.7514	0.047	-0.078	0.29	31.042	Meddle
Junior high students	Teacher C	205	33	11	RANDOM	3.8295	3.2614	3.1174	0.788*	0.469*	0.619*	27.872	Meddle
		206	31	11	DIANA	4.1653	3.6371	3.4073	0.802*	0.563*	0.557*	56.796	High
		207	35	12	FUTS	3.8571	3.1929	3.3643	0.537*	0.022	0.24	64.224	High
		208	34	12	RANDOM	3.9007	3.375	3.3897	0.513*	0.437*	0.558*	63.967	High
	Teacher D	809	31	10	FUTS	3.8088	3.4233	3.4118	0.178	0.423*	0.289	16.665	Low
		810	32	10	DIANA	3.9397	3.7875	3.7372	0.16	0.305	0.308	49.601	High
		813	33	11	RANDOM	3.9567	3.4691	3.3582	-0.092	0.172	0.323	33.273	Meddle

Definition 5: Let $C = \{s_1, s_2, \ldots, s_m\}$ be a set of students in class *C*. Each student's *n* psychological features can be expressed as $F(x) = (f_1(x), f_2(x), \cdots f_n(x))$. The covariance matrix is $\Sigma = \frac{1}{m-1}\sum_{i=1}^{m}(F(s_i)-V)(F(s_i)-V)^t$, where $V = \frac{1}{m}\sum_{j=1}^{m}F(s_j)$. Let *T* represent the number of feature vectors $F(s_i)$ satisfying

$(F(s_i)-V)^t \sum_i^{-1}(F(s_i)-V) \le 1$. Class *C* density is calculated as $D = \frac{T}{[\det(\Sigma)]^{1/2}}$.

```
load ThinkingStyle.dat
avgTS=mean(ThinkingStyle)
[m, n]=size(ThinkingStyle)
ss=zeros
for p=1:m
ss=ss+(( ThinkingStyle (p,:)-avgTS)'*( ThinkingStyle (p,:)-avgTS))
end
corr=ss/(m-1)
t=0
for k=1:m
if ((ThinkingStyle (k,:)-avgTS)*inv(corr)*( ThinkingStyle (k,:)-avgTS)') <= 1
t=t+1
end
end
D=t/sqrt(det(corr))
[F,e]=eig(corr)
```

Fig. 18 A algorithm of measuring density in MATLAB

As the density index data indicate, the elementary school students' thinking styles were relatively dispersed and the junior high students' thinking styles were more centralized. It is unknown whether these distribution differences reflect a natural phenomenon or sampling bias. According to Sternberg's theory, thinking styles develop as individual's age and can be altered by teaching. It is possible that student thinking styles become more narrowly focused due to the effects of institutionalized schooling.

7.2 Group task

Participants were given the following assignment:

"Assume you are in a group of travel agents and your job is to plan an attractive travel itinerary. You have some young (child) customers. They ask you to plan a day tour of Taipei/TaiZhong city, starting from 8:00 am in the morning and returning at 5:00 pm in the afternoon, and the cost for each person must be less than three hundreds dollars [New Taiwan dollars, approximately US$10]. Please write up a plan and create a report in PowerPoint format."

Groups were asked to discuss the assignment, collaborate in collecting information on the Internet, and document their decision processes while selecting scenic spots and locations for lunch and a tea break, as well as in creating the itinerary, traffic plan, and budget. Group reports had to clearly identify which student was responsible for each part of the project. Members were given verbal instruction to focus on the task and to avoid procrastination.

Group task performance was rated by teachers, who were instructed in a unified rating standard at the beginning of the study. The grading criteria included plan originality (30%), report design (30%), plan feasibility (20%), and the quality of the cooperative process (20%).

7.3 Procedure

1. Students were asked to fill out a thinking style questionnaire. Data were

entered into the DIANA/FUTS system.

2. A group list was posted during the first week of the project. Teachers assigned the cooperative design task, encouraged students to work together, and emphasized the need for personal accountability and cooperation. Students were asked to become acquainted with each other, to create names for their groups (i.e., the name of a travel agent), create project names for their excursions, and decide on the responsibilities of each member.

3. During the second week, groups began the process of collecting information via Internet searches and deciding on destinations and itineraries. Instructors tightly controlled student computer time to make sure that they did not perform off-task searches.

4. During the third and fourth weeks, students surveyed mass transportation systems and fares and began creating travel plan reports using PowerPoint.

5. During the fifth week, students were asked to complete a questionnaire consisting of nine items on their perceptions of group member attitudes and eight items on the cooperative process. An example of a member attitude item is, "Other members of my team brought critical knowledge and skills to work on the assigned group task." An example of a cooperative process item is, "Discussions in my team helped us easily reach effective conclusions." Responses were given along a 5-point Likert scale, with 1 = "strongly agree" and 5 = "strongly disagree."

Chapter 8
Results and Discussion

8.1 Descriptive statistics

A small number of students were absent for several days during the four-week experiment and therefore did not finish the entire process. After deleting these students from the follow-up analysis, teacher A ended up with 40 groups, teacher B 47 groups, teacher C 42 groups, and teacher D 29 groups.

Despite efforts to unify the teachers' evaluation standards, results for ANOVA analyses revealed statistically significant differences in grading distribution ($F(3, 154)=49.809$, $p=.000$) (Table 7). Hence, project grades given by each teacher were linearly transformed to keep means and standard deviations as similar as possible. The transformation effectively eliminated all distribution differences among the four teachers' grades ($F(3, 154) =.044$, *ns*). Specifically, no adjustment was made for teacher A's grades, 17 points were added for each of teacher B's students, 3 points were added for each of teacher C's students, and teacher D's grades were divided by 10, squared, and increased by 14 points.

Every effort was made to balance treatment assignments in each teacher's classes, therefore adjustments to group achievement data did not affect differences among treatments. Experimental accuracy was maintained.

Table 7. Summary of Descriptive Statistics and One-way Analysis of Variance of Project Grades among the Four Teachers before and after Linear Transformation.

	Teacher A (n=40)		Teacher B (n=47)		Teacher C (n=42)		Teacher D (n=29)		ANOVA
Achievement	M	SD	M	SD	M	SD	M	SD	$F(3,154)$
Before linear transformation	83.60	7.93	66.13	7.69	80.33	9.29	83.41	4.16	49.809***
After linear transformation	83.60	7.93	83.13	7.69	83.33	9.29	83.75	6.96	.044

*$p < .05$ **$p < .01$ ***$p<.001$

8.2 Comparing achievement among DIANA, FUTS and random composition groups

The first research question addressed the effects of DIANA and FUTS methods on group achievement. A 3 (DIANA, FUTS, random) $\times$ 2 (elementary or junior high student) mixed-designed ANOVA was conducted for group achievement (summary in Table 9; descriptive statistics are displayed in Table 8). Mean group achievements for each grouping method across the two school levels are presented in Fig. 19a, mean group achievements for each school level across the grouping methods are presented in Fig. 19b, and results from a statistical analysis are shown in Table 10. Differences among the main effects of the various grouping methods were statistically significant, $F(2, 158)=6.327$, $p=.002$, suggesting that the DIANA (M=85.53) and FUTS (M=84.78) grouping methods outperformed random composition (M=80.74). There was no significant main effect for school level. There was a significant interaction between school level and grouping method.

Table 8. Means and Standard Deviations for Method Conditions as a Function of School Level Condition (achievement).

Method	N	M	SD
Elementary Students			
Random	34	81.765	8.312
DIANA	32	86.188	6.029
FUTS	21	81.571	8.232
Total	87	83.345	7.755
Junior High Students			
Random	29	79.528	8.937
DIANA	20	84.480	7.281
FUTS	22	87.851	6.023
Total	71	83.502	8.365
Total			
Random	63	80.735	8.609
DIANA	52	85.531	6.523
FUTS	43	84.784	7.778
Total	158	83.415	8.009

Table 9. Summary Table of Two-Way Analysis of Variance for Grouping Method and School Level on Achievement.

Source of Variance	SS	df	MS	F
School Level	22.892	1	22.892	.397
Method	729.877	2	364.938	6.327**
School Level * Method	534.466	2	267.233	4.633*
Within cells	8767.371	152	57.680	
Total	1109455	158		

*p < .05 **p < .01 ***p<.001

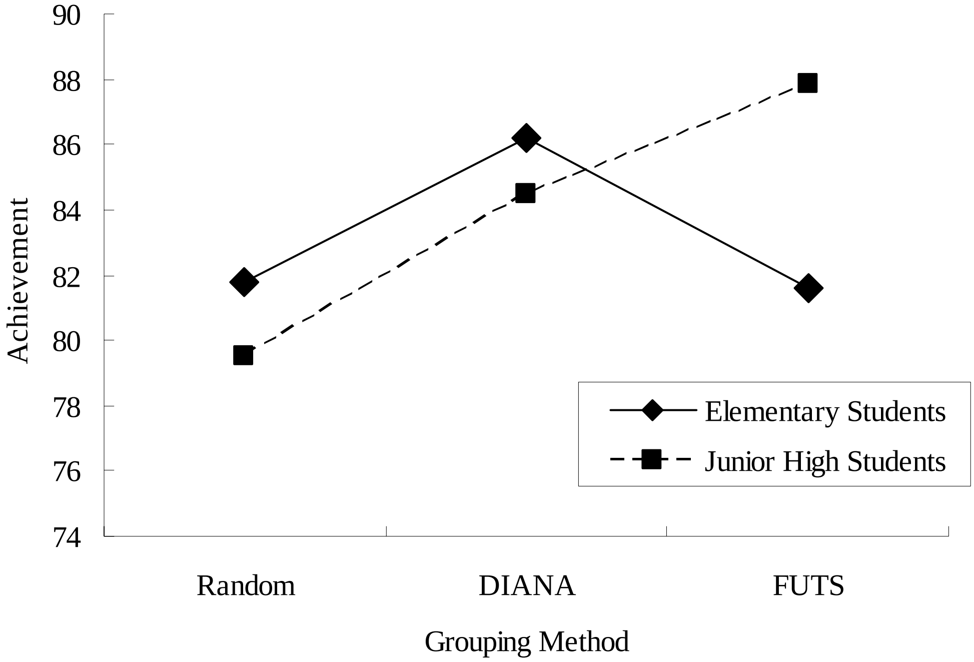
Results from an analysis of simple main effect indicate that when the grouping method is controlled for, junior high students grouped by the FUTS method performed significantly better (M=87.85) than elementary school students grouped by FUTS (M=81.57, F = 8.2, p< .01), but no differences between younger and older students were noted for either DIANA or random grouping (Table 10). The data in Table 10 and Fig. 19 show significant differences in performance between elementary and junior high students across the three grouping methods. For elementary students, the DIANA groups' achievement was significantly higher than for the other two grouping methods (DIANA 86.19 > FUTS 81.57 = random 81.76, $F = 3.61$, $p < .05$). For the junior high students, the FUTS and DIANA groups performed significantly better than the random groups (FUTS 87.85 = DIANA 84.48 > random 79.53, $F = 7.58$, $p < .001$). In other words, the data indicate that DIANA was the best grouping method for the elementary school students and both DIANA and FUTS were the best methods for the junior high school students.

Table 10. Simple Main Effect.

Simple Main Effect	SS	df	MS	F
School Level				
RANDOM	78.303	1	78.303	1.05
DIANA	35.884	1	35.884	.84
FUTS	423.663	1	423.663	8.20**
Method				
Elementary Students	409.520	2	204.760	3.61*
Junior High Students	893.219	2	446.610	7.58***

*p < .05 **p < .01 ***p<.001

(a)



(b)

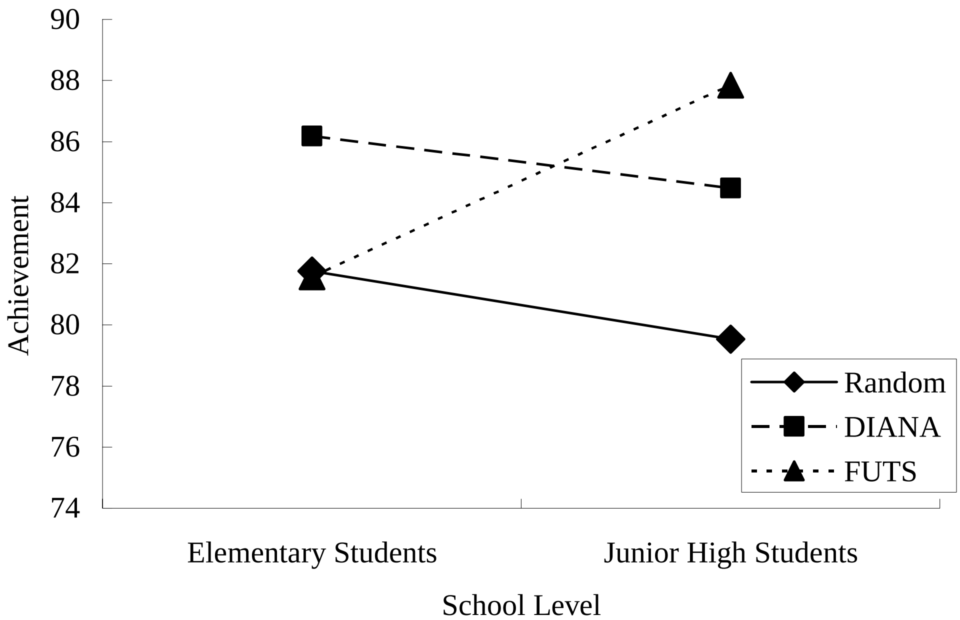


Fig. 19 (a) Mean group achievements for each grouping method across two school levels. (b) Mean group achievements for each school level across the grouping methods

Although the sample distributions appeared to have several correlations with school levels, a separate analysis was performed to shed light on the interaction between sample density and grouping method. Descriptive statistics are displayed in Table 11. Due to the lock of FUTS on middle density, a 2 (low vs. high density) × 3 (DIANA vs. FUTS vs. random) mixed-design ANOVA on group achievement was constructed (results summary presented in Table 12). Mean group achievement for each grouping method across sample densities are presented in Fig. 20a, mean group achievements for each density level across grouping methods are presented in Fig. 20b, and statistical analysis results are shown in Table 13.

Table 11. Means and Standard Deviations for Method Conditions as a Function of density condition (Achievement)

Method	N	M	SD
Low density			
Random	21	79.476	8.171
DIANA	19	86.895	5.174
FUTS	31	83.120	7.899
Total	71	83.052	7.781
Middle density			
Random	33	82.888	8.236
DIANA	13	85.154	7.198
FUTS	-	-	-
Total	46	83.529	7.944
High density			
Random	9	75.778	9.230
DIANA	20	84.480	7.281
FUTS	12	89.083	5.728
Total	41	83.917	8.621
Total			
Random	63	80.735	8.609
DIANA	52	85.531	6.523
FUTS	43	84.784	7.778
Total	158	83.415	8.009

Statistical significance was noted for the main effect of grouping method ($F(2, 112)=11.843$, $p=.000$), suggesting that the DIANA (M=85.66) and FUTS (M=84.78) grouping methods outperformed random assignment (M=78.37). No significant main effect was noted for sample density, but statistical significance was noted for the interaction between grade and grouping method.

Table 12. Summary of Two-Way Analysis of Variance for Sample Density and Grouping Method

Source	SS	df	MS	F
Density	5.954E-02	1	5.954E-02	.001
Method	1282.375	2	641.188	11.843***
Density * Method	449.716	2	224.858	4.153*
Within cells	5738.801	106	54.140	
Total	785672.676	112		

*p < .05 **p < .01 ***p<.001

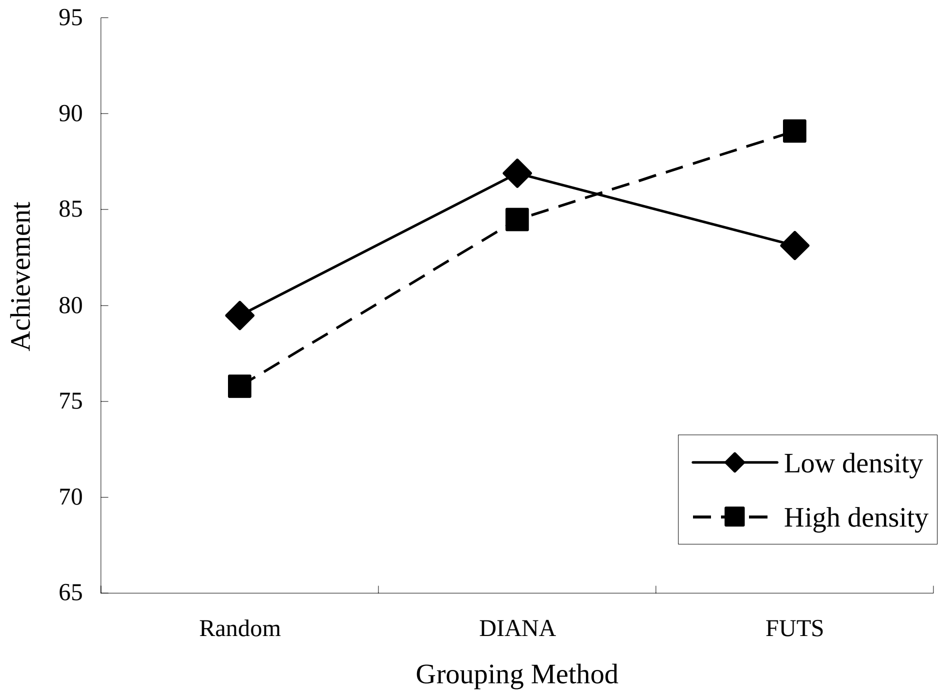
Results from an analysis of simple main effect show that when grouping method was controlled for, students in the high density sample grouped by the FUTS method outperformed (M=89.08) students in the low density sample (M=83.12, $F = 5.649$, $p< .05$) (Table 13). No statistically significant difference was noted between low- and high-density student samples grouped by the DIANA or random methods. The data also indicate significant differences between the low- and high-density samples across the three grouping methods (Table 13, Fig. 20). For the low-density sample, the DIANA groups' achievement was significantly higher compared to the randomly assigned groups (DIANA 86.90 > random 79.48, $F = 5.06$, $p < .01$). For the high-density sample, FUTS and DIANA group achievement were both significantly higher compared to the randomly assigned groups (FUTS 89.08 = DIANA 84.48 > random 75.78, $F = 8.55$, $p < .001$). In summary DIANA was superior to random assignment for students in the low-density samples and DIANA and FUTS both outperformed random assignment for students in the high-density samples.

Table 13. Simple main effect

Simple Main Effect	SS	df	MS	F
Density				
RANDOM	86.173	1	86.173	1.196
DIANA	56.814	1	56.814	1.412
FUTS	307.647	1	307.647	5.649*
Method				
Low	549.224	2	274.612	5.06**
High	922.854	2	461.427	8.55***

*p < .05 **p < .01 ***p<.001

(a)



(b)

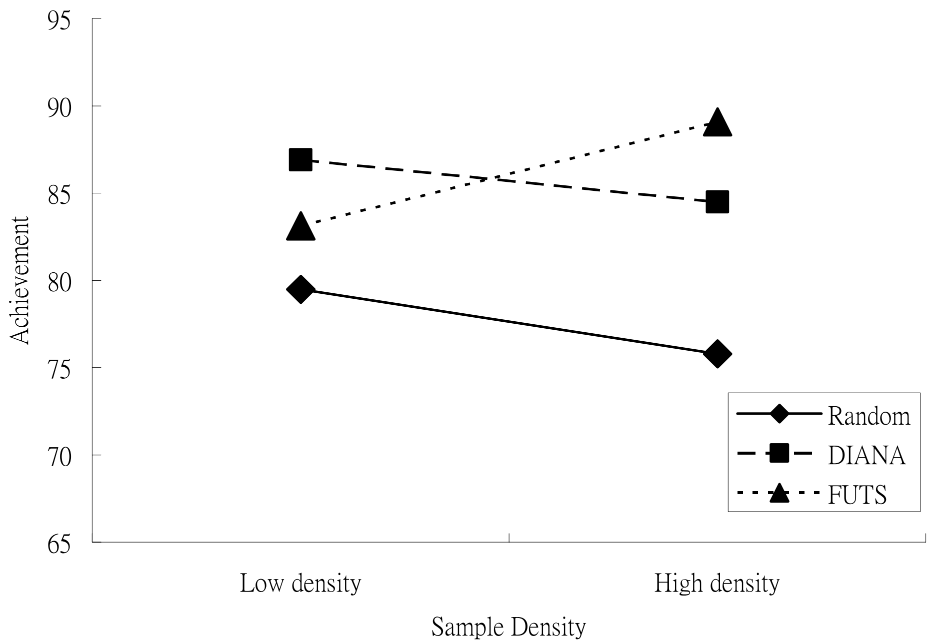


Fig. 20 (a) Mean group achievements for each grouping method across density levels.

(b) Mean group achievements for each density level across the grouping methods

8.2 Comparing satisfaction among DIANA, FUTS, and random composition groups

The second research question addressed whether the DIANA and/or FUTS grouping methods drew a higher number of positive subjective comments concerning group partners and the cooperative learning process. A 3 (DIANA, FUTS, Random) $\times$ 2 (elementary student, junior high student) mixed-design ANOVA was created for group partner and cooperative process satisfaction (descriptive statistics in Table 14, summary in Table 15). Data on mean member satisfaction for each grouping method across the two school levels are presented in Fig. 21a, mean member satisfaction for each school level across the three grouping methods are presented in Fig. 21b, mean process satisfaction for each grouping method across the two school levels are presented in Fig. 22a, and mean process satisfaction for each school level across the three grouping methods are presented in Fig. 22b. Statistical analysis results are shown in Table 16.

The main effect of grouping method on member satisfaction was significant ($F(2, 457)=3.630$, $p=.027$), suggesting that students grouped by DIANA (M=3.49) perceived greater satisfaction with their fellow group members than students grouped randomly (M=3.27). In addition, the main effect of the grouping method on process satisfaction was significant ($F(2, 457)=5.06$, $p=.007$), suggesting that students grouped by DIANA (M=3.46) perceived more overall satisfaction with cooperative learning than FUTS (M=3.22) or randomly grouped students (M=3.19). No significant main effect for school level was observed on either member satisfaction or process satisfaction, but a significant interaction between school level and grouping method was observed for both member and process satisfaction.

Table 14 Means and Standard Deviations for Method Conditions as a Function of School Level condition (Satisfaction)

			Member		Process	
School Level	Method	N	M	SD	M	SD
Elementary Students	Random	96	3.344	.774	3.306	.817
	DIANA	97	3.487	.768	3.464	.701
	FUTS	66	3.156	.914	3.018	.913
	Total	259	3.350	.817	3.292	.818
Junior High Students	Random	91	3.201	.806	3.075	.907
	DIANA	68	3.490	.716	3.451	.822
	FUTS	57	3.488	.501	3.462	.651
	Total	216	3.368	.719	3.295	.837
Total	Random	187	3.274	.791	3.193	.867
	DIANA	165	3.488	.744	3.459	.751
	FUTS	123	3.310	.766	3.224	.830
	Total	475	3.358	.773	3.293	.826

Table 15 Summary of Two-Way Analysis of Variance for Grade and Grouping Method

Source	SS	df	MS	F
	Member			
School Level	.466	1	.466	.796
Method	4.249	2	2.124	3.630*
School Level * Method	4.233	2	2.116	3.617*
Error	274.428	469	.585	
	Process			
School Level	.508	1	.508	.775
Method	6.642	2	3.321	5.060**
School Level * Method	8.492	2	4.246	6.469**
Error	307.827	469	.656	

*p < .05 **p < .01 ***p<.001

The data in Tables 16 and 17 indicate that when grouping method is controlled for, junior high students grouped by the FUTS method had significantly more positive perceptions of their teammates (M= 3.49) and the cooperative process (M= 3.46) than their elementary school counterparts (teammates M= 3.16, F = 6.0, p< .05;

cooperative process M= 3.02, $F = 9.37$, $p < .01$). Random and DIANA grouping did not result in statistically significant differences between the elementary and junior high students. As shown in Tables 16 and 17 and Fig. 21 and 22, elementary and junior high students had significantly different perceptions across the three grouping methods. For elementary students, DIANA groups had significantly higher scores for satisfaction than FUTS groups (Member: DIANA 3.49 > FUTS 3.16, $F = 3.30$, $p < .05$; process: DIANA 3.46 = random 3.31 > FUTS 3.02, $F = 6.09$, $p < .01$). Junior high students in FUTS and DIANA groups had significantly higher perceptions of satisfaction than their randomly assigned counterparts (Member: FUTS 3.49 = DIANA 3.49 > random 3.20, $F = 4.36$, $p < .05$; process: FUTS 3.46 = DIANA 3.45 > random 3.07, $F = 5.70$, $p < .01$). The summarized information in Fig. 21 and 22 demonstrate that DIANA was the best grouping method for elementary students in this study and that junior high DIANA and FUTS group members had better perceptions of satisfaction than randomly assigned group members.

Table 16. Simple main effect (Member)

Simple Main Effect	SS	df	MS	F
School Level				
RANDOM	.95	1	.95	1.53
DIANA	1.718E-04	1	1.718E-04	.00
FUTS	3.38	1	3.38	6.00*
Method				
Elementary Students	4.33	2	2.16	3.30*
Junior High Students	4.37	2	2.18	4.36*

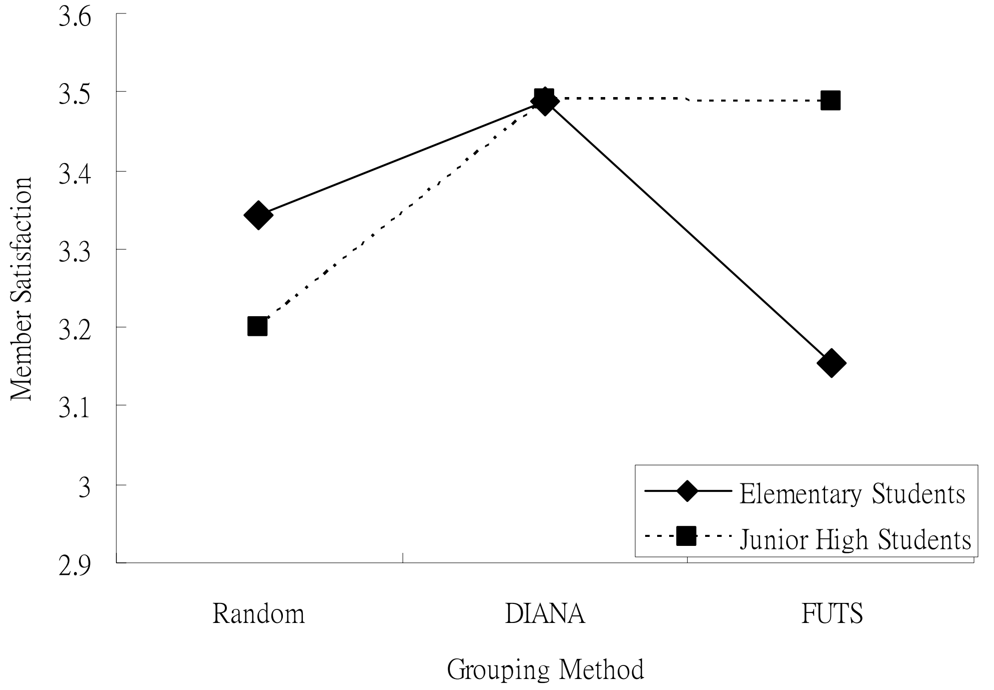
*p < .05 **p < .01 ***p<.001

Table 17. Simple main effect (Process)

Simple Main Effect	SS	df	MS	F
School Level				
RANDOM	2.491	1	2.491	3.35
DIANA	6.585E-03	1	6.585E -03	.012
FUTS	6.038	1	6.038	9.37**
Method				
Elementary Students	7.846	2	3.923	6.09**
Junior High Students	7.662	2	3.831	5.70**

*p < .05 **p < .01 ***p<.001

(a)



(b)

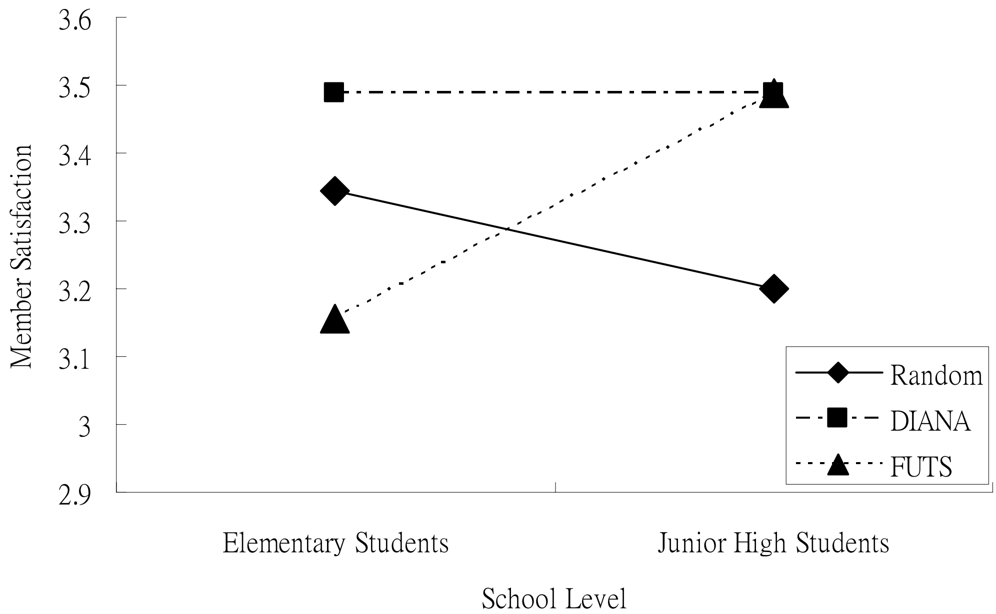


Fig. 21 (a) Mean member satisfactions for each grouping method across two school levels. (b) Mean member satisfactions for each school level across the grouping methods

(a)

(b)

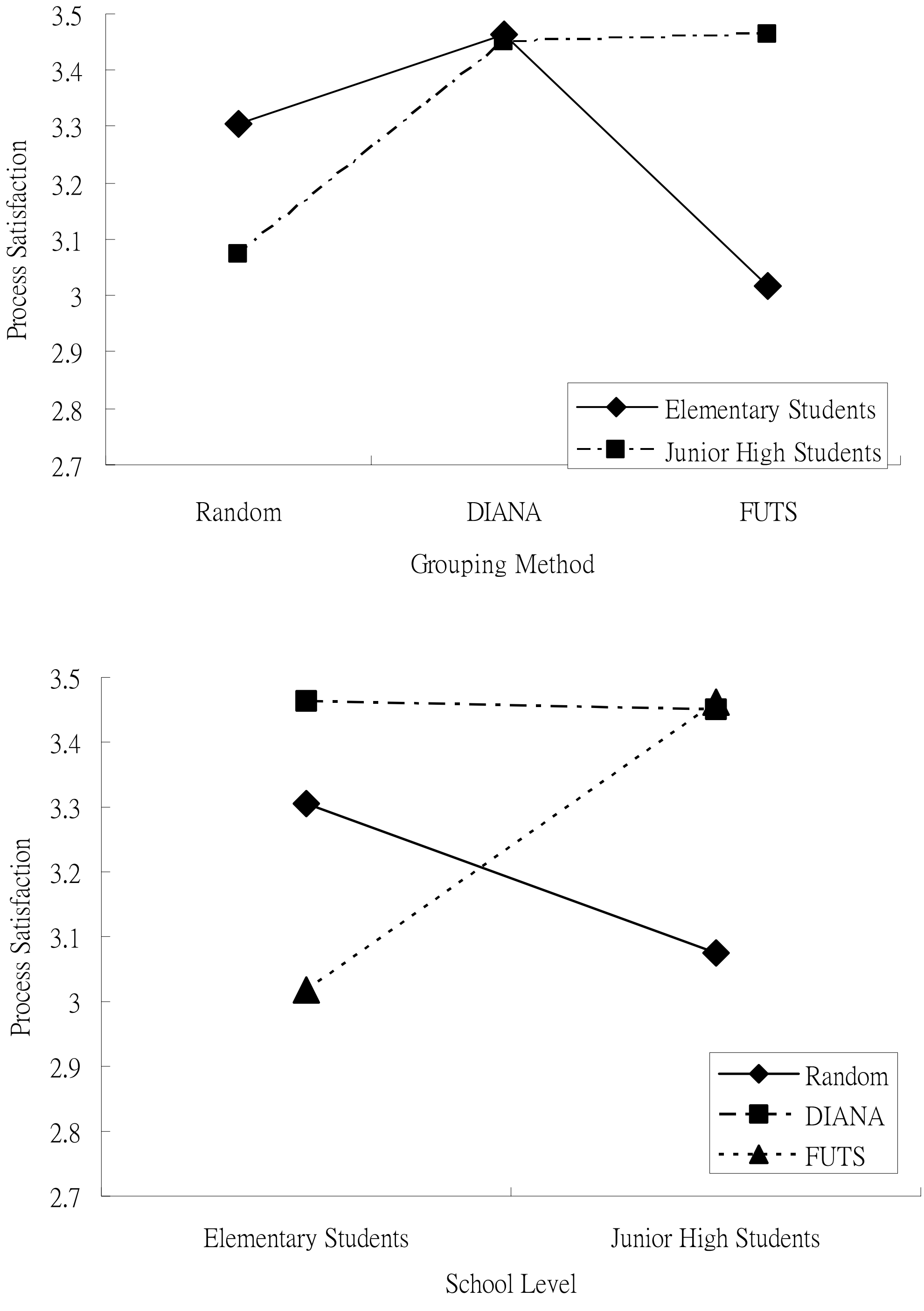


Fig. 22 (a) Mean process satisfactions for each grouping method across two school levels; (b) Mean process satisfactions for each school level across the grouping methods

In a like manner, a 2 (low vs. high density) $\times$ 3 (DIANA vs. FUTS vs. random) mixed-design ANOVA was conducted on group partner satisfaction and cooperative process satisfaction (descriptive statistics in Table 18; results summary in Table 19). Data on mean member satisfaction for each grouping method across the two sample density levels are presented in Fig. 23a, mean member satisfaction for each density level across the three grouping methods are presented in Fig. 23b, mean process satisfaction for each grouping method across the two density levels are presented in Fig. 24a, and mean process satisfaction for each density level across the three grouping methods are presented in Fig. 24b. Results from a statistical analysis are shown in Table 20.

The main effect of grouping method on member satisfaction was significant ($F(2, 337)=9.557$, $p=.000$), suggesting that students grouped by DIANA (M=3.46) or FUTS (M=3.31) perceived greater satisfaction with their group members than students grouped randomly (M=3.08). The main effect of grouping method on process satisfaction was also significant ($F(2, 377)=10.469$, $p=.000$), suggesting that students grouped by DIANA (M=3.45) perceived the highest level of satisfaction with the cooperative learning process, followed by FUTS (M=3.22) and randomly assigned students (M=3.04). No significant main effect for sample density level was observed for either member or process satisfaction. Statistically significant interaction was noted between sample density level and grouping method for both member and process satisfaction.

Table 18 Means and Standard Deviations for Method Conditions as a Function of Density Level condition (Satisfaction)

			Member		Process	
	Method	N	M	SD	M	SD
Low density	Random	61	3.223	.860	3.205	.863
	DIANA	60	3.434	.776	3.456	.722
	FUTS	93	3.264	.819	3.17	.875
	Total	214	3.300	.820	3.260	.837
High density	Random	25	2.720	.651	2.625	.476
	DIANA	68	3.490	.716	3.451	.822
	FUTS	30	3.452	.564	3.389	.654
	Total	123	3.324	.731	3.268	.790
Total	Random	86	3.076	.834	3.037	.812
	DIANA	128	3.463	.742	3.453	.774
	FUTS	123	3.310	.766	3.224	.830
	Total	337	3.309	.788	3.263	.819

Table 19. Summary of Two-Way Analysis of Variance for Sample Density and Grouping Method (Satisfaction)

Source	SS	df	MS	F
		Process		
Density	1.018	1	1.018	1.612
Method	13.222	2	6.611	10.469***
Grade * Method	6.635	2	3.317	5.253**
Within cells	209.021	331	.631	
Total	3813.675	337		
		Member		
Density	.505	1	.505	.855
Method	11.276	2	5.638	9.557***
Grade * Method	5.271	2	2.635	4.467*
Within cells	195.268	331	.590	
Total	3897.293	337		

*p < .05 **p < .01 ***p<.001

As the analysis of simple main effect data presented in Tables 20 and 21 show, low density sample students grouped randomly had significantly better perceptions of teammates and of the cooperative process than their high density counterparts (teammates M= 3.22 versus M= 2.72, $F = 6.888$, $p< .01$ and cooperative process M= 2.62 versus M= 3.21, $F = 9{,}999$, $p< .01$) when grouping method was controlled for. No signficant differences were noted between low and high density samples in terms of FUTS or DIANA grouping. The data in Tables 20 and 21 and Fig.23 and 24 indicate significantly different perceptions for the high density samples across the three grouping methods. FUTS and DIANA groups had significantly better perceptions than the randomly assigned groups (member: DIANA 3.49 = FUTS 3.45 > random 2.72, $F = 12.822$, $p <.001$; process: DIANA 3.45 = FUTS 3.39 > random 2.63, $F =12.398$, $p <.001$). In summary, members of DIANA and FUTS groups in high density classes had better perceptions of fellow team members and the overall process than their randomly assigned counterparts (Fig. 23 and Fig. 24).

Table 20. Simple main effect (Member)

Simple Main Effect	SS	df	MS	F	P
Density					
RANDOM	4.477	1	4.477	6.888**	.010
DIANA	9.995E-02	1	9.995E-02	.180	.672
FUTS	.806	1	.806	1.376	.243
Method					
Low	1.557	2	.779	1.161	.315
High	11.477	2	5.739	12.822***	.000

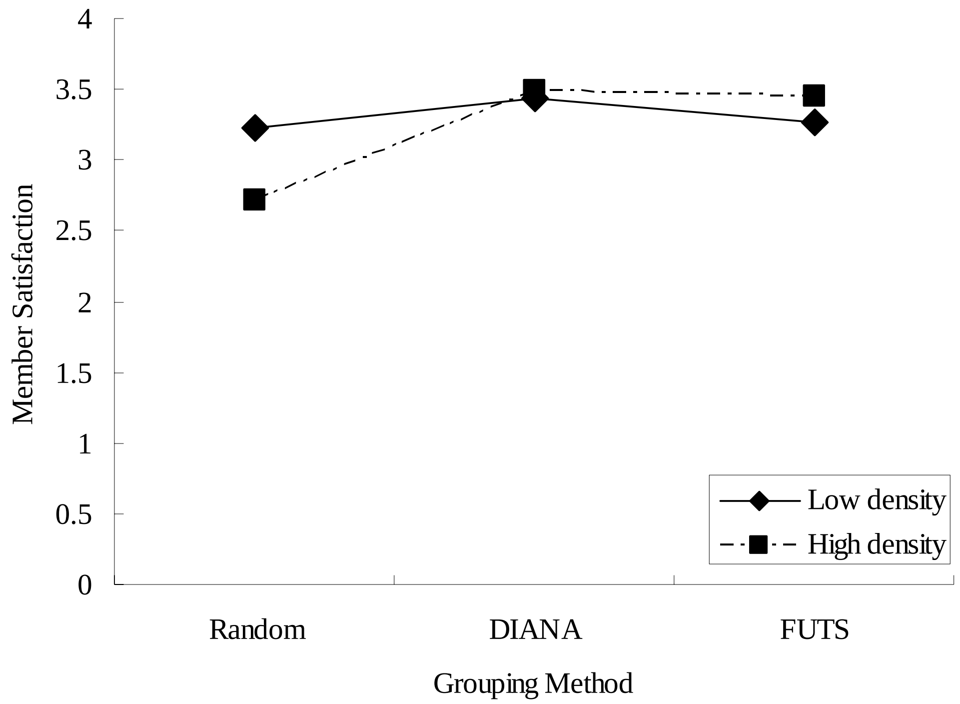
*p < .05 **p < .01 ***p<.001

Table 21. Simple main effect (Process)

Simple Main Effect	SS	df	MS	F	P
Density					
RANDOM	5.966	1	5.966	9.999**	.002
DIANA	7.507E-04	1	7.507E-04	.001	.972
FUTS	1.084	1	1.084	1.582	.211
Method					
Low	3.232	2	1.161	2.337	.099
High	13.045	2	6.522	12.398***	.000

*p < .05 **p < .01 ***p<.001

(a)



(b)

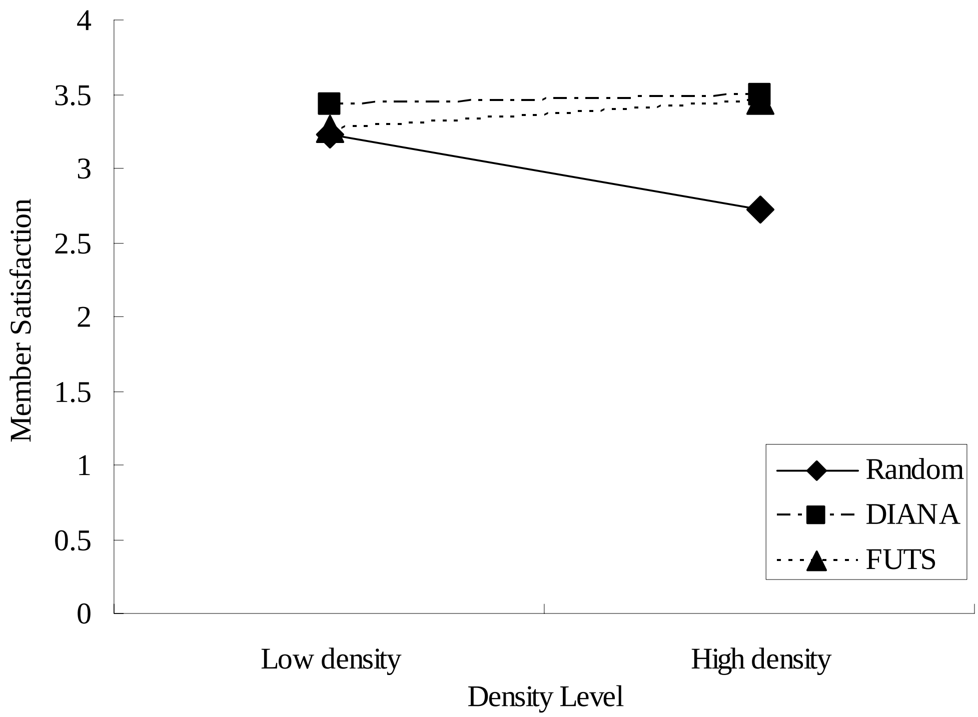
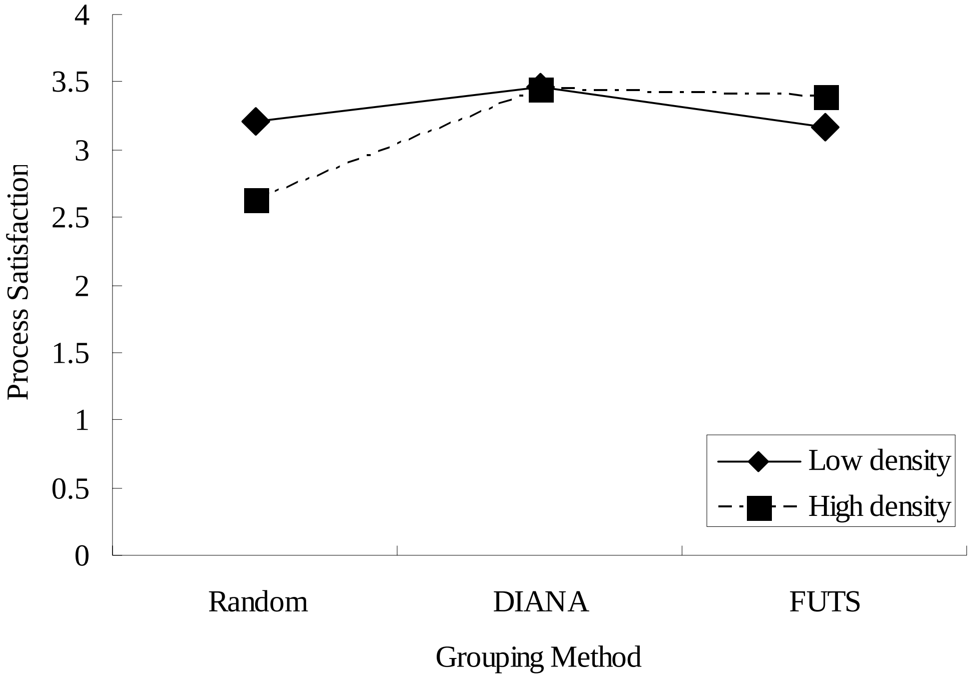


Fig. 23 (a) Mean member satisfactions for each grouping method across two density levels. (b) Mean member satisfactions for each density level across the grouping methods

(a)



(b)

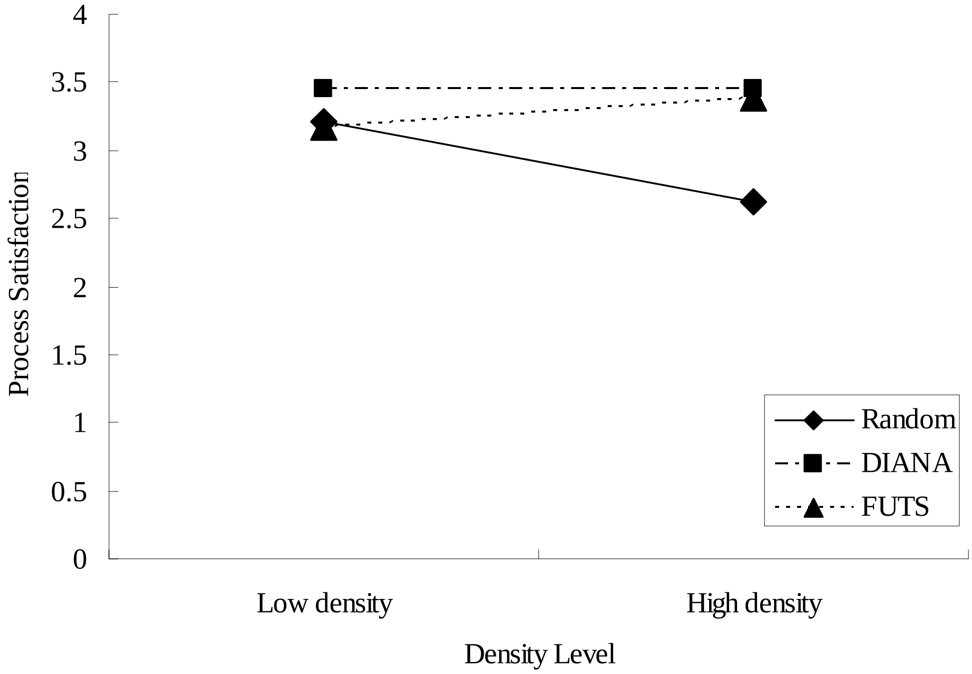


Fig. 24 (a) Mean process satisfactions for each grouping method across two density levels; (b) Mean process satisfactions for each density level across the grouping methods

8.3 Comprehensive discussion

According to the results discussed in the two preceding sections, students in the DIANA groups performed significantly better than randomly assigned group students in the elementary (lower density) and junior high school samples (higher density). Junior high students (high density) grouped by DIANA were more satisfied with their teammates and the cooperative process than those grouped randomly. Overall, the results of the experiment indicate that the DIANA grouping method can lead to greater student achievement and student satisfaction with the learning process. It is therefore suggested that the DIANA grouping method be refined and further tested as a means of improving class performance, assigning students to the most suitable heterogeneous groups, and creating environments for successful cooperative learning.

Note that even though satisfaction levels among DIANA group students were not significantly better than those for randomly assigned group students in elementary schools, they did exceed those of FUTS group students. This difference may be explained by the tendency of FUTS to disperse students who have striking thinking styles to produce more complete groups in terms of thinking style diversity. It may cause that the density within group was large and the density among FUTS groups was large, too. Furthermore, standard deviations for achievement and satisfaction across FUTS-assigned elementary school groups were relatively larger than those for DIANA-assigned elementary school groups (Tables 8, 11 and 14) as well as relatively larger than those for FUTS-assigned junior high school groups. It may be that the thinking styles of the elementary students in this experiment precisely distributed loosely (middle/low density samples) and loose distribution protruded the weakness of FUTS—variant group diversity. Consequently, FUTS group achievement in the elementary school population came third behind DIANA and randomly assigned group achievement.

The lower level of satisfaction with cooperative learning among FUTS group members may be explained by the greater diversity in those groups. The data indicate that FUTS-grouped elementary students felt particularly disappointed with the cooperative process—more than their randomly assigned counterparts. For the junior high participants the distribution of thinking styles was more centralized (that is, differences between group members were smaller), which may partly explain the overall lower FUTS satisfaction scores compared to DIANA-grouped students but overall higher FUTS satisfaction scores compared to the randomly assigned high-density samples or junior high students. This explanation finds support from Webb's theory that extreme differences within a group serve as barriers to cooperation; the explanation also emphasizes the importance of maintaining balance among groups.

For the combined elementary and junior high school populations, FUTS groups outperformed randomly assigned students in terms of achievement, but no differences were noted in terms of satisfaction with fellow members or the cooperative learning process. Among elementary school students, FUTS-assigned group members had less-positive perceptions of the cooperative process than randomly assigned students. This suggests that FUTS is not suitable for assigning students who have very broad differences—specifically, loosely distributed samples can cause FUTS to occasionally produce extremely heterogeneous variant groups whose performance may neutralize the exceptional performance shown by other groups and whose satisfaction scores reflect a lack of cooperation among group members. Thus, FUTS grouping is suggested for older students whose thinking styles eventually become increasingly similar.

Chapter 9
Conclusion

9.1 Summary and suggestions

In previous studies on student grouping techniques, researchers have tended to consider single variables such as ability or achievement (Johnson & Johnson, 1994) or categorical information such as gender or ethnicity (Cohen, 1982; Webb, 1989). The heterogeneous group system described in this paper is unique in that it allows for more complex grouping decisions by taking multiple and continuous variables into account and using psychological variables that are associated with group learning outcomes and intra-group interactions.

Two heterogeneous grouping methods were described, DIANA and FUTS. DIANA designers worked with the limitations that no students should be ignored and that all students should be assigned to the most suitable group possible—in other words, a primary goal was to maintain a constant level of heterogeneity. FUTS designers worked within the constraints of Sternberg's theory that groups containing members representing three thinking styles will succeed in terms of brainstorming.

A two-phase grouping framework was proposed to create heterogeneous groups. DIANA was designed in accordance with principles proposed by educational scholars—namely, using students' psychological features to compose heterogeneous groups and maintaining equity among all students. In order to achieve these combined goals, the categorizing phase of the grouping framework was designed so as to find suitable diversity for an entire class. The grouping phase was designed to manage the level of diversity within all groups and to maintain balance between groups. The framework thus allows all students to participate in cooperative learning on equal ground.

A distinguishing characteristic of the computer supported grouping system described in this dissertation is that it gathers data on student psychological features via an on-line questionnaire, thus eliminating the requirement to collect data on student learning information (e.g., browsing paths used with courseware or exam pass status) and saving time for time-strapped teachers. Furthermore, adopting psychological features for grouping is in accordance with principles laid out in the education literature—that is, psychological features exert a strong effect on learning outcomes. Hence, the proposed system possesses both feasibility and reliability, while at the same time being suitable for use at the beginning that will enter cooperative learning activities soon, and it needs not to go through the individual learning. For this reason, it is convenient for use in traditional classroom environments and do not need to be restricted to web-based learning.

A summary of experiment results is shown in Table 22. It indicates that in all situations, DIANA-assigned groups significantly outperformed randomly assigned groups in terms of achievement and earned higher satisfaction scores than from students in randomly assigned groups. The table data also show that the FUTS-assigned groups from the high-density junior high school samples performed better than their junior high counterparts assigned by either of the other two methods. The results also support the idea taken from cooperative learning researchers to form groups with high levels of intra-group diversity but avoiding extremely heterogeneous or homogenous groups (Abrami et al., 1995; Johnson & Johnson, 1990, 1994; Slavin, 1995; Webb, 1989). Lastly, the results provide further support for Sternberg's (1994)

Table 22 Summary of the experiment results

	DIANA	FUTS	RANDOM
Total			
Achievement	○	○	×
Member	○	—	×
Process	○	×	×
Elementary students			
Achievement	○	×	×
Member	○	—	×
Process	○	×	○
Junior students			
Achievement	○	○	×
Member	○	○	×
Process	○	○	×
Delete middle density			
Achievement	○	○	×
Member	○	○	×
Process	○	×	×
Low density			
Achievement	○	×	—
Member	—	—	—
Process	○	×	—
High density			
Achievement	○	○	×
Member	○	○	×
Process	○	○	×

hypothesis that learning styles strongly affect group learning outcomes. Future researchers may be interested in studying the effects of other variables on successful small group composition.

9.2 Limitations and future works

This research was designed to identify a balance between individual and whole-class performance instead of pursuing extreme heterogeneity. The system was also designed with the constraint that all student needs must be addressed, with no student left out. However, industrial groups, productal groups, and special educational researchers or practitioners may work with different principles and/or with fewer constraints. Although distance-based diversity was not suitable for the present project, it could be appropriate for other cases.

Furthermore, two kinds of methods of heterogeneous grouping were designed for this research, but some scenarios require homogeneous grouping—for example, when considering interest as a grouping factor, Abrami (1995) argues that homogeneous grouping is a better approach. In addition, although researchers often use random grouping as the datum line, a large number make comparisons between homogeneous and heterogeneous grouping, obviously requiring the establishment of homogeneous groups. While the focus in this paper was on heterogeneous group composition, future efforts will look at providing various grouping methods via a common interface on demand according to user requirements. This will require searching for and/or designing algorithms with the long-term goal of constructing a comprehensive computer-supported group composition system to help teachers create various types of learning groups. We suggest that researchers work on constructing other group-composition methods to help teachers achieve such goals as positive interdependence, meaningful interaction, and individual accountability.

A system such as DIANA or FUTS may be considered superfluous for teachers who know their students well enough to develop their own strategies for creating successful small learning groups. On the other hand, they may be particularly useful for teachers who are only starting to understand their students' unique skills or when they want to consider more complex factors for group composition. DIANA and FUTS may also be useful for distance learning educators who need to compose "virtual groups" without the benefit of face-to-face meetings. In addition, business managers may find a tool such as DIANA useful for putting together teams of engineers, designers, and R&D employees—although they would have to be very specific in their use of psychological variables.

The grouping methods described in this paper do share the characteristic of being applied to whole classes. The stated goal is to divide students into groups with the full class serving as the basic unit from which grouping solutions are sought. While this is quite helpful in traditional classroom learning environments, it can also act as a restriction. For example, most web-based courses follow a term, semester, or quarter system to coincide with regular school requirements, but some courses are designed so that students can take them according to their individual schedules and needs. In these kinds of courses (which strongly emphasize individual learning), DIANA, FUTS, or other approaches may not be required or otherwise be unsuitable for cooperative learning purposes.

In this study, two contingency variables (school level and sample distribution) were selected to measure the efficiency of grouping methods. The results indicate that sample distribution exerts a strong effect on grouping method, especially in low-density situations. It should be noted that the definition of density in this case is based on a measure of member populations within a hyperellipsoid in feature spaces corresponding to the standard deviations of cluster features. Variation for different grouping methods in other distribution models (uniform, normal and sphere, etc.) will require further analysis and discussion. It may be possible that a suitable grouping method will be identified via the automatic analysis of sampling distributions.

Finally, the point needs to be re-emphasized that while an efficient grouping technique may assist in setting up the cooperative learning process, it does not guarantee positive group outcomes. Teachers still must focus on social skills training, group task selection, and classroom management techniques in order to promote interdependence among group members.

Reference

Abrami, P. C., Chambers, B., Poulsen,C.,De Simone, C., d'Apollonia,S.,& Howden, J. (1995). *Classroom connections:Understanding and using cooperative learning.* Toronto: Harcourt Brace & Company.

Aimeur, E. & Frasson, C. (1996). Analyzing a new learning strategy according to different knowledge levels. *Computer and Education*, *27*(2), 115-127.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York : W. H. Freeman and Company.

Bishop, A. S., Greer, J. E., & Cooke, J. E. (1997). The co-operative peer response system: CPR for students. In: T. Müldner and T. C. Reeves (eds.) *Proceedings of ED-MEDIA/ED-TELECOM'97 - World Conference on Educational Multimedia/Hypermedia and World Conference on Educational Telecommunications*, Calgary, Canada, 74-79.

Biswas, G., Katzlberger, T., Brandford, J., Schwartz, X. & TAG-V (2001) Extending Intelligent Learning Environments with Teachable Agents to Enhance Learning. In Moore, J.D. et al. (eds.) *Artificial Intelligence in Education*, IOS Press, Amsterdam, 389-397.

Brusilovsky, P. (1999). Adaptive and Intelligent Technologies for Web-based Education, in Rollinger, C. and Petlo, C. (eds.) *Künstliche Intelligenz, Special Issue on Intelligent Systems and Teleteaching, 4*, 19-25.

Chan, T. W. & Baskin, A. B. (1990) Learning companion systems. In Frasson, C. & Gauthier, G. (eds.), *Intelligent Tutoring Systems: At the Crossroads of Artificial Intelligence and Education*, Ablex Publishing Corporation, New Jersey.

Chan T. W. & Chou, C. Y. (1997) Exploring the design of computer supports for reciprocal tutoring. *International Journal of Artificial Intelligence in Education, 8*, 1-29.

Cohen, E. G. (1982). Expectation states and interracial interaction in school setting. *Annual Review of Sociology*, *8,* 209-235.

Cohen, E. G. (1986). *Designing groupwork: Strategies for the heterogeneous classroom.* New York: Teachers College Press.

Cohen, E. G. (1994a). Restructuring the classroom: Conditions for productive small group. *Review of Education Research*, *64*(1), 1-35.

Cohen, E. G. (1994b). *Designing groupwork* (2nd ed.). New York: Teachers College Press.

Cohen, E. G.,& Lotan, R. A. (Eds.) (1997). *Working for equity in heterogeneous classrooms: Sociological theory in practice.* New York: Teachers College Press.

Coleman, D. (1997). *Groupware: Collaborative Strategies for Corporate LANs and Intranets,* Prentice Hall.

Cordero, R., DiTomaso, N., & Farris, G. F. (1996). Gender and race/ethnic composition of technical work group: relationship to creative productivity and morale. *Journal of Engineering and Technology Management, 13*, 205-221.

Dembo, M. H. (1994). *Applying educational psychology* (pp. 172). NY: Longman.

Duda, R. O. & Hart, P. E. (1973) *Pattern Classification and Scene Analysis,*. Wiley, New York.

Hietala, P. & Niemirepo, T. (1998) The competence of learning companion agents. *International Journal of Artificial Intelligence in Education, 9*, 178-192.

Holland, J. H. (1975). *Adaptation in natural and artificial system.* University of Michigan Press.

Hoppe, U. (1995). Use of multiple student modeling to parametrize group learning. In: J. Greer (ed.) *Proceedings of AI-ED'95, 7th World Conference on Artificial Intelligence in Education*, Washington, DC, 234-249.

Huxland, M, & Land, R. (2000). Assigning students in group projects: Can we do better than random? *Innovations in Education and Training International*, *37*(1), 17-22.

Ikeda, M., Go, S., & Mizoguchi, R, “Opportunistic Group Formation”, *8th World Conference on Artificial Intelligence in Education (AIED'97)*, August 20-22, 1997, Kobe.

Johnson, D. W. & Johnson, R. T. (1989). *Cooperation and competition: Theory and research*. Edina, MN: interaction Book Company.

Johnson, D.W., & Johnson, R.T. (1991). *Learning together and alone: Cooperative, competitive, and individualistic (3rd Ed.).* Englewood Cliffs, NJ: Prentice Hall.

Johnson, D. W. & Johnson, R. T. (1994). *Learning together and alone: Cooperative, competitive, and individualistic learning*. Boston: Allyn and Bacon.

Johnson, D. W. & Johnson, R. T. (1990). *Cooperation in the classroom*. Edina, MN: interaction Book Company.

Kagan, S. (1994). *Cooperative learning* (10th ed.). San Juan Capistrano, CA: Kagan Cooperative Learning.

Lin, S. S. J. & Chao, I.-C. (1999). *The Manual for use with Thinking Style Inventory-Taiwan version.* Unpublished manual.

Lin, S. S. J., & Sun. C. T. (2000). Team-forming recommendation for Web-based cooperative learning: Learning effect and partner preference. Paper presented at *the 2000 annual meeting of National Association for Research on Science and Teaching*, New Orleans, USA.

McCalla, G. I., Greer, J. E., Kumar, V. S., Meagher, P., Collins, J. A., Tkatch, R., and Parkinson, B. (1997). A peer help sytem for workplace training. In: B. d. Boulay and R. Mizoguchi (eds.) *Artificial Intelligence in Education: Knowledge and Media in Learning Systems*. (Proceedings of AI-ED'97, 8th World Conference on Artificial Intelligence in Education, Kobe, Japan, 18-22 August 1997) Amsterdam: IOS, 183-190.

Oakley, B., Felder, R. M., Brent, R. & Elhajj, I. (2004) Turning student groups into effective teams. *Journal of Student Centered Learning, 2* (1), 2004.

Russell, S. J., & Norvig, P. (1995). *Artificial Intelligence: A modern approach.* NJ: Prentice-Hall Inc.

Savicki, V., Kelley, M., & Lingenfelter, D. (1996). Gender and group composition in small task groups using computer-mediates communication. *Computers in Human Behavior, 12*(2), 209-224.

Scardamalia, M. & Bereiter, C. (1994). Computer Support for Knowledge-building Communities. *The Journal of the Learning Sciences*, 3, 265-283.

Sharan, S. (1999). *Handbook of cooperative learning methods* (2nd ed.). Westport, CT: Praeger.

Sharan, Y.,& Sharan, S. (1992). *Expanding cooperative learning through group investigation.* New York: Teachers College Press.

Slavin, R. E. (1995). *Cooperative Learning*: *Theory, research, and practice.* Boston: Allyn and Bacon.

Sternberg, R. J. (1994). Thinking styles: Theory and assessment at the interface between intelligence and personality. In R. J. Sterberg & Ruzgis, P. (Eds.), *Personality and Intelligence* (pp.169-187). New York: Cambridge University Press.

Sternberg, R. J. (1998). *Thinking styles.* NY: Cambridge University Press.

Sternberg, R. J. & Louise, S. S. (1996). *Teaching for thinking.* Washington, DC :American Psychological Association.

Strijbos, J. W., Martens, R. L., & Jochems, W. M. G. (2004). Designing for interaction: Six steps to designing computer-supported group-based learning. *Computers & Education, 42*, 402-424.

Sun, C. T. & Lin, S. S. J. (2003). Internet cooperative learning project. Unpublished technical report for National Science Foundation, Taiwan (NSC 91-2520-S-009-001, and NSC 91-2520-S-009-009)

Suthers, D. & Jones, D. (1997) An Architecture for Intelligent Collaborative Educational Systems. *8th World Conference on Artificial Intelligence in Education (AIED'97),* August 20-22, 1997, Kobe.

Tang, T. Y. & Chan, K. C. (2002). Feature Construction for Student Group Forming Based on Their Browsing Behaviors in an E-learning System. *Lecture Notes in Computer Science*, Springer, 512-521.

Vosniadou, S., Corte, E. De, Glaser, R. & Mandl, H. (1996) *International perspectives on the design of technology supported learning environments*, Mahwah, NJ: Lawrence Erlbaum.

Wang, D. Y., Lin, S. S. J., Sun, C.T. (2006) Computer-Supported group composing system: Help teachers to form balanced teams and avoid rare dream teams. *WSEAS Transactions on Computers, 5*(1), 55-60.

Webb, N. (1989). Peer interaction and learning in small groups. *International Journal of Educational Research, 13*, 21-39.

Webb, N. (1985). Verbal interaction and learning in peer-directed groups. *Theory into Practice,* 24, 32-38.

Wessner, M. & Pfister, H.-R. (2001) Group Formation in Computer-Supproted Collaborative Learning. *GRPUP'01*, Sept. 30-Oct. 3, 2001, Boulder, Colorado, USA.