ELSEVIER

DIANA: A computer-supported heterogeneous grouping system for teachers to conduct successful small learning groups

Dai-Yi Wang [a,*], Sunny S.J. Lin [b,1], Chuen-Tsai Sun [a,2]

[a] *Department of Computer Science, National Chiao Tung University, 1001 Ta Hsueh Road, HsinChu 300, Taiwan, ROC*
[b] *Institute of Education, National Chiao Tung University, 1001 Ta Hsueh Road, HsinChu, Taiwan, ROC*

Available online 20 March 2006

Abstract

Teachers interested in small-group learning can benefit from using psychological factors to create heterogeneous groups. In this paper we describe a computer-supported grouping system named DIANA that uses genetic algorithms to achieve fairness, equity, flexibility, and easy implementation. Grouping was performed so as to avoid the creation of exceptionally weak groups. We tested DIANA with 66 undergraduate computer science students assigned to groups of three either randomly (10 groups) or using an algorithm reflecting [Sternberg, R. J. (1994). Thinking styles: theory and assessment at the interface between intelligence and personality. In R. J. Sterberg, & P. Ruzgis (Eds.), *Personality and Intelligence* (pp. 169–187). New York: Cambridge University Press.] three thinking styles (12 groups). The results indicate that: (a) the algorithm-determined groups were more capable of completing whatever they were "required to do" at a statistically significant level, (b) both groups were equally capable of solving approximately 80% of what they "chose to do," and (c) the algorithm-determined groups had smaller inter-group variation in performance. Levels of satisfaction with fellow group member attitudes, the cooperative process, and group outcomes were also higher among members of the algorithm-determined groups. Suggestions for applying computer-supported group composition systems are offered.
© 2006 Elsevier Ltd. All rights reserved.

---

[*] Corresponding author. Tel.: +886 3 5712121x59284; fax: +886 3 5721490.
E-mail addresses: ophelia@cis.nctu.edu.tw (D.-Y. Wang), sunnylin@cc.nctu.edu.tw (S.S.J. Lin), ctsun@cis.nctu.edu.tw (C.-T. Sun).
[1] Tel.: +886 3 5731714; fax: +886 3 5738083.
[2] Tel.: +886 3 5731972; fax: +886 3 5721490.

1. Introduction

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). Numerous studies have been conducted on factors that influence cooperative learning success, including intra-group interdependence, group development, task demands, resources, process, and race and ethnicity (Abrami et al., 1995; Cohen, 1994b; Johnson & Johnson, 1994; Kagan, 1994; Sharan & Sharan, 1992; Slavin, 1995).

However, managing cooperative or small-group learning poses challenges for teachers, who often deal with students who lack the requisite social skills or who have problems with social loafing and 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.

Teachers who are committed to cooperative learning must make two important decisions. First, they need to identify specific student characteristics for establishing groups. Suggested characteristics include race, gender, and ability (Cohen & Lotan, 1997; Cordero, DiTomaso, & Farris, 1996; Savicki, Kelley, & Lingenfelter, 1996). Other researchers have reported that psychological features such as self-efficacy (Bandura, 1997) and learning style (Sternberg, 1998) strongly affect group-learning outcomes.

Second, teachers must consider group type – either heterogeneous or homogeneous. According to Dembo (1994), many cooperative and small-group learning researchers believe that heterogeneous groups are more effective in terms of performance and process. In contrast, heterogeneous groups are thought to: (a) provide ample 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, extreme differences among group members can impair cooperation (Webb, 1989).

Teachers who are willing to consider multiple psychological variables to create heterogeneous groups must deal with major computational requirements. To assist them in this task, we designed a computer-supported grouping system called *Differences In And Non-differences Among groups*, or DIANA. The system is the result of a four-year Internet-based cooperative learning project conducted by Sun and Lin (2003) to test various grouping techniques.

2. Literature review

According to the literature on cooperative learning, the majority of teachers use one of three methods to assemble small learning groups:

1. They allow students to form their own groups. However, as Abrami et al. (1995) note, students tend to form teams based on friendship or common interests in a topic, and friendship-based groups generally result in homogeneous groups. While cooperation

may be facilitated as a result of harmonious communication, it may also lead to 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. They use proximity or other simple methods, e.g., 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 groups may consist of low-ability students who are less successful at performing complex tasks. Another potential problem is the unintentional creation of groups that are unbalanced in terms of ethnic or social/economic position, with higher status students dominating their lower status classmates (Cohen, 1994b).

3. They use specific characteristics, usually ability or prior achievement. Teachers who do not know their students very well cannot use this strategy, but those that do can consider individual characteristics to purposefully form heterogeneous or homogeneous groups. More details were discussed below.

2.1. Grouping based on specific characteristics

Abrami et al. (1995) note that creating heterogeneous groups based on ability has benefits for students at both ends of the spectrum, although there is a risk that high-ability students may 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 can encourage high-ability students to reach or exceed their potential, but it may also lead to classroom polarization, with low-ability students having fewer opportunities for improvement.

After reviewing 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 (i.e., they lack 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. Webb therefore concluded that cooperative learning groups perform best when they contain a mix of high- and low-ability members.

Abrami et al. (1995), Cohen (1986), Cohen (1994a), and Web (1985) have examined how group composing characteristics such as gender, ethnic status, social economic status, and personality type affect learning performance and cooperative interaction. 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 individuals in the other two groups. In a separate study, Web (1985) observed that when girls outnumber boys in small learning groups, they tend to let boys deal with most of the problems.

Since a considerable number of researchers suggest that heterogeneous grouping promotes positive interdependence, better group performance and effective interaction, in this study we chose heterogeneity as our grouping goal.

Huxland and Land (2000) studied the creation of heterogeneous groups of students based on individual psychological features, using 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. In their study, the heterogeneous groups performed as well as the groups created by random selection.

2.2. Using thinking styles to compose cooperative groups

Sternberg (1998) uses the term *thinking style* to describe personal tendencies and attitudes associated with utilizing one's own skills. Thinking style is not the equivalent of talent or ability. Instead, it entails personal preferences for methods that determine the use of intelligence.

Sternberg uses a mental government analogy to describe how individuals manage their various cognitive capacities: *legislative*, *executive*, and *judicial* thinking styles exist within what he describes as a *functionality dimension*. 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 do not pay much attention to rules, preferring instead to compare ideas and to make judgments based on their benefits and deficiencies. Sternberg claims that positive performance occurs when an individual's thinking style matches environmental conditions and requirements. To improve the odds of finding or creating a match, he believes teachers should establish cooperative teams that are balanced in terms of thinking styles.

Teachers who use thinking style or any other psychological variable for grouping purposes must address two issues. First, since psychological variables often involve continuous data, it is difficult to identify reasonable cut-off scores for purposes of categorizing students. Second, the grouping process becomes increasingly complex as the number of psychological variables increases; in some situations, teachers may want to consider several variables instead of only one. We took these issues into consideration when designing our grouping strategy.

2.3. AI grouping algorithm

Lin and Sun (2000) designed and tested several computer-supported grouping techniques. They tabulated student thinking style scores from a questionnaire (Lin & Chao, 1999), and treated each student as a single point along three orthogonal vectors of thinking styles. Then they used an artificial intelligence algorithm based on Russell and Norvig (1995) Random Mutation Hill Climbing (RMHC) principle to group students based on distances between points denoting individual scores. Student differences within this space were viewed in the same manner as Euclidian distances. When three students formed a triangular shape, they were considered a single group. The goal was to compose heterogeneous groups of individuals whose thinking style points created the largest possible triangles.

Defining intra-group differences by distance made it possible to find an optimal solution using an exhaustive algorithm. The first step was to construct a distance matrix of all possible pairs, then aggregate those pairs with the largest distances and proceed until three points were established. The process was repeated until no more triads could be found or formed. In light of the complexity of such an exhaustive algorithm, Lin and Sun adopted RMHC for the purpose of finding optimal solutions as quickly as possible.

1. Students distributed throughout   2. Distance-based grouping.   3. Optimal groups.
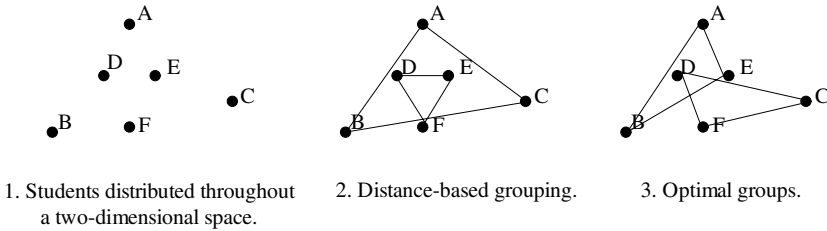   a two-dimensional space.

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

Using a distance-based RMHC grouping algorithm appeared to be intuitively reasonable, but many of Lin and Sun's RMHC-recommended groups were not very heterogeneous. This problem is illustrated in Fig. 1, in which a teacher wants to compose two groups of three students each according to 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.

Using a grouping algorithm based on computing distance can produce triangles that vary in size. When that size decreases, so do intra-group differences. This type of greedy algorithm therefore forms extremely heterogeneous and homogeneous groups. However, identifying an appropriate cut-off point for the two group types is problematic. The grouping result would be in direct conflict with the educational equity goal of assigning all students to their most suitable groups. In terms of educational equity, the optimal groupings is shown in the sequence 3 of Fig. 1 where A, B, and E are assigned as group 1 and C, D, and F as group 2. The two groups have sufficient levels of intra-group diversity – that is, the triangles should have similar shape.

3. The DIANA computer-assisted grouping system

Whereas the RMHC method is based on distance, our proposed DIANA method is based on shape. We designed DIANA to create groups that exhibit internal diversity and external balance with other groups. To accomplish these goals, we focused on finding similarities in shape among identified triangles. DIANA therefore generates groups that are similar in terms of heterogeneity, which fits well with our system goals of *fairness* (in the form of groups having the same size), *equity* (assigning all students to their most suitable group), *flexibility* (allowing teachers to address single or multiple psychological variable), and *heterogeneity* (guaranteeing individual diversity for promoting intra-group interactions).

Fig. 2 shows the interface of DIANA grouping system, and its manipulation is easy and flexibility. The first step of using DIANA is loading data on student characteristics collected via psychological questionnaires. After determining optimal group size based on instructional and classroom management objectives, teachers can use a report generated by DIANA that lists student characteristic(s) and team numbers for composing heterogeneous groups. Teachers may load different psychological variables according to task requirements or instructional goals. In its present form, DIANA can consider a maximum
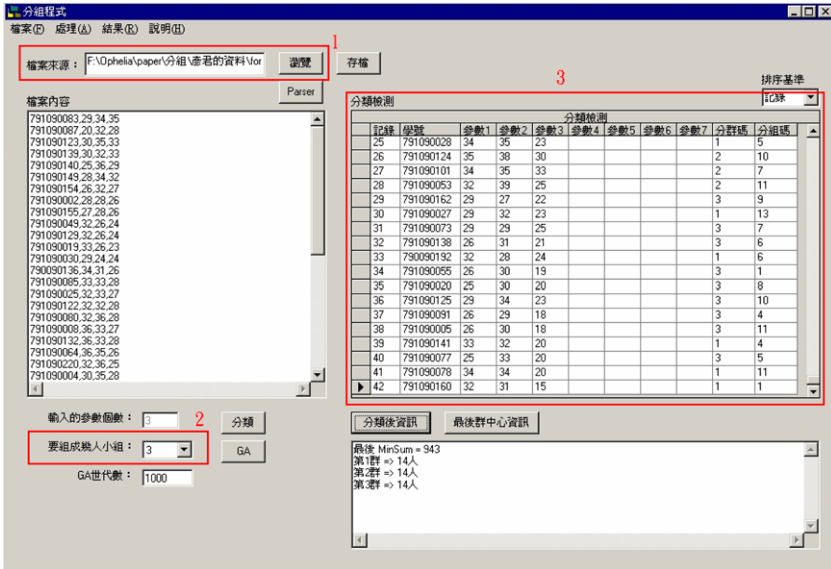
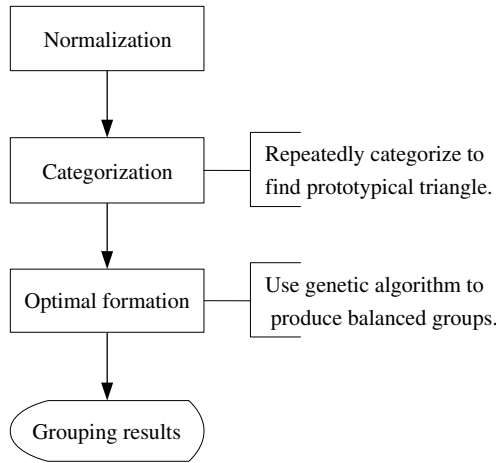Fig. 2. The interface of DIANA grouping system.

Fig. 3. DIANA grouping system flow chart.

of seven variables to compose groups consisting of 3–7 members; both parameters can be increased with minor system modifications.

As shown in Fig. 3, DIANA consists of three stages:

1. *Normalization*. In this stage, all data are normalized as 0 or 1, thus giving equal weight to each factor.
2. *Categorization*. The goal of this stage is to maintain intra-group diversity and inter-group balance. Its four steps are: (a) deciding the initial locations of all category centers; (b) allocating individual students to their nearest category; (c) reapportioning
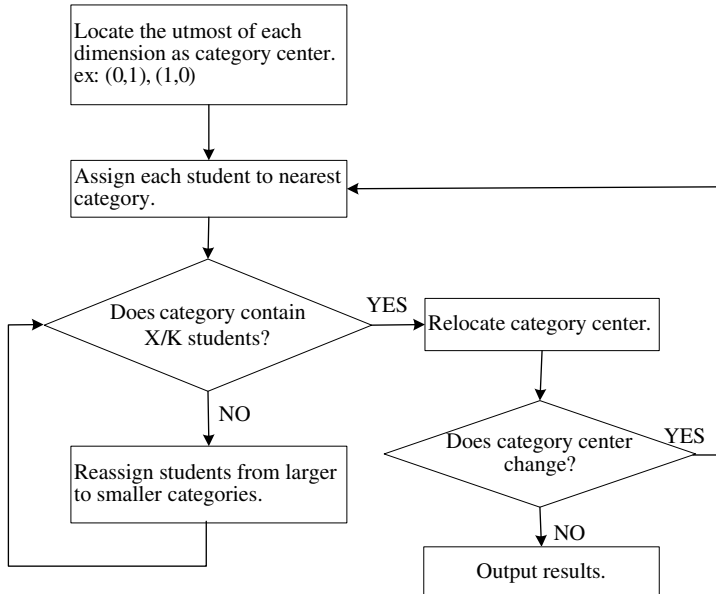
Fig. 4. Categorization stage flow chart for X students assigned to K groups.

students to maintain categories with equal numbers of members; (d) computing category centers and returning to step b whenever a category center changes (Fig. 4). The method organizes students around category centers; few individuals are situated in between categories, creating a high level of dispersal. The triangular shape of the final category centers is considered a prototype that represents the structure of all heterogeneous groups. Once group structure is defined, all group shapes must be identical or very similar to the prototypical triangle.

3. *Optimal formation*. After determining each student's category identity, DIANA uses a genetic algorithm (GA) (Holland, 1975) to produce approximate solutions for optimal group formation. 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 this study, one chromosome represents one group and each gene within a chromosome represents one 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. 5.

(2) *Fitness*. To avoid problems associated with the RMHC grouping principle, we did not use distance to measure intra-group differences. Since 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. As shown in Fig. 6, the target shape for the three final category centers is triangular. Differences between actual and targeted chromosome shapes are computed, with chromosomal fitness equaling the inverse of the absolute value of the difference. The higher the fitness value, the better the performance.
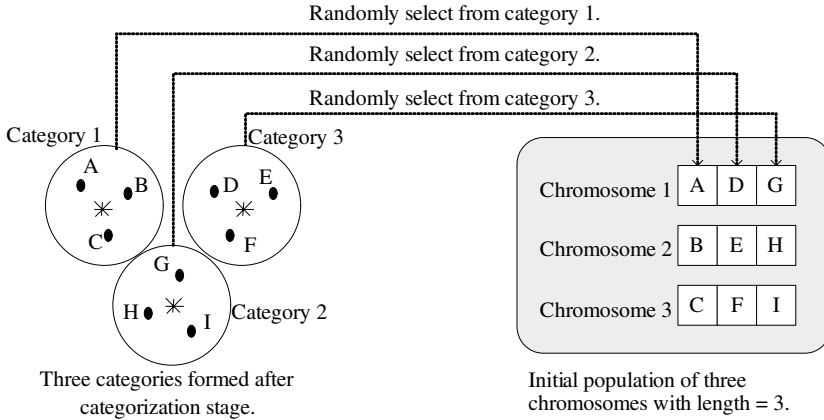
Fig. 5. Chromosome decoding and initial population.
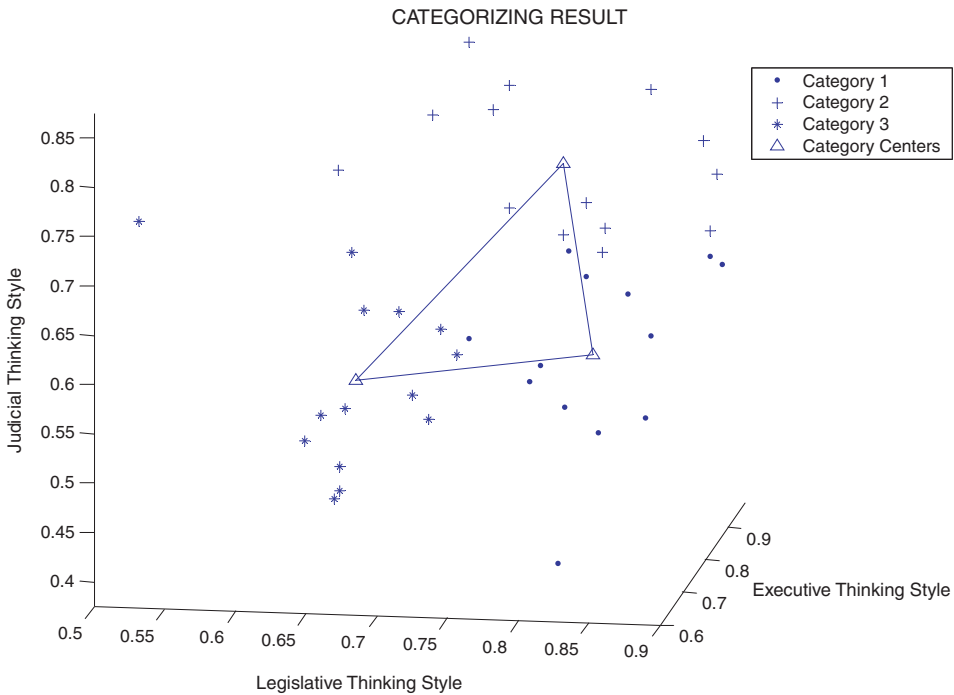
Fig. 6. Classification results for small sample of 36 students. The three category centers form a triangle.

(3) *Crossover.* Two chromosomes randomly selected from a population are 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.

(4) *Mutation.* This operator allows for a crossover of two chromosomes even if the fitness value does not improve.

Accordingly, 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 increases 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.

For the current study the generation (iteration) number was 1000.

4. Experiment

To test DIANA's capabilities, we designed an experiment to answer two research questions:

1. Which group type (heterogeneous or randomly assigned) performs better in a cooperative learning environment?
2. Which group type offers more positive subjective comments concerning group partners, group outcomes, and the cooperative learning process?

The treatment in our experimental design was the grouping method and the dependent variable the achievement of cooperative learning. We chose heterogeneity as our grouping goal based on the suggestions of a large number of researchers that heterogeneous grouping promotes positive interdependence, better group performance, and more effective interactions. In the second part of the experiment we investigated participant perceptions concerning the cooperative process.

4.1. Participants

Study participants were 66 freshmen enrolled in an introductory computer science class at a technical university in northern Taiwan. They were randomly assigned to two sectors. The 36 students in the first sector were divided into 12 groups of 3 individuals each using the DIANA system. The remaining 30 students were randomly divided into 10 groups. All teams were given the same four-week cooperative design assignment.

4.2. Group task

The participants were asked to design a combined Intranet/Internet computer network for a fictitious company. Each group was given a company floor map and a hierarchy chart for network security considerations. Groups were asked to discuss the assignment, to collaborate on a solution, and to document the cooperative process as they made design decisions on hardware and software requirements, specific network functions, an employee mail system, network security, and network typology. Group reports had to clearly identify which student was responsible for each part of the project. A weekly evaluation of group member activities was also required to discourage procrastination.

4.3. Group task assessment

Group task performance was rated by two computer science graduate students with considerable experience as teaching assistants. Since design projects always produce varied results based on design priority and individual style, we looked at both completion rates and correct scores when assessing task performance. "Completion scores" were given whenever a group presented a task solution, regardless of its correctness. Percentages of correct scores for all requirements were calculated and recorded as accuracy of request (AR) scores. For groups that were unable to finish all of the required tasks, percentages of correct scores for all completed tasks were calculated and recorded as accuracy of completion (AC) scores. The formula for calculating total scores was:

$$\text{Total score} = \frac{2 \times \text{AR} \times \text{AC}}{\text{AR} + \text{AC}} = \frac{2 \times \text{correct score}}{\text{request} + \text{completion score}},$$

$$\text{where AR} = \frac{\text{correct score}}{\text{request}} \text{ and AC} = \frac{\text{correct score}}{\text{completion score}}$$

4.4. Procedure

1. During the third week of the semester, students were asked to fill out a thinking style questionnaire. The data were entered into the DIANA system.
2. A group list was posted during the eighth week of the semester. Students were asked to become acquainted with each other during class time.
3. Assignments were completed between weeks 9 and 12. Instructors gave their students 1 h of class time per week for group work. To emphasize the need for personal accountability and cooperation, group members took turns organizing and handing in their assignments during weeks 10, 11, and 12.
4. During week 13, students were asked to complete a questionnaire consisting of seven member attitude perception items, four cooperative process items, and three group outcome items. An example of an 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 to easily reach effective conclusions." An example of a group outcome item is, "I am satisfied with my team's outcome." Responses were given along a 5-point Likert scale, with 1 = "strongly agree" and 5 = 'strongly disagree."

5. Results

5.1. Descriptive statistics and categorization result

Mean, standard deviation, and correlation data on the students' thinking styles is presented in Table 1. A significant correlation was observed 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. Thus, in this particular sample it was impossible to compose heterogeneous groups with each member representing one distinct thinking style.

Table 1
Descriptive statistics and correlation matrix of thinking styles as grouping factors

Thinking style	Mean	SD	Executive	Legislative	Judicial
Executive	31.93	3.42	–		
Legislative	30.33	3.73	$r = 0.247$	–	
Judicial	25.33	4.56	$r = 0.408^{**}$	$r = 0.200$	–

[**] $p < 0.01$.

We successfully addressed this problem using our proposed DIANA system. As shown in Fig. 6, DIANA classified students into three categories with final 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.

5.2. DIANA-assigned and randomly assigned group achievement

Because of the small number of groups (12 DIANA-assigned and 10 randomly assigned), we used a significance statistic of $p < 0.1$ in our calculations. A more common cut-off value of $p < 0.05$ may have resulted in an unacceptably high probability of type II errors.

AC scores were very high – 82.4% for the randomly assigned groups and 85.8% for the DIANA-assigned groups (Table 2); the difference between groups was not statistically significant. These scores indicate that both types of groups were equally capable of completing those tasks that they focused on as part of the assignment, regardless of whether or not they completed the entire assignment.

However, a statistically significant difference was found in AR scores – 64.1% for the DIANA-assigned groups and 48.4% for the randomly assigned groups. This result indicates that the DIANA-assigned groups were more capable of completing all network design tasks. A statistically significant difference was also noted in combined AR/AC scores between the two group types.

As shown in Table 2, standard deviations for the AR, AC, and total scores for the DIANA-assigned groups were smaller than those for the randomly assigned groups. F-test results revealed significant differences among these standard deviations for the two group types (Table 3). The data suggest that the DIANA-assigned groups were better than the random groups in terms of completing design tasks, and that fewer differences in

Table 2
Descriptive statistics and t-test results on differences in achievement between DIANA-assigned and randomly assigned groups

		Group #	Mean	SD	t-Test (p)
AR	Random groups	10	0.4840	0.2748	−1.691
	DIANA groups	12	0.6413	0.1548	(0.106*)
AC	Random groups	10	0.8242	0.1908	−0.540
	DIANA groups	12	0.8577	0.0942	(0.595)
Total score	Random groups	10	0.5759	0.2641	−1.716
	DIANA groups	12	0.7237	0.1284	(0.102*)

[*] $p < 0.10$.
AR, accuracy of request; AC, accuracy of completion.

Table 3
F-test results on achievement variances between DIANA and randomly assigned groups

	Group type	Group number	SD	*F*-test
AR	Random	10	0.2748	3.151**
	DIANA	12	0.1548	
AC	Random	10	0.1908	4.264**
	DIANA	12	0.0942	
Total Score	Random	10	0.2641	4.231**
	DIANA	12	0.1284	

** $p < 0.01$.
AR, accuracy of request; AC, accuracy of completion.

Table 4
Percentages of and χ^2 analysis results for student satisfaction among participants in DIANA and randomly assigned groups

Group type	Members' attitude	Group process	Group outcome	χ^2-Test
Random	43.33%	37.50%	46.67%	9.32 **
DIANA	56.76%	55.26%	57.89%	1.01
χ^2-Test	21.99**	21.49**	30.21**	

** $p < 0.01$.

achievement occurred among the 12 DIANA-assigned groups than among the 10 randomly assigned groups.

5.3. Subjective student perceptions

Students that responded positively to answers 4 and 5 on the questionnaire were categorized as "satisfied" participants; all others were categorized as "unsatisfied." As shown in Table 4, a larger number of students in DIANA-assigned groups responded positively to these items compared to their randomly assigned counterparts, regardless of their responses to items on fellow member attitudes (56.76%, $\chi^2 = 21.99$), group process (55.26%, 21.49), or group outcome (57.89%, 30.21). The data suggest that more than half of all DIANA-assigned group members felt satisfied with their fellow members' attitudes, the cooperative process, and group outcomes. Statistically significant differences were noted between these scores and those for randomly assigned students in terms of satisfaction with fellow group member attitudes, group process, and group outcome ($\chi^2 = 9.32$). The smallest satisfaction percentages among the randomly assigned students were for the cooperative process (37.50%), followed by fellow member attitudes (43.33%) and group outcomes (46.67%).

Based on a combination of AR scores and subjective participant perception data, we suggest that the DIANA-assigned groups outperformed the randomly assigned groups for two reasons: they cooperated in a more effective manner to complete the assignment, and individual group members brought distinctive ways of thinking to the design task.

6. Conclusions and implications

In past student grouping studies, researchers have tended to consider single variables such as ability or achievement (Johnson & Johnson, 1994) or categorical information such

as gender and ethnicity (Cohen, 1982; Webb, 1989). DIANA 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. When designing DIANA, we accepted the principles that no students should be ignored and that all students should be assigned to the most suitable group possible – in other words, one of our primary goals was to maintain a constant level of heterogeneity.

Our results indicate that both types of groups in this study were equally capable of correctly completing those tasks that they selected, but the DIANA-assigned groups correctly completed a significantly larger percentage of tasks. Overall, the results indicate that the DIANA-formed groups: (a) performed better than the randomly assigned groups and (b) showed less inter-group performance variance. The results also support our attempt to follow the suggestions of cooperative learning researchers to form groups with higher levels of intra-group diversity while 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) hypothesis that learning styles strongly affect group learning outcomes. Future researchers may be interested in selecting other variables to study their effects on successful small-group composition.

The most important limitation to this study is its small sample size (66 freshmen computer science majors), which limits the generalizability of our findings. Furthermore, the small sample size influenced our decision to use a significance value of $p < 0.1$ rather than the more common 0.05. Researchers may be interested in testing the effectiveness of DIANA with students at academic universities or in other major fields.

A system such as DIANA may be less useful to teachers who know their students well enough to develop their own strategies for creating successful small learning groups. On the other hand, DIANA 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 may also be useful for distance learning educators who need to compose "virtual groups" without the benefits of face-to-face meetings. In addition, business managers may find a tool such as DIANA useful for putting together groups of engineers, designers, and R&D employees, although they would have to be very specific in their use of psychological variables.

While this paper addresses heterogeneous group composition, DIANA can also assist with other group composition needs. On occasion, educators must compose groups with various homogeneous, heterogeneous, or balanced characteristics. We will continue to search for and design 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 future researchers construct other group-composition methods to help teachers achieve such goals as positive interdependence, meaningful interactions, and individual accountability.

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

References

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.

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

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.

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*. New York: Longman, p. 172.

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

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.

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

Johnson, D. W., & Johnson, R. T. (1990). *Cooperation in the classroom*. 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.

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.

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.

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 & P. Ruzgis (Eds.), *Personality and intelligence* (pp. 169–187). New York: Cambridge University Press.

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

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).

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

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