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Developing a Fuzzy Clustering-Based Method for Categorizing Young Adolescent Students Based on Their Empathy Scores and Exploring the Relationship Between Their Empathy and Learning Behaviors

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Abstract

Background: Empathy is a skill that has been proved effective in learning and teaching processes.
Objectives: The aim of this study was to explore the relationship between students' empathy and their learning behaviors.
Methods: A fuzzy clustering-based method (an area of artificial intelligence) was used, according to which students were classified to clusters based on their empathy measures. Students' empathy was assessed through a questionnaire. Overall, 345 students (11 to 13 years old) from six schools located in three different areas of Tehran, Iran, participated in this study, selected by multistage cluster sampling. In this method, similar samples are classified in one cluster and, then, clusters can be labeled based on their attributes (empathy measures). Two teacher-reported and student-reported questionnaires were used to assess the learning behavior and empathy levels of students. Questionnaires were completed by the students and their teachers during school year 2017 and 2018 (from autumn 2017 to spring 2018). All calculations were performed in MATLAB, a multi-purpose programming environment.
Results: Although statistical parameters showed a strong relationship between students' empathy and their learning behaviors, AI clustering process provides a more exact analysis due to its nature. The results revealed a significant relationship between empathy scores and learning among male students. A P value of 0.0031 indicates a meaningful relationship between empathy scores and learning behavior measures.
Conclusions: Number of students in each cluster showed that females are more uniform than males in the sense of empathy. Cultural backgrounds have significant effects on answers to questions. Processes revealed a meaningful difference between males and females when their connection of empathy and learning behaviors were investigated. Cognitive components seem to be more determinative than affective components.

Keywords: Fuzzy Clustering, Classroom Empathy, Learning Behaviors, Young Adolescent

1. Background

Empathy is one's ability to understand what another person is thinking and feeling in a given situation and contains two aspects, namely cognitive and affective (1).

Students' emotions experienced during learning can have a drastic effect on their learning experience (2). An instructor, who establishes emotional and social connections with his/her students in addition to a cognitive understanding, enhances the learning experience (3).

Likert scales or associated coding are often used in connection with opinions/valuations/ratings, especially in terms of questionnaires with a pre-specified response format (4).

Sullivan and Artino (1) assumed that the distance among the alternatives is not equal; in other words, the differences between "always," "often," and "sometimes" on a frequency response of Likert scale are not necessarily equal. This would lead to a more exact analysis.

The questionnaire developed by Zoll and Enz (5) consists of two cognitive and affective aspects for measuring empathy levels of students. Each item in this questionnaire relates to one of these aspects.

The aim of this work was to determine the relationship between empathy levels of 11- to 13-year-old students and their learning behavior by means of a second questionnaire designed by McDermott et al. (6). Researches have shown that teaching learning behaviors to students will improve learning performances (7-10). In the recent years, learning behaviors have become teachable, visible, and measurable, and many efforts have been made to design tools for measuring learning behaviors and assessing the validity and reliability of these tools. One of the tools designed for measuring and assessing learning behaviors is the learning behaviors scale, the final version of which was published by McDermott et al. (11). In many researches, psychometric characteristics of this scale have been practically confirmed (12-14).

Conflicting evidence has been obtained from systematic literature reviews and meta-analyses regarding the association between empathy and externalizing behaviors, where some studies have reported only a small or moderate negative relationship between the two variables, while others have reported a strong relationship. Some authors have suggested that parts of the variability in these findings can be attributed to differences in the measurement methods of empathy since many researchers continue to operationalize empathy as a single global construct (15).

A fuzzy-based method has been proposed to measure Likert scales by Li (16) and Vonglao (17). In the same way, Hirasawa et al. (18) proposed a method for questionnaire analysis via clustering. In Ishida et al.'s research (19), a newer method based on probabilistic latent semantic indexing (PLSI) was proposed for questionnaire analysis. In the current study, fuzzy clustering was used to combine two approaches for questionnaire analysis.

The fuzzy method is a tool for mathematical analysis of ambiguities. Fuzzy sets have been introduced by Zadeh (1965). It is noteworthy that fuzzy sets were considered as a new method for the analysis of vagueness in the real world. Objects belong to all sets in a fuzzy system; for example, it is assumed that all students are categorized to three fuzzy sets, including good students, weak students, and medium students. A specific student belongs to all these sets yet with different membership degrees. S/he belongs to the set of good students with a degree of 0.6, the set of weak students with a degree of 0.3, and the set of medium students with a degree of 0.85. Good and weak students are fuzzy sets because we cannot define a clear boundary for these two sets. Membership functions determine the degree of belonging of an object to a fuzzy set. These concepts of fuzzy sets and, consequently, fuzzy calculations lead to a soft computation, in which computational and logical errors are reduced. In some applications of fuzzy computations (fuzzy reasoning), such as students' assessment (20), experts are needed to create fuzzy rules. A fuzzy rule is something like this:

If student A is good at C1 AND excellent at C2 Then she/he is clever.

A fuzzy rule maps the input (antecedent) to the output (consequent). Here, the parts "good at C1 AND excellent at C2" and "she/he is clever" are the antecedent and the consequent of the rule, respectively. An expert can estimate such relationship between inputs and outputs by her/his knowledge and experience. This form of analysis is called expert analysis.

In the present research such relationships between the antecedent and consequent do not exist; rather, rules are obtained using a clustering process and mapping clusters to certain attributes of students within clusters. These types of rules, which are called fuzzy rules, can be extracted from the data like the one in Tables 1-3. An example of a rule can be as follows:

If sub-scale 1 is High AND sub-scale 2 is Medium, THEN this student has a particular attribute.

In this research, attribute can be new clusters created by performing a clustering process on learning behavior data, or some other attributes of students.

In terms of classification (a field of AI), each subscale of empathy is considered as one dimension of two dimensional features. In other words, each student is represented by a two-dimensional feature, including the affective and cognitive aspects of empathy. In this case, each student determines a point in a two-dimensional plane. If there are more than two dimensions, each student will be represented by a multi-dimensional point in a multidimensional space. This space is called the features space in AI literature.

A cluster is a set of similar samples, where similarity means the neighborhood of samples in features space. A sample is usually represented by majuscules and its features are represented by minuscule. For the case of empathy, if we have:

$$X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

x_1 and x_2 are cognitive and affective subscales of empathy for a particular student X. For example, suppose that nine students in mathematics and chemistry have obtained the following scores:

Math = [12 14 11 12 16 17 18 18 17]

Chem = [17 13 12 14 12 16 20 19 18]

Locations of these nine students are shown in Figure 1, where the x-axis and y-axis indicate math and chem scores, respectively.

Euclidean distance is the measure representing the distance between two points in feature's space. For example, the distance between the first and the second students is as follows:

$$d_{12} = \sqrt{(12-17)^2 + (14-13)^2} = 5.099$$

For an n-dimensional feature, the distance between points A and B is as follows:

$$d_{AB} = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \cdots + (a_n - b_n)^2}$$

Where a_i and b_i are the ith subscales of samples A and B.

One can observe that clustering these nine students into two sets, cannot be a good idea. The two samples in the middle of the features plane are in an equal distance from the four samples on the right side and the three samples on the left side. In other words, the selection of three clusters is a better choice for the clustering process. If students are represented with their mean scores, the result will be:

Mean = 14.5 13.5 11.5 13 14 16.5 19 18.5 17.5

Considering the above-mentioned points, two-dimensional features could be reduced to one dimension and, as a result, the three clusters cannot be discriminated from each other.

For instance, the two students with mean scores of 14 and 14.5 are, in fact, placed in two different clusters when two-dimensional features are considered, while their mean scores are very close to each other. Obviously, the task will become more difficult if samples are represented in an n-dimensional features space ($n > 2$).

There are a large number of automatic clustering methods, in which the best number of clusters is proposed; however, researchers sometimes prefer to find the number of clusters through trial and error to obtain the best possible results. However, the current study proposes a method based on a variable number of clusters.

The method used in this research was the “C - means fuzzy clustering (FCM)” method, proposed by Bezdek (1993).

2. Objectives

This research was an attempt to examine the relationship between students’ empathy and their learning behaviors in the classroom. To this end, the following research questions were explored:

1- How are students categorized based on their empathy? This is a prerequisite for responding to the second research question.

2- Is there any significant relationship between a particular empathy cluster and what they behave towards a learning experience in the classroom?

3. Methods

The method used in this research was based on fuzzy clustering, an area of artificial intelligence (AI). Unlike statistical methods, AI methods provide a more exact analysis due to their variety of tools. This research performed all calculations (both AI and statistical) in the MATLAB Environment. It provides all necessary tools for all calculations, such as statistical, AI (such as clustering, neural networks, and fuzzy calculations), data mining, and so on.

Participants in this research consisted of 345 young adolescent grade-six primary school students (11- to 13-year-old students), including 178 male and 167 female students. These students were studying at six different schools, located in three areas of Tehran, Iran. These areas were selected due to their social, culture, and economic diversification. Two schools were selected randomly from each area. Randomly selected students from the six schools answered the questions, in others words half of the students in each class of these schools voluntarily answered the questions. After collecting all filled questionnaires, incomplete answered questionnaires were excluded from the trial. Although equal participation of male and female students was the primary intention in this research, the number of males was a little more than females. This will not change the results.

By means of the questionnaire, empathy is assessed as students’ self-reported dispositional reaction towards hypothetical situations. The empathy questionnaire included 28 five-choice items (from strongly agree to strongly disagree). Sixteen questions of 28 measured affective subscale and the other 12 questions measured the cognitive subscale of empathy. Respondents choose one of the five possible answers (e.g., from strong agree to strong disagree). To rate the learning behaviors of students, a maximum value was assigned to the choice “strongly agree” and a minimum value was assigned to the choice “strongly disagree”. A value between -2 and +2 was assigned to each choice. After calculating the score of each subscale, the resulting value was normalized between -1 and +1.

A second questionnaire was filled by teachers to investigate students’ learning behavior. Four sub-scales were measured in this questionnaire. The items of this questionnaire had three options, including most often apply, sometimes apply, and don’t apply. As in the case of empathy, the respondents also assigned a value to each item. Regarding McDermott et al. (6), the subscales in learning behavior include competence motivation (eight questions), attitude toward learning (five questions), attention/persistence (seven questions), and learning strategy (five questions). In Iran for the learning behaviors subscales, its validity is confirmed using factor analysis and its reliability is determined using two test-retest (0.92) and Cronbach’s alpha (0.83) methods by Abedi et al. (21). Questionnaires were filled by students and their teachers during school years 2017 and 2018 (from autumn 2017 to spring 2018).

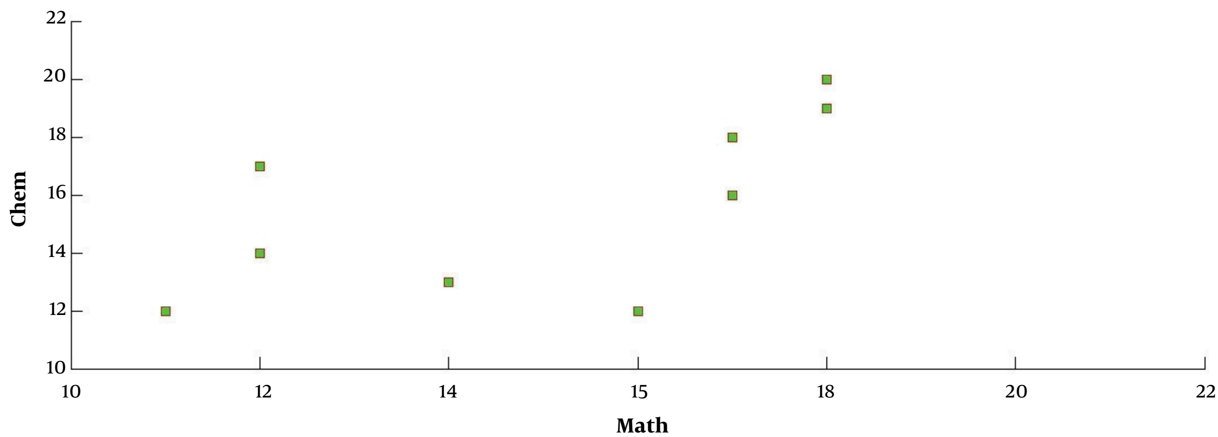

Figure 1. Nine students in a two-dimensional features space in which mathematics and chemistry scores as features. Three clusters can be distinguished in the features space.

3.1. Clustering Using Empathy Subscales

The clustering of empathy data was performed using two-dimensional features. These features are the subscales of empathy measures, including cognitive and affective aspects of empathy. There are a large number of clustering methods, yet the method used here is the fuzzy clustering method developed by Bezdek. This method provides a soft computational approach that usually produces better results in classification and clustering tasks. A successful classification or clustering is the process of assigning a sample to a proper class or cluster.

The first step in clustering problems is often determining the number of clusters. In the majority of research projects, it is preferred to find the best value for the number of clusters in a trial-and-error manner. However, it is necessary to obtain an estimation of the primary value. As a very fast estimation, two clusters can be selected for clustering. In this case, a student is either an empathic person or an apathetic one, yet there seems to be a very crisp selection. Therefore, a minimum of three clusters should be selected in the clustering process. In this situation, we are interested in investigating the results by repeating the clustering process with more than three clusters. Therefore, some rules are required for choosing a name for each cluster. In case of three clusters, they are expected to be as follows: The first cluster includes students with high degrees of empathy. High degree here means high values in both cognitive and affective subscales of empathy. The second cluster includes students with intermediate degrees of empathy. Finally, the third cluster encompasses students with low degrees of empathy. Indeed, programming also proved the predictions about these three clusters. The researchers chose the following names for these clusters: fully empathic, rather empathic, and fully apathetic for the clusters with high, intermediate, and low degrees of empathy, respectively. For clustering with more than three clusters, a rule for naming the clusters is required.

3.2. Statistical Calculations

Figure 2 shows the histogram plot of empathy (x axis: the scores of empathy, y axis: frequency). It demonstrates a Gaussian distribution for the empathy scores. This kind of distribution reflects reliability (especially internal consistency) of the questionnaire.

Cronbach's alpha for the empathy questionnaire was equal to 0.84. Also, using "corrcoef " function in MATLAB, the value of correlation and P value between empa-

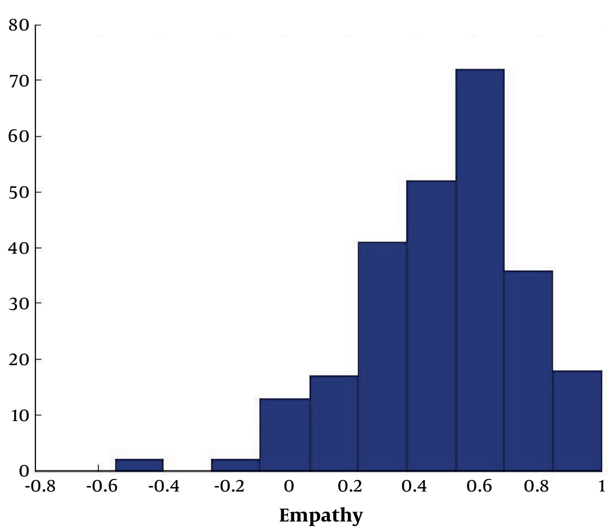

Figure 2. Histogram plot of empathy scores

thy scores and learning behaviors measures were calculated. A value of 0.0031 was obtained for the P value. Such a value indicates a meaningful correlation between empathy scores and learning behavior measures. As mentioned before, since the method used here was not based on statistical calculations, the researchers did not rely on statistical values.

4. Results

Table 1 shows the results of the clustering process with three clusters. Sample's demographic characteristics for the clustering process were as follow: 178 males, 167 females, 11 to 13 years old, three different family-economic levels (rather low, medium, and high), and schools were selected from three different urban areas. As it was predicted, these three clusters include fully empathic, rather empathic, and fully apathetic clusters.

To assign these names to clusters, the interval [0, 1] was divided to three ranges, as shown in Figure 3. All empathy and learning behavior scores were normalized in the interval [0, 1].

A relative Gaussian distribution can be seen in Table 1. Taking a glance at Table 1, one can realize that the average value of learning behavior witnessed an increase with a decrease of the average value of empathy. This becomes clearer when the clustering process is performed only on single-gender students. Tables 2 and 3 show the results of clustering only on females and males, respectively. In Table 3, two new names for clusters are presented. These are affective empathic and rather affective apathetic. These two new names come from a more general naming rule, which is explained in the next section. As it can be realized from Tables 2 and 3, while the average scores of empathy for females were higher than that of males, the average scores of learning behaviors for females were smaller than that of males.

4.1. The Rule for Naming the Clusters

In this section, a naming rule for clusters was proposed. In Figure 3, the interval [0, 1] was divided to three regions, each of which was labeled by a name. This definition has already been used for naming clusters based on

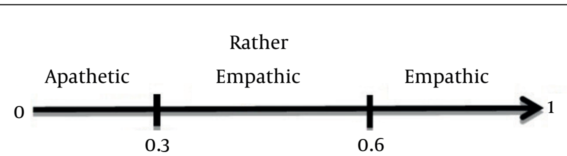

Figure 3. Dividing the interval [0, 1] to name different clusters

the average values of empathy scores. Now, it has been generalized to subscales as well.

A cluster's name contains two sections. Section 1 specifies the predominant aspect of empathy (i.e. affective or cognitive). The second one determines the level of empathy itself. When the clustering process is performed with more than three classes, there is usually a need to use the following naming rule. However, this naming rule was used in Table 3 even when there were only three clusters. There were three clauses for the current naming method:

(A) The average score of empathy determines the second section of clusters' names, according to Figure 3. The second section can be one of the three following names:

(1) Empathic if the average value is greater than 0.6,

(2) Rather empathic if the average value is between 0.3 and 0.6,

(3) Apathetic if the average value is smaller than 0.3.

(B) If both cognitive and affective subscales lie in one of the three intervals in Figure 3, the cluster's name only has one section, as in Tables 1 and 2.

(C) If one subscale lies in a higher interval in Figure 3, it dominates the other subscales. Hence, the first section of cluster naming describes this domination. An example can be seen in the first and second rows of Table 3.

Table 4 shows the results of clustering data to six clusters. As it can be seen in this table, new clusters appeared when the number of clusters was increased. A rapid inference of Table 4 is that empathic clusters usually contain an affective component when they are not fully empathic. Conversely, apathetic clusters usually have a cognitive component if they are not fully apathetic. The same result is obtained when the number of clusters increases.

5. Discussion

Analyzing the values of learning behaviors led to an unexpected conclusion. As one can realize from Table 1, there was a reverse relationship between empathy and learning behaviors. This relationship can be observed particularly in subscales one and two and to some extent in subscale three. Based on the data extracted from Table 1, students with better learning behaviors are weaker in empathy. This result was obtained when the clustering process is performed on all students, i.e. both females and males. However, when clustering is performed only on males (Table 2) and females (Table 3), it will be realized that such a reverse relationship will be at play only for males. Comparing Tables 2 and 3, shows that females were generally more empathic than males. This complies with the consequences of other findings (22-24). Nanda (22) states that females are often more empathetic than males. However, experimental and neuropsychological measures show no consistent

Table 1. Clustering Results When Samples Were Clustered to Three Clusters

Clusters	NS	Empathy Measures			Learning Behavior Measures				
		Cog.	Aff.	Ave.	Sub1	Sub2	Sub3	Sub4	Ave.
Fully empathic	100	0.66	0.8	0.73	0.6606	0.5431	0.3456	0.4338	0.4958
Rather empathic	109	0.35	0.53	0.44	0.6972	0.5654	0.3412	0.4197	0.5059
Fully apathetic	44	0.175	0.024	0.099	0.7756	0.6420	0.3920	0.4375	0.5618

Abbreviations: NS, number of samples; Ave, average of subscales.

Table 2. Clustering Results When Samples Are Clustered to Three Clusters (Only Female Students Were Considered)

Clusters	NS	Empathy Measures			Learning Behavior Measures				
		Cog.	Aff.	Ave.	Sub1	Sub2	Sub3	Sub4	Ave.
Fully empathic	50	0.7125	0.8350	0.774	0.6388	0.5450	0.3250	0.4163	0.4813
Rather empathic	52	0.3782	0.5577	0.468	0.6334	0.5084	0.3365	0.4026	0.4702
Fully apathetic	65	0.0199	0.0063	0.013	0.6356	0.5279	0.3375	0.4587	0.4899

Table 3. Clustering Results When Samples Were Clustered to three Clusters (Only Male Students Were Considered)

Clusters	NS	Empathy Measures			Learning Behavior Measures				
		Cog.	Aff.	Ave.	Sub1	Sub2	Sub3	Sub4	Ave.
Affective empathic	63	0.5136	0.6889	0.601	0.7667	0.6312	0.3625	0.4146	0.5437
Rather affective apathetic	31	0.1818	0.3439	0.263	0.8438	0.6741	0.3571	0.4509	0.5814
Fully apathetic	84	0.057	0.011	0.034	0.8378	0.6622	0.4152	0.4301	0.5863

Table 4. The Result of Clustering When the Number of Clusters Is Increased to Six

Clusters	Cognitive	Affective	Average
Fully empathic	0.7994	0.8467	0.8230
Affective empathic	0.5039	0.7813	0.6426
Rather empathic	0.5304	0.4928	0.5116
Rather affective rather empathic	0.1793	0.5400	0.3600
Rather cognitive apathetic	0.3118	0.2026	0.2572
Fully apathetic	0.0500	0.0009	0.0254

gender effect, and self-report data consistently indicates greater empathy in females (23).

Some research implicate a direct relationship between affective behaviors and academic achievement (25-28). Besides many research have concentrated on teacher's empathy (29) yet the current research was in the area of student's empathy. However, these works are not exactly the same as the current. They have addressed the role of affective aspects in academic achievement. Affective behaviors are only one aspect among other aspects in empathy.

According to Table 3, it can be seen that male students have a better cognitive subscale in comparison to their affective subscale, in the same way as female students. A reverse relationship was shown in Tables 1 and 3, which is due to the fact that male students did not answer honestly to the empathy questions. This has also been mentioned implicitly previously (22). This is because males have a high cognitive ability, in other words, since males had a relatively high cognitive ability, they pretended that they were not affective at all. This research found that such an ability of cognitions supported them to gain a desirable learning behavior from teacher's point of view. Since there was no study in which two aspects of empathy were simultaneously examined with academic performances, the current study showed a relationship between such variables as well.

This may be rooted in cultural differences. In the Iranian culture, families teach boys to be strong and tough humans, not to cry, and even not to be compassionate persons. These types of instructions from parents (and also the society) cause boys to believe that they should have no feelings or emotions towards others. If so, they are strong men and are probably acceptable to their parents, teachers, and friends. They often pretend that they are apathetic and this is what differentiates boys from girls.

Looking at Table 3, it could be realized that even girls with lower empathy (students in apathetic cluster) have better learning behavior scores. This emphasizes that the results were obtained from Tables 1 and 2. The analysis performed for boys can be repeated here for the third cluster of girls. Because of the same reason mentioned for boys, this group of girl students had better learning behaviors with respect to other clusters of girls. Also, in all apathetic clusters for both boys and girls, the cognitive component was higher than the affective component. This is why the researchers claimed apathetic students had generally a great cognitive component of empathy.

5.1. Suggestions for the Future Research

The following suggestions are proposed for future research:

A new student-reported learning behaviors questionnaire can be used in future research. In this case, students will be more aware of their individual behaviors. The second suggestion for researchers is to use a new learning behaviors questionnaire, in which some questions can be designed with concentration on students' behavior in group learning.

In the same way, some positive questions in the empathy questionnaire may be redesigned and adapted according to the culture of the Iranian society. For instance, some questions may be designed in an indirect form.

Apathetic clusters usually have a cognitive component if they are not fully apathetic.

5.2. Conclusions

Females are generally more empathic than males yet cognitive components of empathy seem to be more determinative than affective components in learning behaviors towards academic achievement.

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Footnotes

Authors' Contribution: Samaneh Sadat Musavian: Study concept and design, acquisition of data, analysis and interpretation of data, and statistical analysis. Ebrahim Talaee: Administrative, technical, and material support, study supervision. Hashem Fardanesh: Critical revision of the manuscript for important intellectual content.

Ethical Considerations: Questionnaires were filled with the parents' satisfaction.

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