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Group formation in collaborative learning contexts based on personality traits: An empirical study in initial Programming courses

Oscar Revelo-Sánchez[1], César A. Collazos[2], Miguel A. Redondo[3],

[1] University of Nariño, 52001 San Juan de Pasto, Colombia, orevelo@udenar.edu.co
[2] University of Cauca, 190001 Popayán, Colombia, ccollazo@unicauca.edu.co
[3] University of Castilla-La Mancha, 13071 Ciudad Real, Spain, Miguel.Redondo@uclm.es

Abstract. Considering that group formation is one of the key processes when developing activities in collaborative learning contexts, this paper aims to propose a technique based on an approach of genetic algorithms to achieve homogeneous groups, considering the students' personality traits as grouping criteria. For its validation, an experiment was designed with 132 first semesters engineering students, quantifying their personality traits through the "Big Five Inventory", forming workgroups and developing a collaborative activity in initial Programming courses. The experiment made it possible to compare the results obtained by the students applying the proposed approach to those obtained through other group formation strategies. It was demonstrated through the experiment that the homogeneous groups generated by the proposed technique produce better academic results compared to the grouping technique by students' preference, traditionally used by the teachers when developing a collaborative activity.

Keywords: Collaborative learning, Empirical study, Genetic algorithms, Group formation, Personality traits.

1 Introduction

Outside of academia, groups constitute a basic social structure. They are formed and reformed in different ways for various purposes: people meet in social situations, coordinate to perform work-related tasks or constitute commissions because of common interests. Although, in academic fields, groups are also formed easily and for very diverse purposes, group creation in the classroom can be a complicated and stilted process. However, for collaborative learning to be successful, it is important to make effective groups [1].

Specifically, homogeneous grouping presents certain advantages for some types of learning activities, especially those that involve guided discovery, development of skills, review of material that has already been learned, or in highly structured tasks of competencies construction, allowing students to progress at a similar rate, which is beneficial for the achievement of specific goals [1–4]; this grouping type promotes a positive effect on collaborative learning [5–7]. Such is the case of activities that support learning processes in initial programming courses, the context of this study;

where, also, considering the personality traits of students in the group formation process enhances their collaborative performance, when it comes to software development activities [8–17]

This paper presents the results of the research process carried out to structure a homogeneous group formation technique in collaborative learning contexts, formation based on personality traits. For this, the “Big Five Inventory” is used as an instrument for measuring the traits of the participants' personality, a standardized inventory or questionnaire based on the psychological model of the Big Five [18]. On the other hand, given that group formation is a combinatorial problem that involves multiple characteristics, the heuristic search offered by genetic algorithms was used as an optimization technique. The literature review by Cruz & Isotani [19] concerning group formation demonstrates the great interest of researchers in using this technique as a solution to the problem, given its relevance in dealing with a large number of variables and their ability to quickly generate optimal solutions, that is useful groups.

The characteristics from which homogeneous groups are formed and the operators implemented in the genetic algorithm are the main contributions of this work. Most of the existing studies in the field of group formation that use genetic algorithms, focus the grouping according to the students’ knowledge level, their learning styles, and their demographic information among other characteristics, and use crossover and mutation basic operators. The proposed approach exploits the traits derived from the five dimensions of the Big-Five personality model (Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness), to improve collaboration and learning outcomes, both at the group and individual level. Likewise, a modification of the crossover operator named C1 is used, which is suggested for problems where genes should not be repeated, as is the case under study; and, for mutation, a variation of the swap mutation operator is used. These modified genetic operators allow a more complete search in the solution space, providing new genetic information to the population, preventing the algorithm from being trapped in a local minimum.

The proposed technique was validated with four different groups belonging to the Academic Programs of the Faculty of Engineering of the University of Nariño Camus Pasto, Systems Engineering and Electronic Engineering, for the initial Programming course in the academic period B-2019. Two of these groups were managed as experimental groups and the other two as control groups. Finally, a comparative analysis of the results of the proposed evaluative activities was carried out, applying statistical tests, for purposes of a basic initial measurement of the level of learning achieved by the students participating in the experiment. This allowed showing a positive incidence of the treatment given to the experimental groups compared to the control groups, that is, academic performance benefits.

The paper is organized as follows: initially, the proposed solution is presented in detail in Section 2; Section 3 subsequently describes the empirical process developed; Section 4 presents the results of the proposed experiment. Finally, Section 5 presents a set of conclusions.

2 Related works

Although the domain of computer-assisted collaborative learning contains the words "computer-assisted", group formation does not always occur with technological support [20]. For cases where such support exists, the literature describes multiple techniques to achieve group formation: genetic algorithms, hybrid genetic algorithms, fuzzy algorithms, brute force search, particle swarm optimization, machine learning and integer linear programming, among others. The same occurs with the characteristics of the students to be taken into account as grouping criteria. The literature describes the following characteristics: arbitrary matrix of attributes, demographic information, motivation, learning styles, academic profiles, psychosocial profiles, cognitive profiles, leadership profiles, learning roles, and prior knowledge, among others. Below are some of the most important related works of the recent five years, including a brief description of their application.

Moreno et al. [21] present a proposal that exhibits several characteristics: from an operational point of view, it is very flexible because it allows several group sizes and an arbitrary matrix of grouping attributes, and it can be easily adapted to consider several homogeneity/heterogeneity criteria; from an algorithmic point of view, it combines the best of two apparently opposite worlds: it uses a local brute force search within an iterative process guided by a random heuristic criterion; experiments with multiple data sets, with student numbers ranging from 20 to 3,500, demonstrate reasonable performance and execution times; and, the authors make both data sets and source code available to allow more objective comparisons of approaches.

Sun & Chiarandini [22] propose a novel method to form intra-heterogeneous and inter-homogeneous groups based on relevant students' characteristics. This method allows the consideration of multiple characteristics of the students and can handle both numerical and categorical types of characteristics simultaneously. Solve the grouping problem as a lexicographic optimization problem in the given order. Formulate the problem in terms of mixed-integer linear programming and solve it optimally. The authors conducted a pilot experiment considering three general characteristics (with 13 specific characteristics) including the level of knowledge, demographic information, and motivation.

García-Vélez et al. [23] in their research present a system capable of exploring the best alternatives to automatically organize homogeneous study groups that favor the best performance. The proposal uses a personalized genetic algorithm, based on the students' learning styles and their academic profiles.

Imbrie et al. [24] in their work propose the use of genetic algorithms to form groups optimized for heterogeneity. The genetic algorithm uses a discrete integer-based chromosome representation and group alleles to represent each group. Standard genetic operators allow the algorithm to adapt to any optimization criteria the instructor deems appropriate. They apply restrictions based on gender and ethnicity to minimize demographical imbalance between groups.

Zervoudakis et al. [25] present a method that uses computational intelligence techniques to classify students according to the principles of differentiated instruction. They apply a clustering algorithm based on particle swarm optimization to two data sets that emerge from the holistic assessment of the students' particular characteristics and needs. The results show the contribution of the algorithm to the effective formation of heterogeneous student groups, each of the members having homogeneous characteristics of skills, difficulties, psychosocial and cognitive profiles.

Ullmann et al. [26] in their work propose an adaptation of the particle swarm optimization algorithm based on three criteria: level of knowledge, interests and leadership profiles; forming groups with different levels of knowledge, similar interests and distributed leadership, providing better interaction and knowledge construction.

Chen & Kuo [27] propose a novel group formation scheme based on genetic algorithms with a penalty function, which considers the heterogeneity of students' knowledge levels and learning roles, and the homogeneity of social interactions measured by social network analysis among the members of the group, generating collaborative groups with balanced learning characteristics, in a collaborative learning environment based on problems.

Garshasbi et al. [28] successfully implemented and applied a multi-objective version of genetic algorithms, that is, a non-dominated sorting genetic algorithm, to improve the performance and accuracy of optimally formed learning groups. In contrast to the previous related works applying single-objective algorithms, the main advantage of this work is the simultaneous satisfaction of multiple targets predefined for the formation of optimal learning groups, especially the inter-homogeneity and intra-heterogeneity of each learning group, which significantly enhance both effectiveness and accuracy of optimal grouping processes in the underlying intelligent systems.

Garcia-Velez et al. [29] in their work present an intelligent system that determines the best alternatives to automatically generate student groups to address practice activities and problems. The proposal uses a genetic algorithm to analyze the students' personality and their academic profiles.

Lambić et al. [30] present group formation as a mathematical optimization problem. Based on the proposed approach and the variable neighborhood search algorithm, they create the application that solves the problem and provides the appropriate division of groups. The proposed approach considers pretest scores, interpersonal relationships, and prosocial behavior/openness skills of students.

Andrejczuk et al. [31] present a computational model that incorporates key factors for performance in a group: competencies, personality and gender, by forming heterogeneous groups. In addition, they propose efficient algorithms to divide a classroom into groups of uniform size and homogeneous performance. The first algorithm is based on an integer linear programming formulation. For small problem cases, this approach is appropriate. However, this is not the case of great problems for those who propose a heuristic algorithm.

Torres et al. [32] propose a fuzzy-based multi-agent model for group formation based on nine roles defined by Belbin typology, using the strengths and ideal responsibilities for each group member role. To better balance the different working groups based on existing roles, they employ a fuzzy logic approach that allows classifying the role performance of each individual into the group.

Joseph et al. (2017) in their work propose an approach in which students' preferences are taken into account regarding the composition of the group to which they would like to belong. Machine learning algorithm (K-Means) is applied to group large student groups and analyze their preferences. They consider prior knowledge and communication skills, as well as student preferences. Initially, groups are formed using student preferences. Then an attempt is made to include in each group students with good academic performance and communication skills.

3 Proposed technique

The technique is explained below in three parts: the first describes, in general, the methodological proposal, the second presents the instrument proposed for the measurement of personality traits, followed by a description of how the formation of working groups as such is carried out, through the application of genetic algorithms.

3.1 Methodological proposal

The group formation in collaborative learning contexts based on personality traits is presented as a sequential process comprising three stages that are described in the following sections. The boxes at the top are the inputs required in each stage, and the boxes at the bottom describe the outputs at each stage. Fig. 1 schematically summarizes this process.

It is clarified that, as such, the proposed group formation technique would only go up to the second stage. Stage three, related to the collaborative activity or activities to be developed, is incorporated into the process solely to validate the technique. This stage would be relative to the academic space in which it will be implemented.

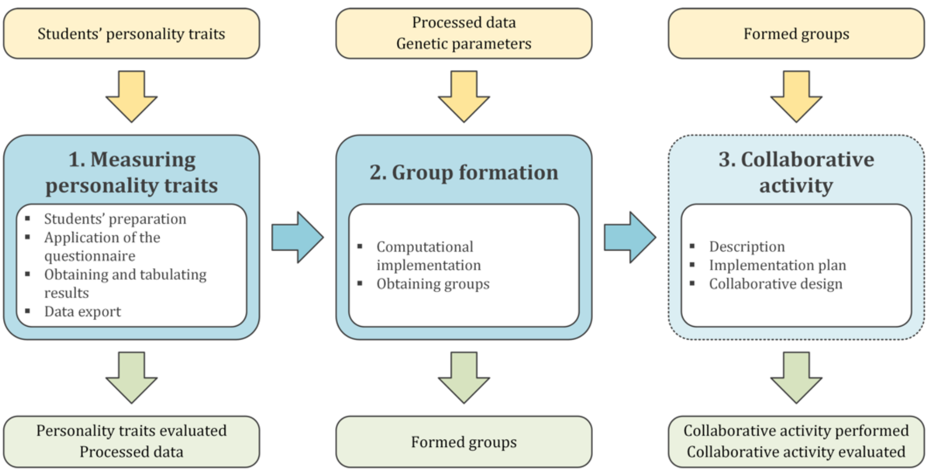

Fig. 1. Methodological scheme.

3.2 Measurement of personality traits

A Spanish adaptation of the BFI (Big Five Inventory) by John et al. is used as an instrument to measure the personality traits of students [33]. The aim of using this instrument is to have a scientifically accepted way to quantify the personality traits of an individual, which, as will be seen later, is the input required by the grouping algorithm. At no time is it intended to issue any type of concept or psychological diagnosis of the study participants, as this is outside the scope of this. The adaptation of the BFI into Spanish by Oliver P. John and Verónica Benet-Martínez [34] is used, with the corresponding consent for investigative purposes.

Once the BFI has been applied to each of the *n* students to be grouped, the results obtained must be stored in a table, where each row corresponds to a student, the first two columns being their identifier and his name, and the remaining five columns correspond to each of the personality dimensions considered by the "Big Five" model: extraversion, agreeableness, conscientiousness, neuroticism and openness.

3.3 Group formation

Considering the principles of Genetic Algorithms, as well as the nature of the problem of interest, the proposed method for the group formation is described in detail in this section. This method is based on the work of Moreno et al. [35], who propose a method to group elements (not necessarily students) in a homogeneous way.

Representation of students. Since the idea is to consider not only one, but several characteristics of the students, each student n can be represented using a vector in the following way, where M is the number of characteristics:

$$E_n = \{C_1, C_2, \ldots, C_M\} \tag{1}$$

These characteristics could have a different nature, for example, demographic (age, sex, etc.), psychological (*personality traits*, abilities, etc.), academic (grades, pretests, self-assessment, etc.), and cognitive (learning styles, types of intelligence, etc.), among others. This representation requires that every characteristic m ($1 \leq m \leq M$) be quantified by a numerical value in a predefined range, which does not mean that they can be considered categorical attributes. In these cases, a prior numerical discretization process would be required. For example, if an attribute takes values "high", "medium" and "low", these could be changed from 1, 2 and 3, respectively.

The total number of students can be represented by an $M \times N$ matrix, where N is the number of students, as shown in

Table **1**.

Table 1. Representation of a total set of students.

Id	C_1	C_2	…	C_M
1	70	0.50	…	25
2	20	0.83	…	-10
⋮	⋮	⋮		⋮
N	45	1.22	…	13

Once the data are organized in this way, they may need to be scaled to a common range, so that there are no disturbances in the calculation and that they are easily comparable. A simple way to achieve this is for all the data to be in the range 0 - 1, applying statistical normalization based on the unit [36], using the following expression:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

Representation of individuals. In the following, by individual we mean a specific collection of *G* groups, each with up to *N*/*G* students, with *N* being the total number of students. In most studies that use genetic algorithms, the data structure used is a vector where each position corresponds to a gene in the solution. In the proposed model it is proposed to use a matrix, where the number of rows corresponds to the desired number of groups *G* and the number of columns corresponds to the maximum size of each group *N*/*G*. In this way, each gene that makes up the chromosome contains the identifier of an element, and its position within the matrix defines the group to which it would belong. This representation, in addition to its clarity, facilitates the use of the genetic crossover operator proposed below.

In the group formation problem, as well as in other combinatorial problems, a chromosome cannot have repeated genes [35], which means that an individual (feasible solution) is one in which each element is in a single position of the chromosome. For example, if you have a total of 20 students and you want to form 4 groups, each one would contain exactly 5 students. In this case, a possible individual, if the students are numbered consecutively, could be like the one presented in Table 2.

Table 2. Representation of an individual.

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20

Fitness measure. Since the objective of this method is to obtain homogeneous groups concerning all the students, it is necessary to define a measure of this homogeneity. One possible way to do this is described below. First, the average of each characteristic of the totality of students (*TM*) is calculated:

$$TM = \left\{ \overline{C_1}, \overline{C_2}, \ldots, \overline{C_M} \right\} \tag{3}$$

Then for each group g ($1 \le g \le G$) of each individual, the average of each characteristic is calculated. Since each individual i is represented as a vector X^i, these averages (*IM*) can be represented as follows:

$$IM_g^i = \left\{ \overline{X_{g,1}^i}, \overline{X_{g,2}^i}, \ldots, \overline{X_{g,M}^i} \right\} \tag{4}$$

Subsequently, the sum of the squared differences between the M characteristics for each group g of individual i and the average of each characteristic in all the elements is calculated, as follows:

$$D^i = \sum_{g=1}^{G} \left[\left(\overline{C_1} - \overline{X_{g,1}^i} \right)^2 + \left(\overline{C_2} - \overline{X_{g,2}^i} \right)^2 + \ldots + \left(\overline{C_M} - \overline{X_{g,M}^i} \right)^2 \right] \tag{5}$$

The lower this value (with a minimum of 0), the more similar each of the groups will be on average concerning the total number of students. Therefore, the objective function of the problem could be expressed as follows:

$$\min Z = \sum_{g=1}^{G} \left[\left(\overline{C_1} - \overline{X_{g,1}^i} \right)^2 + \left(\overline{C_2} - \overline{X_{g,2}^i} \right)^2 + \ldots + \left(\overline{C_M} - \overline{X_{g,M}^i} \right)^2 \right] \tag{6}$$

Initial population and evolution. In the example represented in Table 6, a trivial group formation is shown: assign each student in an orderly manner to a group according to the identifier they have. The first N/G students (in this case 3) belong to Group 1, the next N/G to Group 2 and so on. Although this formation is valid, the idea of the initial population is to generate k individuals randomly, using the matrix representation described in the Section "*Representation of individuals*" and fulfilling the restriction that each element must be in one and only one of the positions in the array.

Once the initial population is obtained, and following the general scheme of a genetic algorithm, the evolution process is carried out in which it is passed from one generation to another using the genetic selection operators (roulette for minimization [37]), crossover (C1 operator [38]), and mutation (by swap [39]) until a desired fitness measure is obtained or until a total of h generations is reached.

4 Method

The research process was developed with an empirical design based on a quasi-experiment as shown in Table 3, seeking to verify one of the following hypotheses: H_0: the means of the grades obtained by the students in the topic of the collaborative activity are equal (null hypothesis); H_1: the means of the grades obtained by the students in the topic of the collaborative activity are different (research hypothesis). It is a quasi-experiment since the study groups (described below) were already formed before the experimentation, they were intact groups (the reason why they arose and the way they were formed have nothing to do with the experiment, it is a task that corresponds to the registration and academic control University office for each new academic period) [40].

Table 3. Experimental design.

	Experimental stimulus	Post-Test
G_1 (Experimental group)	X	O_1
G_2 (Experimental group)	X	O_2
G_3 (Control group)	-	O_3
G_4 (Control group)	-	O_4

The validation of the proposed group formation technique was carried out with a total of 132 students, divided into four different groups belonging to the Academic Programs of the Faculty of Engineering of the University of Nariño, Systems Engineering and Electronic Engineering, for the initial Programming course in the academic period B-2018. Table 4 shows the experimental design applied in each course:

Table 4. Experimental design by program.

Program	Course	Experimental design		
Systems Engineering	Programming I	G_1	X	O_1
		G_3	-	O_2
Electronic Engineering	Programming Foundations	G_2	X	O_3
		G_4	-	O_4

Groups G_1 and G_2 correspond to the experimental groups of each program and G_3 and G_4 were the control groups respectively, in addition, X was the experimental treatment that consisted of forming the required groups applying the proposed technique and of carrying out an activity collaborative learning named "Peer Code Evaluation"[41], during the work sessions scheduled for the control structures theme. In turn, O_1, O_2, O_3 and O_4, were the post-tests applied at the end of the experiment for both the experimental and control groups, which consisted of the same questionnaire (for each of the courses) with exercises related to the topic of control structures addressed in the collaborative activity.

The first experimental group G_1 was made up of 43 students from the Programming I - Group 1 course of the first semester of Systems Engineering, to whom the experimental treatment X and the post-test (O_1) were applied. The control group G_3

was made up of 36 students from the Programming I - Group 2 course, from the same semester and academic period, to whom the experimental treatment was not applied, only post-test (O_2).

The second experimental group G_2 was made up of 32 students from the Programming Foundations - Group 1 course of the first semester of Electronic Engineering, to whom the experimental treatment X and the post-test (O_3) were applied. The control group G_4 was made up of 21 students from the Programming Foundations I - Group 2 course, from the same semester and academic period, to whom the experimental treatment was not applied, only post-test (O_4).

5 Results

In this section, the results obtained in the development of the research are presented in detail, starting with a description of how a class session would be carried out applying the proposed technique, then the results of the application of the instrument for the measurement of personality traits in students, and ends with the results obtained in the development of the experiment.

5.1 Class session

Before presenting the results obtained in the research process, it is convenient to show at an example level how a class session would be carried out in which you want to form groups with the proposed technique. A class session is taken as an example to support the theme of "Control Structures (conditionals and cycles)" in an initial Programming course. To do this, the teacher, considering the methodological scheme presented in Fig. 1, performs the steps indicated in the activity diagram shown in Fig. 2.

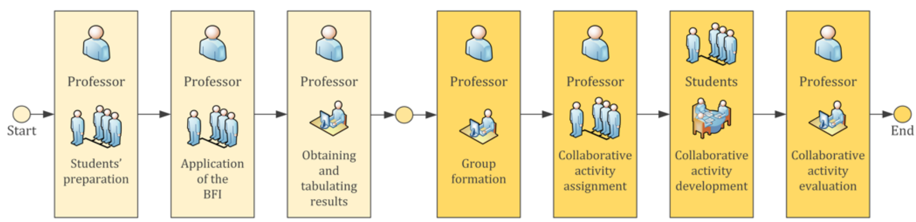

Fig. 2. Activity diagram class "Control Structures".

It is important to clarify that the first three activities, corresponding to the measurement of the personality traits of the students, are carried out once in the academic period (for the particular case, once a semester), since the group, generally, remains stable throughout the period, and the results can be used as many times as desired for the formation of new working groups, in terms of members or quantity.

5.2 BFI Results

As mentioned in Section 3, groups G_1 and G_2 are the groups to which the experimental treatment was applied, initially requiring the application of the instrument for measuring personality traits described above. The BFI results should be organized in a table as described in Section 3.2, considering that the students who do not fill out the instrument (if any) should be assigned as values to each of the dimensions considered, the mean of the total group in each of them. This situation occurred with 7 students from group G_1 and with 8 students from group G_2. Tables like these were supplied to the genetic algorithm, the processing results of which are presented below.

5.3 Group formation

Once acceptable parameters have been established for the configuration of the genetic algorithm, we proceed to form groups of four students for the two experimental groups (G_1 and G_2), using a test application, preparing the corresponding plain text files with the results of the BFI in each of the groups. Given that the total number of students in G_1 is not a multiple of four, one of the 11 groups was made up of three students. The group formation was obtained in 100 generations, with a population size of 2500 individuals, with a survival of 40%, and with a mutation probability of 0.01, which yielded an adaptation of 0.4525 in a time of 44.72 seconds.

5.4 Experiment results

Finally, the most important analysis was carried out on the final results of the experiment, which consisted of contrasting the measurements of the experimental groups versus those of the control groups, seeking to verify in a basic way if there is an improvement in the learning process by applying the proposed technique versus the group formation technique based on students' preference, traditionally used by teachers when developing a collaborative activity. Next, a parallel is made between the experimental and control groups for each of the courses involved in the study.

Fig. 3 shows the positive impact of the experimental treatment proposed for the Programming I course of the Systems Engineering Program. The results show that, on average, the grades obtained in the post-test by the experimental group are higher than those obtained by the control group. Similarly, the positive impact of the experimental treatment proposed for the Programming Foundations course of the Electronic Engineering Program is shown. The results show that on average the grades obtained in the post-test by the experimental group are higher than those obtained by the control group.

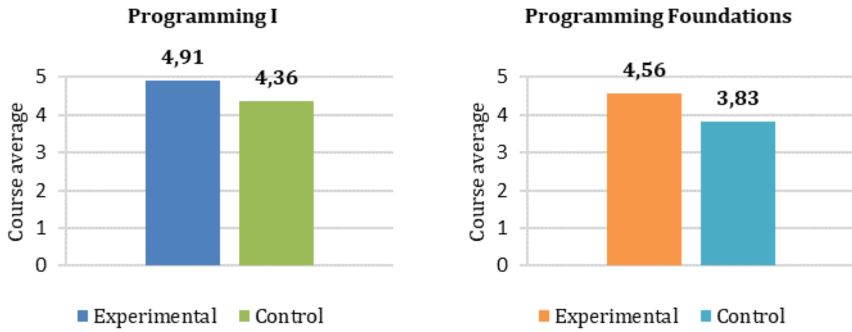

Fig. 3. Experimental groups versus Control groups.

Finally, and to provide some conclusion regarding the goodness of the proposed group formation technique, an analysis was carried out using the Mann Whitney U and Student's t tests, used for the comparison of two independent samples; seeking to determine a possible statistical difference between the grades obtained by the experimental groups versus the control groups, that is, a basic difference in the level of learning achieved by the students in the specific subject. These tests were used considering that the students' grades in the Programming I course do not follow a normal distribution, and in the Programming Foundations course the grades do follow a normal distribution.

The results of the application of the normality test are shown in Table 5, which were obtained using SPSS™ , with a significance level of 95% and considering the following hypotheses: H_0: the students' grades follow a normal distribution, H_1: the students' grades do not follow a normal distribution. The Shapiro-Wilk test was used considering that the corresponding sample sizes are less than 50.

Table 5. Normality tests.

Course	Group Type	Statistic	df	sig
Programming I	Experimental	,337	43	,000
	Control	,514	36	,000
Programming Foundations	Experimental	,964	32	,362
	Control	,986	21	,982

It is observed that the sig-value in the two groups of the Programming I course is less than 0.05. Therefore, the null hypothesis (H_0) is rejected in favor of the alternative hypothesis (H_1), with a confidence level of 95%, that is, the students' grades in this course do not follow a normal distribution. On the other hand, in the Programming Foundations course, the sig-value in the two groups is greater than 0.05. Therefore, the alternate hypothesis (H_1) is rejected in favor of the null hypothesis (H_0), with a confidence level of 95%, that is, the students' grades in this course follow a normal distribution.

The results of the application of the Mann Whitney U test are shown in Table 6, which were obtained using SPSS™ , with a significance level of 95% and considering the following hypotheses: H_0: the means of the students' grades are similar, H_1: the means of the students' grades are different.

Table 6. Mann Whitney U test.

Variable	Group Type		Z	U	p
	Experimental (G_1) n = 43	Control (G_3) n = 36			
	Mean Rank	Mean Rank			
Grades	46,16	32,64	-3,417	509	,001

When comparing the experimental group G_1 with the control group G_3 of the Programming I course, a *p*-value of 0.001 was obtained; as this value is less than 0.05, the null hypothesis is rejected in favor of the alternative hypothesis, with a significance level of 95%, that is, the means of the students' grades are different, with a difference of 0.7673 in favor of G_2.

The results of the application of the Student's t-Test are shown in Table 7, which were obtained using the Microsoft Excel™ Data Analysis tool, with a significance level of 95% and considering the following hypotheses: H_0: the means of the students' grades are similar, H_1: the means of the students' grades are different.

Table 7. Student's t-Test.

	G_2	G_4
Mean	4,5625	3,7952
Variance	0,0566	0,2465
Observations	32	21
Pooled Variance	0,1311	
Hypothesized Mean difference	0	
df	51	
t Stat	7,5464	
P(T<=t) one-tail	0,0000	
t Critical one tail	1,6753	
P(T<=t) two tail	0,0000	
t Critical two tail	2,0076	

When comparing the experimental group G_2 with the control group G_4 of the Programming Foundations course, a *P*-value of 0.0000 was obtained; as this value is less than 0.05, the null hypothesis is rejected in favor of the alternative hypothesis, with a significance level of 95%, that is, the means of the students' grades are different, with a difference of 0.7673 in favor of G_2.

The previous statistical analysis demonstrates the positive impact of the treatment presented in this research in the experimental groups compared to the control groups, establishing that forming homogeneous groups for collaborative learning contexts considering the personality traits of the students, benefits their academic performance.

6 Conclusions

From the results obtained, both from the methodological implementation of the proposed group formation technique and from the controlled experiment described above, the following conclusions can be stated:

- The measurement of personality traits through the “Big Five Inventory - BFI” turned out to be a practical and easy process at the time of its computational implementation, which greatly facilitated the collection of the data required by the optimization algorithm. It is clarified that, for the study, only the purely quantitative process was considered, qualitative aspects related to the personality of the participating students were not considered.
- Considering that the problem of obtaining homogeneous (equitable) groups from a group of students where not only one but several of their personal characteristics are taken into account, is difficult to solve by analytical or exhaustive search methods due to the combinatorial explosion which may occur depending on the number of students and groups, a heuristic search method such as genetic algorithms is a good candidate to solve it.
- With the results obtained through the controlled experiment, the usefulness of the method could be verified, since it manages to obtain quite homogeneous groups (considering the proposed aptitude measure) for multiple characteristics, even when the number of possible combinations is high, without implying high computation time.
- As mentioned above, the homogeneous grouping has certain advantages for some types of learning activities, especially those that involve guided discovery, skill development, review of material already learned, or in highly structured skills-building tasks, allowing students to progress at a similar rate, which is beneficial for the achievement of specific goals. Such is the case of the collaborative peer code evaluation activity, used in experimentation to support learning processes in initial programming courses, the context of this study.
- It was demonstrated through the experiment that the homogeneous groups generated with the proposed technique produced better academic results compared to the grouping technique by students’ preference, traditionally used by teachers when developing a collaborative activity.
- The grades obtained in three of the four courses are above the quantitative scale of 4.0 / 5.0, which shows that there is an important appropriation of the specific subject by the students, at the end of the collaborative support activity.
- In the field of programming teaching, it is necessary to involve didactic aspects that place the student as a central and active element of the learning process, instilling in them the need for self-learning in a collaborative environment that improves the attitudes and study aptitudes and the group work.

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References

1. Barkley E.F., Major C.H., Cross K.P.: Collaborative learning techniques: A handbook for college faculty, Jossey-Bass, San Francisco, CA, USA, (2014)
2. Bekele R.: Computer-Assisted Learner Group Formation Based on Personality Traits, http://ediss.sub.uni-hamburg.de/volltexte/2006/2759/, (2005)
3. Zheng Y., Li C., Liu S., Lu W.: An improved genetic approach for composing optimal collaborative learning groups, Knowledge-Based Systems, 139, pp. 214–225, (2018)
4. Fahmi F.Z., Nurjanah D.: Group Formation Using Multi Objectives Ant Colony System for Collaborative Learning. In: Proceedings of the 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), pp. 696–702. IEEE, Malang, Indonesia, October (2018)
5. Acharya A., Sinha D.: A “Mixed” Strategy for Collaborative Group Formation and Its Learning Outcomes, Journal of Educational Technology Systems, 46, pp. 440–462, (2018)
6. Sanz-Martínez L., Martínez-Monés A., Bote-Lorenzo M.L., Muñoz-Cristóbal J.A., Dimitriadis Y.: Automatic Group Formation in a MOOC Based on Students’ Activity Criteria, in Data Driven Approaches in Digital Education. EC-TEL 2017. Lecture Notes in Computer Science, pp. 179–193, Springer, Cham, Switzerland, (2017)
7. Roldán Roa E., Roldán Roa É., Chounta I.-A.: Learning Music and Math, Together as One: Towards a Collaborative Approach for Practicing Math Skills with Music, in Collaboration Technologies and Social Computing. CollabTech 2020. Lecture Notes in Computer Science, pp. 143–156, Springer, Cham, Switzerland, (2020)
8. Acuña S.T., Gómez M.N., Hannay J.E., Juristo N., Pfahl D.: Are team personality and climate related to satisfaction and software quality? Aggregating results from a twice replicated experiment, Information and Software Technology, 57, pp. 141–156, (2015)
9. Akarsu Z., Orgun P., Dinc H., Gunyel B., Yilmaz M.: Assessing Personality Traits in a Large Scale Software Development Company: Exploratory Industrial Case Study, in Systems, Software and Services Process Improvement. EuroSPI 2019. Communications in Computer and Information Science, vol. 1060, pp. 192–206, Springer, Cham, Switzerland, (2019)
10. Chowdhury S., Walter C., Gamble R.: Toward Increasing Collaboration Awareness in Software Engineering Teams. In: Proceedings of the Frontiers in Education Conference (FIE), pp. 1–9. IEEE, San Jose, CA, USA, October (2018)
11. Gilal A.R., Omar M., Gilal R., Waqas A., Afridi S., Jaafar J.: A decision tree model for software development teams, International Journal of Innovative Technology and Exploring Engineering, 8, pp. 241–245, (2019)
12. Licorish S.A., MacDonell S.G.: Communication and personality profiles of global software developers, Information and Software Technology, 64, pp. 113–131, (2015)
13. Omar M., Syed-Abdullah S.-L.: Finding the Effectiveness of Software Team Members Using Decision Tree, in Pattern Analysis, Intelligent Security and the Internet of Things. Advances in Intelligent Systems and Computing, vol. 355, pp. 107–115, Springer, Cham, Switzerland, (2015)
14. Pieterse V., Leeu M., van Eekelen M.: How personality diversity influences team performance in student software engineering teams. In: Proceedings of the Conference on Information Communications Technology and Society (ICTAS), pp. 1–6. IEEE, Durban, South Africa, March (2018)
15. Soomro A.B., Salleh N., Nordin A.: How personality traits are interrelated with team climate and team performance in software engineering? A preliminary study. In: Proceedings of the 9th Malaysian Software Engineering Conference (MySEC), pp. 259–265. IEEE, Kuala Lumpur, Malaysia, December (2015)
16. Yilmaz M., Al-Taei A., O’Connor R. V.: A Machine-Based Personality Oriented Team

Recommender for Software Development Organizations, in Systems, Software and Services Process Improvement. EuroSPI 2015. Communications in Computer and Information Science, vol. 543, pp. 75–86, Springer, Cham, Switzerland, (2015)
17. Yilmaz M., O'Connor R. V, Colomo-Palacios R., Clarke P.: An examination of personality traits and how they impact on software development teams, Information and Software Technology, 86, pp. 101–122, (2017)
18. Soto C.J., Kronauer A., Liang J.K.: Five-Factor Model of Personality, in The Encyclopedia of Adulthood and Aging, pp. 1–5, John Wiley & Sons, Inc., Hoboken, NJ, USA, (2015)
19. Cruz W.M., Isotani S.: Group Formation Algorithms in Collaborative Learning Contexts: A Systematic Mapping of the Literature, in Collaboration and Technology. CRIWG 2014. Lecture Notes in Computer Science, vol. 8658, pp. 199–214, Springer, Cham, Switzerland, (2014)
20. Borges S., Mizoguchi R., Bittencourt I.I., Isotani S.: Group Formation in CSCL: A Review of the State of the Art, in Higher Education for All. From Challenges to Novel Technology-Enhanced Solutions. HEFA 2017. Communications in Computer and Information Science, vol. 832, pp. 71–88, Springer, Cham, Switzerland, (2018)
21. Moreno J., Sánchez J.D., Pineda A.F.: A hybrid approach for composing groups in collaborative learning contexts, Heliyon, 7, pp. e07249, (2021)
22. Sun Z., Chiarandini M.: An Exact Algorithm for Group Formation to Promote Collaborative Learning. In: Proceedings of the 11th International Learning Analytics and Knowledge Conference LAK21, pp. 546–552. ACM, Irvine, CA, USA, April (2021)
23. García-Vélez R., Moreno B.V., Ruiz-Ichazu A., Rivera D.M., Rosero-Perez E.: Automating the Generation of Study Teams Through Genetic Algorithms Based on Learning Styles in Higher Education, in Advances in Artificial Intelligence, Software and Systems Engineering. AHFE 2020. Advances in Intelligent Systems and Computing, pp. 270–277, Springer, Cham, Switzerland, (2021)
24. Imbrie P.K., Agarwal J., Raju G.: Genetic Algorithm Optimization of Teams for Heterogeneity. In: Proceedings of the Frontiers in Education Conference (FIE), pp. 1–5. IEEE, Uppsala, Sweden, October (2020)
25. Zervoudakis K., Mastrothanasis K., Tsafarakis S.: Forming automatic groups of learners using particle swarm optimization for applications of differentiated instruction, Computer Applications in Engineering Education, 28, pp. 282–292, (2020)
26. Ullmann M.R.D., James D.F., Camilo C.G., Nogueira T. do C.: Group Composition for Collaborative Learning With Distributed Leadership in MOOCs Using Particle Swarm optimization. In: Proceedings of the Congress on Evolutionary Computation (CEC), pp. 1–10. IEEE, Glasgow, UK, July (2020)
27. Chen C.-M., Kuo C.-H.: An optimized group formation scheme to promote collaborative problem-based learning, Computers & Education, 133, pp. 94–115, (2019)
28. Garshasbi S., Mohammadi Y., Graf S., Garshasbi S., Shen J.: Optimal learning group formation: A multi-objective heuristic search strategy for enhancing inter-group homogeneity and intra-group heterogeneity, Expert Systems with Applications, 118, pp. 506–521, (2019)
29. Garcia-Velez R., Robles-Bykbaev V., Lopez-Notes M., Calle-Lopez D., Barros-Ponton M., Galan-Mena J.: An Intelligent System Based on Genetic Algorithms to Generate Study Groups Using Personality Traits and Academic Profiles in Higher Education. In: Proceedings of the Congreso Internacional de Innovación y Tendencias en Ingeniería (CONIITI), pp. 1–6. IEEE, Bogotá, Colombia, October (2018)
30. Lambić D., Lazović B., Djenić A., Marić M.: A novel metaheuristic approach for collaborative learning group formation, Journal of Computer Assisted Learning, 34, pp. 907–916, (2018)
31. Andrejczuk E., Bistaffa F., Blum C., Rodriguez-Aguilar J.A., Sierra C.: Heterogeneous Teams for Homogeneous Performance, in PRIMA 2018: Principles and Practice of Multi-

Agent Systems. Lecture Notes in Computer Science, pp. 89–105, Springer, Cham, Switzerland, (2018)
32. Torres S., Salazar O.M., Ovalle D.A.: A Fuzzy-Based Multi-agent Model for Group Formation in Collaborative Learning Environments, in Methodologies and Intelligent Systems for Technology Enhanced Learning. MIS4TEL 2017. Advances in Intelligent Systems and Computing, pp. 3–11, Springer, Cham, Switzerland, (2017)
33. Rammstedt B., John O.P.: Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German, Journal of Research in Personality, 41, pp. 203–212, (2007)
34. Benet-Martínez V., John O.P.: Los Cinco Grandes across cultures and ethnic groups: Multitrait-multimethod analyses of the Big Five in Spanish and English., Journal of Personality and Social Psychology, 75, pp. 729–750, (1998)
35. Moreno J., Rivera J.C., Ceballos Y.F.: Agrupamiento Homogéneo de Elementos con Múltiples Atributos Mediante Algoritmos Genéticos (in Spanish), DYNA, 78, pp. 246–254, (2011)
36. The International Statistical Institute: The Oxford Dictionary of Statistical Terms, Oxford University Press, New York, NY, USA, (2006)
37. Weise T.: Global Optimization Algorithm: Theory and Application, Self-Published, Anhui, China, (2009)
38. Reza Hejazi S., Saghafian S.: Flowshop-scheduling problems with makespan criterion: A review, International Journal of Production Research, 43, pp. 2895–2929, (2005)
39. Araujo L., Cervigón C.: Algoritmos evolutivos: Un enfoque práctico (in Spanish), Alfaomega Grupo Editor, Ciudad de México, México, (2009)
40. Kirk R.E.: Experimental Design - Procedures for the Behavioral Sciences, SAGE Publications, Inc., Los Angeles, CA, USA, (2013)
41. Revelo-Sánchez O., Collazos C.A., Solano A.F., Fardoun H.: Diseño colaborativo basado en ThinkLets como apoyo a la enseñanza de la Programación (in Spanish), Revista Colombiana de Computación, 21, pp. 22–33, (2020)