The Effect of Facial Perception and Academic Performance on Social Centrality

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***Abstract*—Facial perception is of significant influence on the positions of people in social networks. Particularly, students' facial traits can affect their social centrality in educational settings (e.g., students looking intelligent can attract more friends). However, in educational environments, the social biases associated with appearances have alarming consequences, and little research has been done to investigate the effect of facial perception on social networks. Therefore, it is necessary to comprehensively analyze the influence of perceived facial traits on students' status in social interaction. In this paper, we explore the effect of facial perception on the social centrality of students in social networks. Because students' social centrality is based on both their study ability and facial traits, this study does a comparative analysis of how facial perception and academic performance influence the social centrality of students. Subsequently, the experimental results demonstrate that facial perception, as well as academic performance, closely correlates with the social centrality of students. Finally, this study contributes to a comprehensive and deep understanding of social networks by analyzing facial trait-based social biases.**

***Index Terms*—Facial perception, academic performance, bias, social networks, social centrality.**

I. Introduction

ALTHOUGH an adage recommends not to judge a book by its cover, people usually judge others' personality traits based on their facial appearance [1]. In general, the social judgments on one person, such as trustworthiness and aggressiveness, can be made after a mere 100-millisecond exposure of his/her face [2], [3], [4]. Typically, research has shown that facial perception often results in assumptions regarding additional judgments [5]. For instance, criminal sentencing can be influenced by the facial traits of the defendant in hypothetical crime verdicts [6]. Furthermore, the social centrality of individuals is often affected by the biases of facial perception [7], [8]. For example, in the community leader elections, people tend to vote for the person with a kind face rather than someone with a tough-looking [9], [10]. Moreover, when people seek certain individuals for help, advice, and cooperation, their perception of that person's face is also an essential influencing factor [11], [12]. Consequently, facial perception bias plays a vital role in social interactions and affects the centrality of people in social networks to some extent [13], [14].

There are many ongoing studies about facial perception [15], [16], [17]. However, little research has been done for investigating the effect of perceived facial traits on social networks. In particular, the analysis of the social centrality influenced by facial perception is scarce, while it may contribute to a deeper and more comprehensive understanding of social networks. Therefore, this paper investigates the effect of facial perception on the social centrality of people, particularly, the social centrality of students in the educational environment.

In the educational environment, there are kinds of special social networks, such as school friendship networks [18], academic networks [19] and collaboration networks [20], called educational networks in this paper. In educational networks, the centrality of students correlates with their actual academic performance [21]. For instance, people usually tend to make friends with students who study well, so the students with good study scores are usually the centre nodes in the school friendship networks. Nevertheless, not only the actual study score of students but also their facial traits can influence their positions in the educational networks. For example,students who look intelligent tend to get higher expectations and have more friends [22]. Thereby, the social bias led by facial perception is a vital impact factor of the centrality in the educational networks [23], [24].

However, the social biases in educational environments can have alarming consequences [25]. For example, teachers' expectation bias can lead to a drop in confidence for some students. Hence, it is necessary to analyze the effect of bias led by facial perception on the educational networks. In particular, because students' positions in the educational networks are influenced by both their actual academic performance and facial traits, this paper does a comparative analysis of facial perception and academic performance.

In this study, we first analyze and compare the effect of facial perception and actual academic performance on the social centrality of students. Then, a new facial perception and actual academic performance based centrality prediction framework is proposed. We predict students' positions in the educational networks based on both their study performance and facial traits. The experimental results demonstrate that both facial perception and actual academic performance correlate with the centrality of students in the educational networks. In addition, the actual academic performance is more indicative than their facial traits to predict the centrality. The main contributions of this study are as follows:

1) We investigate the impact of facial perception on social

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networks, particularly, the influence of facial perception on the social centrality of students in educational networks.

2) In this study, a novel facial perception and actual academic performance based centrality prediction framework is proposed. Specifically, we predict the social centrality of students in the educational networks based on both their facial traits and academic performance.
3) To the best of our knowledge, we are the first to use machine learning techniques to analyze the effect of facial perception bias on social centrality.

The rest of the paper is organized as follows. Section II reviews related work. Section III introduces the data we collected in the experiments. Section IV details the proposed methodology. Section V presents experimental results and analysis. Finally, we conclude our work and discuss future research in Section VI.

II. Related Works

A. Factors Influencing Perceived Academic Performance

1) Intelligence and Conscientiousness: Previous research has suggested that intelligence and conscientiousness are both important factors for perceived academic performance [26], [27], [28]. Empirical studies have shown that intelligence is a predictor of academic performance, whereas others have argued that conscientiousness is a better predictor of academic performance than intelligence [29], [30]. Moreover, Intelligence Compensation Theory (ICT) suggests conscientiousness can help less intelligent individuals achieve academic goals [31], [32]. Therefore, students looking both intelligent and conscientious are likely to be perceived as good academic performers. Conversely, those with less intelligent-looking faces may be perceived as needing to work harder to get better grades.

2) Attractiveness: Some studies suggest that there is little evidence for a potential relationship between apparent attractiveness and actual academic performance [33]. However, it is well documented that there is a relationship between apparent attractiveness and the perceptions of academic performance [34]. For example, studies demonstrated a significant correlation between facial appearance and academic performance-related positive attributes. Specifically, students who are perceived as being more attractive and having positive personality traits often get higher expectations of academic performance [35], [36]. Consequently, although a relationship between perceived attractiveness and actual academic performance has received weak supporting evidence, a relationship between perceived attractiveness and perceived academic performance has been proven.

B. Network Positions

Previous studies have focused on studying the impact of a variety of personal factors on individuals' social network positions, such as personality traits, health status, behaviours, socioeconomic background, and academic achievement. For example, researchers have found that people with personality traits such as extraversion, agreeableness, optimism, conscientiousness, intense well-being, and high empathy seem to achieve positive social network positions [37], [38]. Specifically, people with agreeableness are considered to have qualities as being generous, polite, and cooperative [39]. Meanwhile, they are expected to have supportive relationships with others, which may increase the attractiveness of agreeable people as potential friends [40]. Other researchers have argued that people with psychological or physical health problems hold marginal social network positions [41], [42]. Sterrett et al. [43] found that children with autistic spectrum disorder, physical disability, or obesity have trouble in social interactions with others, which led to fewer reciprocal friendships.

In a social network, a node with high social centrality indicates that this node is important or influential within the network [44]. People who offer favourable behaviour such as being cooperative and considerate to others are likely to be close to the centrality of social networks and vice versa [45]. Furthermore, according to Kong et al. [46], higher academic achievements can also make people become the foci of social networks. Education levels can determine individuals' insights into and expectations of others, to some extent. That is, highly educated people are considered adequate to be the centrality of social networks.

III. Data Collection

In this paper, in order to obtain the facial traits of students, we firstly take photos of 495 volunteers living in the same residential area of the university. Then, we recruit other 142 participants to rate these faces for perceived traits on a seven-point Likert scale. On the other hand, the Grade-Point Averages (GPAs) of these 495 students are collected for their actual academic performance.

A. Ethical Considerations

This research is given ethical approval through the university's ethical approval process. Before photographs are taken and rated for perceived traits, we have already asked for participants' consent. Participants also agree to release their academic records for the study. Furthermore, participants are given the option to freely withdraw at any time during the study or omit any particular answers without providing a reason. Students' pictures and information are kept coded and confidential, and the questionnaire data are kept with separate IDs (e.g., letter code for faces, number code for other data). The key relating codes are kept separately in a password-protected file. This study is not anticipated to cause any distress, but if participants were distressed for any reason, they were encouraged to contact the student support service.

B. Facial Perception Ratings and Academic Performance Measures

A total of 495 first-year university students(age 18-25, 182 females, 313 males) are recruited for the study by online advertisements. These participants need to live in the same specified residential area. They are assigned to the lab and instructed to sit down and look at the centre of the camera lens with neutral expressions, hair pulled back, and no adornment. They are photographed under consistent lighting conditions with a fixed camera distance. We use a Fujifilm FinePix S5 Pro digital SLR camera (60 mm fixed length lens) and a photo booth painted white with calibrated D65 white lighting. These facial photographs are aligned according to interpupillary distance. We resize and crop the photographs to ensure equal proportions of neck and hair are displayed. This process results in 495 images.

Afterwards, another 142 students (age 18-29, 65 females, 77 males) separate from those 495 participants are recruited with payment by online advertisements. They are instructed to rate the attractiveness, intelligence, and conscientiousness of the people in these photos. Each participant is shown different 50 face images randomly selected from the entire set. Then, they rate these photos on a seven-point Likert scale for facially perceived attractiveness, intelligence, and conscientiousness, respectively. The highest score is 7, and the lowest score is 1. To ensure participants' concentration, each person is given about 15 minutes to look at the pictures and rate them. Finally, each image is rated by at least 30 different participants for three facial features, including attractiveness, intelligence, and conscientiousness.

To obtain the actual academic performance of these 495 students whose facial traits have been collected, we also collect their GPA. In this study, we collect their GPA for the first semester, which is gained from the university database as the actual academic data. Consequently, we obtained the three facial features and GPA of students to analyze their impact on students' social centrality in educational networks.

C. Social Networks in Educational Settings

As mentioned above, these 495 participants live in the same specified residential area in the university. Therefore, these students can be seen as being in the same social network. It is worth mentioning that a majority of residents (93%) in this area are successfully recruited. These participants are asked to nominate community members regarding six critical dimensions of educational networks: academic advice, support, cooperation, intelligence, and good/bad news sharing. They are asked to write down five to eight names of students living in this area (The 495 names of students are given as a reference list.). Specifically, they need to answer six questions: "Whom you would like to go for academic advice?"; "Whom you would like to go for support?"; "Whom you would like to go for cooperation?"; "Please choose five to eight names from the list who are intelligent."; "Whom you would like to go for sharing good news?"; "Whom you would like to go for bad news?".

In the questionnaire, each question corresponds to a dimension of educational networks, and for each one, participants need to write down five to eight names of students. Selectors and selectees can be linked in each dimension based on the participant's answer to each question. For example, for the question "Whom would you like to go for cooperation?", if a participant gives five names of students, the participant will be

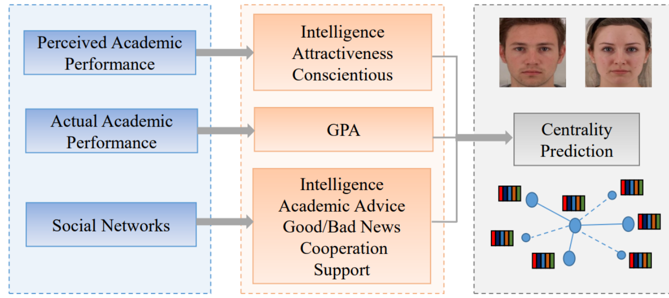


Fig. 1. The facial perception and academic performance based centrality prediction framework. The centrality of students in six different educational networks is predicted according to their facial features and academic performance.

connected to these five individuals in the cooperative dimension of the educational network. Therefore, the six dimensions can be regarded as six special sub-networks of educational networks, respectively. For instance, the cooperation network is a graph based on the cooperation among students. Thus, after this questionnaire survey, we can get the information of these six educational networks (intelligence network, academic advice network, good news sharing network, bad news sharing network, support network, and cooperation network). In these six networks, nodes are linked according to different factors. For example, in the cooperation network, the connected nodes are connected by the willingness of students to cooperate. Therefore, the social centrality of the six networks is affected by six different factors. We then analyze the influence of the obtained facial features and academic performance on these six educational networks.

IV. Methodology

To explore the impact of both facial perception and academic performance on students' positions in educational networks, we first analyze the structure of educational networks. Then, we compare the relationship between academic performance and social centrality with the relationship between facial traits and social centrality. Afterwards, we propose a new facial perception and actual academic performance based centrality prediction framework (see Fig. 1). As shown in Fig. 1, the facial traits of students are obtained by rating their photos for attractiveness, intelligence, and conscientiousness, respectively. On the other hand, the actual academic performance is represented by students' GPA. Afterwards, we predict the social centrality of students in the six educational networks based on these four features (attractiveness, intelligence, conscientiousness, and GPA). Here, attractiveness, intelligence, and conscientiousness are the facial features, while GPA is the feature that can represent the actual academic performance of students. To avoid the issues of portrait rights, the two faces in Fig. 1 are fake images synthesized by software. In this section, we introduce the detail of our method.

A. Problem Formulation

Given a full vector $V_i = (f_{i1}, f_{i2}, f_{i3}, g_i)$, the objective of network centrality prediction is to learn a predictive function

$$f : V_i = (f_{i1}, f_{i2}, f_{i3}, g_i) \rightarrow y_i, \tag{1}$$

which can be used to predict the value y_i for each student s_i. Here, y_i is a Boolean value with 0 representing the averaged social centrality. f_{i1}, f_{i2}, f_{i3} indicate three facial traits scores of student s_i, and g_i is the GPA value of student s_i. It is worth noting that these three facial traits scores of each student are graded by 30 people from the perspectives of attractiveness, intelligence, and conscientiousness, respectively. Additionally, the GPA of each student is the grade of the first semester.

B. Network Analysis

To understand students' positions and social centrality in educational networks, we apply several network analysis metrics to the six different educational networks.

1) Degree Centrality and Closeness Centrality: In social network analysis, degree centrality is the most direct way of measuring the centrality of a node [47]. The higher degree centrality of one node denotes this node is more important in the network. Generally, the calculation of degree centrality DC_i is defined as follows:

$$DC_i = \frac{k_i}{N-1}, \tag{2}$$

where k_i is the degree of student s_i in a social network, and N denotes the number of nodes in the network.

Closeness centrality is another important metric evaluating a node's network centrality [48]. For student s_i in a network, the average distance d_i from s_i to others is calculated as:

$$d_i = \frac{1}{N}\sum_{j=1}^{N} d_{ij}, \tag{3}$$

where d_{ij} is the distance from student node s_i to s_j. The relative value of d_i can reflect the relative importance of s_i in the network to some extent, with a lower value of d_i denoting node s_i is as closer to the others. Therefore, the closeness centrality CC_i of node s_i is defined as the reciprocal of d_i:

$$CC_i = \frac{1}{d_i} = \frac{N}{\sum_{j=1}^{N} d_{ij}}. \tag{4}$$

In this paper, we analyze the effect of facial perception and academic performance on students' positions based on the correlation between four proposed features and the degree centrality of students in the six educational networks. The correlation between them is calculated by Spearman's rank correlation coefficient, which will be introduced later. In addition, we also analyze the relations between academic performance (GPA) and the average closeness centrality distribution of the six networks.

2) Degree Correlation and Assortativity Coefficient: In this study, to profile the six educational networks better, we analyze the degree correlation and assortativity coefficient of the six networks by representing the joint probability and the excess average degree distribution.

The degree correlation of a network can be represented by the joint probability and the excess degree distribution [49]. Firstly, the joint probability $P(j,k)$ is defined as the proportion of edges between nodes with degrees j and k in all edges of a network. The joint probability can be calculated as follows:

$$P(j,k) = \frac{m(j,k)\mu(j,k)}{2M}, \tag{5}$$

where $m(j,k)$ is the number of edges connecting nodes with degrees j and k, and M denotes the number of edges in the network. If $j = k$, then $\mu(j,k) = 2$. Otherwise, $\mu(j,k) = 1$. Then, the excess degree distribution $P_n(k)$ is defined as the probability that a neighbor node of a randomly selected node has the degree of k. It can be calculated as:

$$P_n(k) = \sum_{j=k_{min}}^{k_{max}} P(j,k), \tag{6}$$

where k_{min} and k_{max} indicate the minimum and maximum degree of nodes, respectively. For simplicity, we denote $P_n(k)$ as q_k, and $P(j,k)$ as e_{jk}. Lastly, the degree correlation of a network is related with both the joint probality and the excess degree distribution. Therefore, the degree correlation of a graph is dependent on both the proportion of edges between nodes with two specified degrees in all edges and the probability that a node has the same degree as its neighbor. A network has no degree correlation if it satisfies the following equation:

$$e_{jk} = q_j q_k, \forall j,k. \tag{7}$$

On the contrary, this network has degree correlation.

In a network with degree correlation, if the nodes with high degrees tend to connect with nodes having high degrees, this network is seen as assortative. The assortativity coefficient of a network is calculated as:

$$r = \frac{1}{\sigma_q^2}\sum_{j,k} jk(e_{jk} - q_j q_k), \tag{8}$$

where $\sigma_q^2 = \sum_k k^2 q_k^2 - [\sum_k k q_k]^2$ is the variance of the excess degree distribution q_k. Evidently, the value of r ranges from -1 to 1. If $r > 0$, then the network is seen as assortative. If $r < 0$, the network is disassortative.

3) Clustering Coefficient: The clustering coefficient C of a network is the average of the nodes' clustering coefficient in a network:

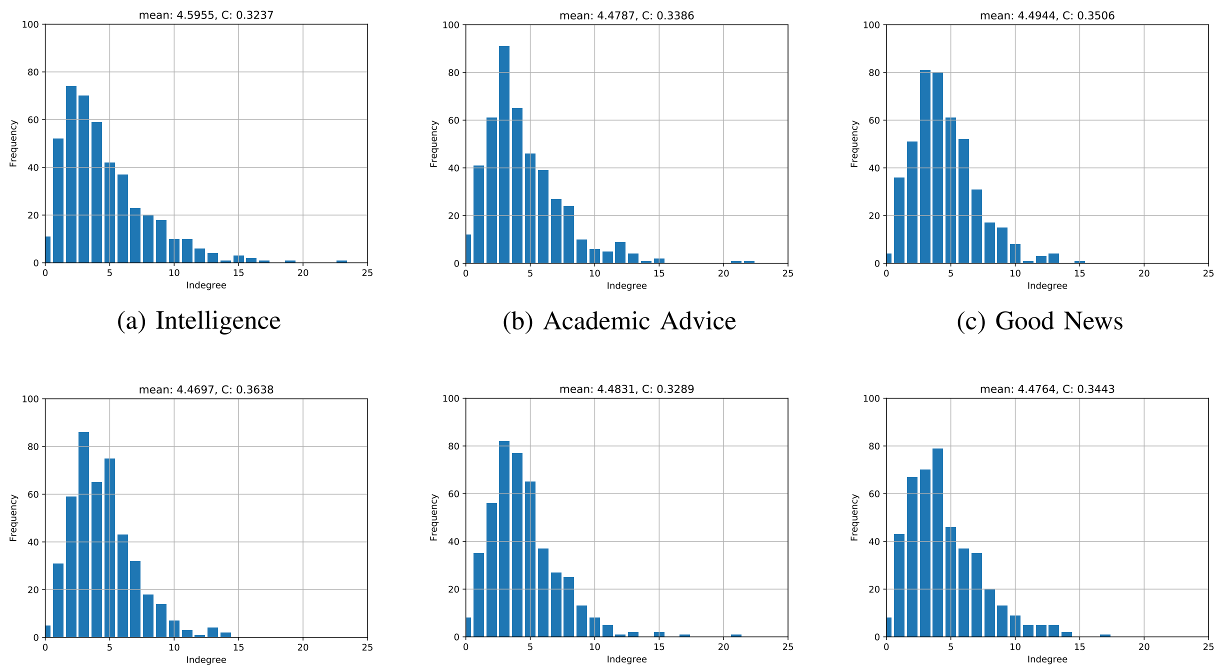
$$C = \frac{1}{N}\sum_{i=1}^{n} C_i, \tag{9}$$

where the clustering coefficient of the node s_i which has the degree of k_i is defined as:

$$C_i = \frac{E_i}{k_i(k_i-1)/2}, \tag{10}$$

where E_i and $k_i(k_i-1)/2$ are the number of actual existed edges and possible existed maximum edges between the neighbors k_i of node s_i, respectively.

This paper uses clustering coefficient as one of the indicators analyzing the indegree distribution of the six educational networks.



(a) Intelligence (b) Academic Advice (c) Good News

(d) Bad News (e) Support (f) Cooperation

Fig. 2. Basic information of six educational networks.

C. Correlation Coefficient Analysis

To explore the relationship between different features and their impacts on students' positions in educational networks, we apply two methods of correlation coefficient analysis: Pearson's correlation coefficient and Spearman's rank correlation coefficient. Therefore, the extent to the influence of facial perception and actual academic performance on the social centrality of students can be represented. Also, the relations between facial traits and academic performance of students can be explored.

1) Pearson's Correlation Coefficient: Pearson correlation coefficient (PCC), also called the Pearson product-moment correlation coefficient (PPMCC) [50], is a measure of the linear correlation between two variables X and Y. Given a pair of random variables (X, Y), the formula for the PCC ρ is:

$$\rho(X,Y) = \frac{cov(X,Y)}{\sigma_X \sigma_Y}. \tag{11}$$

Here, $cov(X,Y)$ is the covariance between X and Y, and σ_X and σ_Y denote the standard deviations of X and Y. The formula for ρ can also be expressed in terms of mean and expectation, which is written as:

$$\rho(X,Y) = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}, \tag{12}$$

where μ_X and μ_Y are the mean of X and Y, and $E(\cdot)$ indicates the expectation. The value of $\rho(X,Y)$ is ranged between -1 and 1, where 1 indicates total positive linear correlation, 0 is no linear correlation, and -1 denotes total negative linear correlation. In this study, we use it to compare the relationship between the four features (attractiveness, intelligence, conscientiousness, and GPA) in this paper.

2) Spearman's Rank Correlation Coefficient: Spearman's rank correlation coefficient (SRCC) [51], denoted as r_s, is a nonparametric measure of rank correlation. It assesses how good the relationship between two variables by using a monotonic function. The Spearman's rank correlation coefficient between two variables is equal to the Pearson's correlation coefficient between the rank values of those two variables. Different from the Pearson's correlation coefficient assessing linear correlation, the Spearman's rank correlation coefficient assesses monotonic relationships (whether linear or not).

For a sample of size n, the i-th pair of raw variables X_i and Y_i are converted to rank variables rk_{X_i} and rk_{Y_i}. Then, r_s is calculated as:

$$r_s = \rho_{rk_{X_i}, rk_{Y_i}} = \frac{cov(rk_{X_i}, rk_{Y_i})}{\sigma_{rk_{X_i}} \sigma_{rk_{Y_i}}}, \tag{13}$$

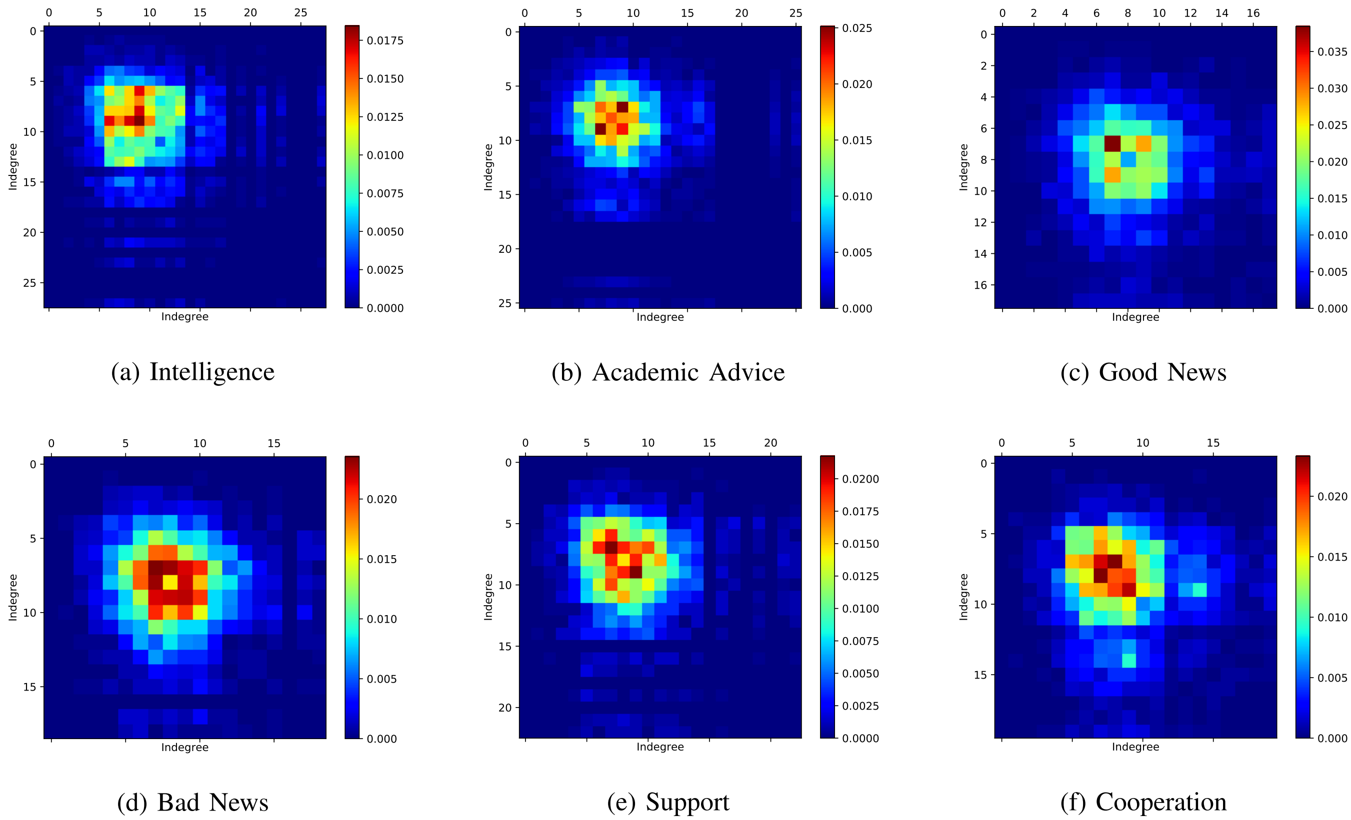
where ρ denotes the usual Pearson's correlation coefficient in terms of the rank variables. Only if all the rank variables are distinct integers, r_s can be computed using the general formula:

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2-1)}, \tag{14}$$

where $d_i = rk_{X_i} - rk_{Y_i}$ is the difference between the two rank variables rk_{X_i} and rk_{Y_i}. n is the number of observations. Here, we use the Spearman's rank correlation coefficient to compare the correlation between four features and the degree centrality of students in the six educational networks.

D. Prediction Models

In this paper, the prediction problem is defined as a binary classification task. It is to detect whether the degree centrality



(a) Intelligence (b) Academic Advice (c) Good News

(d) Bad News (e) Support (f) Cooperation

Fig. 3. Joint probability distributions of six educational networks.

of a node is above the average degree centrality or not. Specifically, the centrality is predicted based on the facial perception and actual academic performance of students. Here, to predict the network positions of students, we apply three classification methods of machine learning: K Nearest Neighbor (KNN), Linear Regression (LR), and linear Support Vector Machines (SVM). In the prediction task, if the result of one student's position is 1, the degree centrality of the student is above average, and 0 otherwise.

1) K-Nearest Neighborhood: Neighbors-based classification is a type of instance-based learning that does not attempt to construct a general internal model and simply stores instances of the training data [52]. Classification is computed from a majority vote of the nearest neighbors of each point: a query point is assigned to the data class that has the most representatives within the nearest neighbors of the point. The K-nearest neighbor classifier is the most commonly used technique, which implements learning based on the nearest neighbors of each query point. k is an integer value specified by the user. Based on the previous experiences, k is set equal to 5 in this experiment.

2) Logistic Regression: Generally, logistic regression is a machine learning method used to solve binary classification (0 or 1) problems [53]. Compared with linear regression, logistic regression is a generalized linear model, where dependent variable y is assumed to obey both Bernoulli distribution in logistic regression and Gaussian distribution in linear regression.

Based on linear regression, the logarithmic probability function is defined as:

$$y = \frac{1}{1+e^{-z}}. \tag{15}$$

Here, $z = w^T x + b$, x is independent variable, w indicates weight and b denotes bias. The range of y is between 0 and 1.

3) Linear Support Vector Machines: The basic idea of classification learning is to find a hyperplane that can differentiate the types of samples based on a training set [54]. In the space of samples, the division of the hyperplane can be described as a linear kernel function as follows:

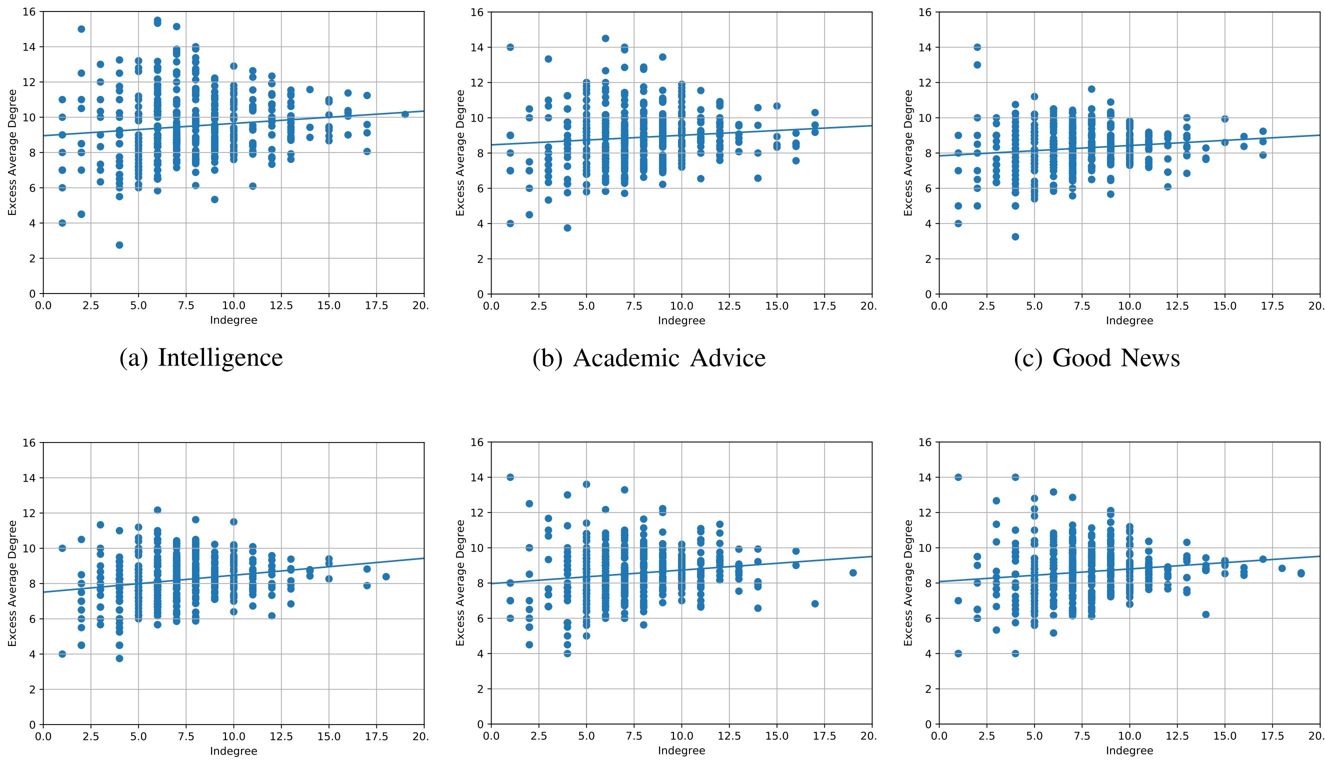
$$\boldsymbol{w^T x} + b = 0, \tag{16}$$

where $\mathbf{w} = (w_1; w_2; ...; w_d)$ is a normal vector deciding the direction of the hyperplane. b is a bias deciding the distance between the hyperplane and original point. Obviously, the division of the hyperplane is decided by the normal vector $\mathbf{w}$ and the bias b. In a support vector classifier, the main objective is to maximize the margin between support vectors and the hyperplane, which can be formulated as:

$$\begin{cases} max_{\mathbf{w},b} \quad \dfrac{2}{||\mathbf{w}||} \\ \quad s.t. \quad y_i(\mathbf{w}^T x_i + b) \geq 1, \quad i = 1, 2, 3 \cdots, \end{cases} \tag{17}$$

Obviously, maximizing the distance is to maximize $||w||^{-1}$, which is equal to minimize $||w||^2$.

The prediction performance of these three classification methods are shown in the next section.



(a) Intelligence (b) Academic Advice (c) Good News

(d) Bad News (e) Support (f) Cooperation

Fig. 4. Excess average degree distribution of six educational networks.

V. Experimental Results

A. The Analysis of Educational Networks

Firstly, the basic information of the six educational networks is presented. As shown in Fig. 2, the subfigures (a) to (f) are the indegree distributions of the intelligence network, academic advice network, good news sharing network, bad news sharing network, support network, and cooperation network, respectively. In each subfigure, the horizontal axis represents the different indegree values, and the vertical axis shows the number of nodes. Also, the average indegree (denoted as "mean" in the figure) and the clustering coefficient (denoted as "C" in the figure) of each network are calculated.

In Fig. 2(a), the indegree distribution of the intelligence network is a long tail distribution with the degrees of around 70% of nodes (about 345 of 495 nodes) laid in $[0, 6]$. Similar to the intelligent network, the degrees of about 72% of nodes (355 of 495 nodes) in the support network and cooperation network are laid in $[0, 6]$ (see Fig. 2(e) and 2(f)). It indicates that nodes with high degrees (more than 6 degrees) are the minority in these three networks. Fig. 2(b) shows the indegree distribution of the academic advice network. As the growth of indegree, the number of nodes first increases and then begins to have a descending trend after it reaches the peak number of about 90. In addition, there are almost 45% of nodes (about 220 of 495 nodes) have degrees with 2, 3, and 4. It indicates that almost half of students tend to ask only 2 to 4 people for academic advice.

In Fig. 2(c) and 2(d), it can be seen that the good news and bad news sharing networks have obvious Poisson-like distribution with most of the nodes (around 65%) having degrees laid in $[2, 6]$. Therefore, around 65% of students like to share news with 2 to 6 friends. Also, compared with the other four networks, the good news and bad news sharing networks own a relatively higher clustering coefficient, with 0.3506 and 0.3638 respectively. This fact indicates that students tend to share news with those who are close to them. Relatively speaking, they will not consider whether the person whom they think intelligent and ask for academic advice, support, and cooperation is their close friend.

The indegree distribution shows the topology characteristics of the six networks. However, networks with the same degree distribution can be very different in other properties. To better profile the six educational networks, we then consider the higher-order topology properties of these networks. We analyze the degree correlation and assortativity coefficient of the six networks by representing the joint probability and excess average degree distributions of the six educational networks.

Fig. 3 shows the joint probability distributions of six networks. In these six figures, the red color refers to a higher probability, and the blue color refers to a lower one, while the white color refers to a median probability. Although these six networks have different joint probability distributions according to the color distribution of each subfigure, the nodes in all the six networks generally have degrees from 5 to 10. Therefore, it indicates that most students can attract five to ten friends in all six networks. Furthermore, we list the max joint probability at the right of each subfigure. Among them, the good news sharing network owns the highest max joint probability, with more than 0.035, while those of the other five networks are all less than 0.03. Consequently, the degree correlation of node pairs in the good news sharing network is the highest. Specifically, the max joint probability of academic, bad news, support, and cooperation networks are similar, with around 0.025, while it of the intelligence network is lowest, with less than 0.02. This fact indicates that the degree correlation of the node pairs in the intelligence network is not obvious.

Fig. 4 shows the excess average degree distributions of the six networks. In each subfigure, the horizontal axis represents the different indegree values, and the vertical axis shows the values of excess average degree. Interestingly, all of these six networks have a similar slight ascending trend. In general, nodes tend to be connected to nodes that have the same degree. Thus, It can be inferred that students are more willing to build relationships with someone similar to them.

B. Correlation Analysis

To analyze the relations between perceived facial traits and students' academic performance, we first represent the correlations between the three facially perceived features (attractiveness, intelligence, conscientiousness) and actual academic performance (GPA). Then, we specifically analyze the correlation between actual academic performance and the social centrality of students in the six educational networks. Afterward, we compare the effect of facial perception and actual academic performance on the social centrality of students in educational networks. Lastly, the six educational networks are visualized for a better understanding of the networks.

1) Facial Traits and Academic Performance: Initially, Fig. 5 shows the statistical distributions of the three facial features and the GPA of students. The horizontal axis shows the four features, and the vertical axis shows the scores of each feature. For better comparison, We enlarge the range of GPA scores from $[1, 4]$ to $[1, 7]$. It can be seen that the scores of attractiveness are generally lower than the other three features. Oppositely, the scores of conscientiousness are higher than the other two facial features. This fact indicates that students generally tend to trust others. For intelligence, the scores of outliers are generally around $[2, 2.5]$. On the other hand, the GPA scores are in a wide distribution, which is quite different from the facial features.

To analyze the correlations within the four selected features, Pearson's correlation coefficient is calculated among attractiveness, intelligence, conscientiousness, and GPA. The experimental results are shown in Table I. In general, all four features have positive correlations with each other. Specifically, it is clear that there are higher correlations among the three facial features, whereas the correlation between GPA and facial features is relatively lower. These results show that facial features are highly correlated with each other, but relatively speaking, students' facial features have no significant relationship with their actual academic performance. Therefore, students' actual

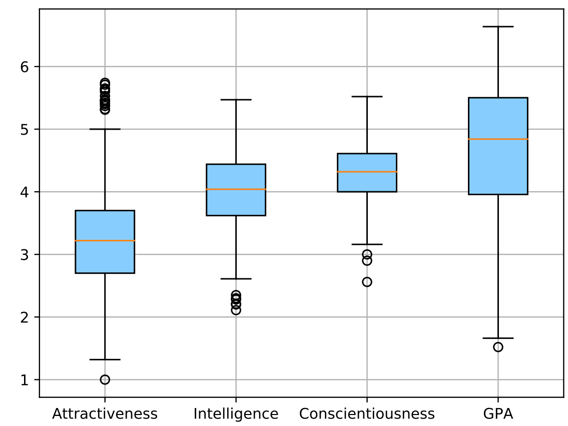


Fig. 5. Statistical distribution of four features including attractiveness, intelligence, conscientiousness, and GPA.

TABLE I
PEARSON'S CORRELATION COEFFICIENT

	Attractiveness	Intelligence	Conscientious	GPA
Attractiveness	1	0.735	0.609	0.118
Intelligence	0.735	1	0.637	0 .097
Conscientious	0.609	0.637	1	0.169
GPA	0.118*	0.097	0.169	1

ability can not be judged only by the perceived academic performance based on facial features.

2) The Correlation between Actual Academic Performance and Social Centrality: To analyze the correlation between the actual academic performance of students and their social centrality, we represent the correlation between GPA and the average closeness centrality of students in the six educational networks. The results are shown in Table II. We group the results of average closeness centrality distribution into six groups according to GPA. Obviously, with the increasing GPA scores, the average closeness centralities of all the six networks grow as well. As mentioned above, a higher closeness centrality score refers to a closer relationship with others. Therefore, Table II shows that students tend to maintain closer relationships with those who possess higher abilities.

3) Comparing the Effects of Actual and Perceived Academic Performance on Social Centrality: We calculate Spearman's correlation coefficients to analyze the relationships between

TABLE II
AVERAGE CLOSENESS CENTRALITY DISTRIBUTION OF THE SIX NETWORKS

GPA	Intelligence	Academic Advice	Good News	Bad News	Cooperation	Support
0.5–1	0.239	0.247	0.239	0.235	0.231	0.242
1–1.5	0.239	0.246	0.249	0.250	0.243	0.245
1.5–2	0.246	0.246	0.246	0.249	0.245	0.251
2-2.5	0.252	0.251	0.249	0.248	0.249	0.254
2.5–3	0.255	0.252	0.250	0.253	0.250	0.255
3-3.5	0.259	0.255	0.254	0.251	0.256	0.256
3.5–4	0.279	0.266	0.256	0.255	0.266	0.261

TABLE III
CORRELATION BETWEEN FOUR OBSERVED FEATURES AND THE DEGREE CENTRALITY OF STUDENTS IN SIX EDUCATIONAL NETWORKS

	Intelligence	Academic Advice	Good
Attractiveness	0.069	0.041	0.175
Intelligence	0.108	0.030	0.129
Conscientious	-0.005	-0.044	0.059
GPA	0.471	0.404	0.197
	Bad	Cooperation	Support
Attractiveness	0.130	0.072	0.120
Intelligence	0.059	0.063	0.088
Conscientious	0.004	0.002	0.047
GPA	0.172	0.356	0.184

the proposed four features (attractiveness, intelligence, conscientiousness, GPA) and the degree centrality of students in the six educational networks. Then, the effects of actual (GPA) and perceived academic performance (facial traits) on the social centrality of students can be compared.

Table III shows Spearman's correlation coefficients between each feature and the degree centrality of students in the six educational networks. According to Table III, the main conclusion is that facial features, as well as actual academic performance, are all related to the degree centrality of students. As shown in Table III, all of the absolutes of the correlation between conscientiousness and the degree centrality of students in the six networks are less than 0.6. This indicates that the one who looks most conscientious may not have more friends. In the good news sharing network, the correlation coefficient between attractiveness and degree centrality is 0.175. In the bad news sharing network, the correlation coefficient between attractiveness and degree centrality shows a similar pattern, with a score of 0.13. Therefore, it indicates that attractiveness is a significant facial feature when students share news.

Generally, facial perception is an important factor that influences the structure of educational networks. Also, the centrality of students in the educational networks is affected by their facial traits. However, compared to facial features, GPA has the highest correlation with the degree centrality of students in all the six educational networks. Therefore, the actual academic performance is the main impact factor of social centrality. In all these six educational networks, people tend to be close to the students who study well.

4) Visualizing the Six Educational Networks: Lastly, to visualize the six educational networks in this paper, the sketches of the six educational networks are shown in Fig. 6. In the figures, each node represents one student, and the edges of each node refer to the relationships with others. Moreover, we use deeper colors to represent the nodes owning a higher degree. As shown in Fig. 6, compared with the other four networks, there are several darker nodes in the good news and bad news networks. It indicates that there are always several students, who have strong centrality in the good news and bad news networks, attracting significantly more friends to share news. In the contrast, there are fewer students with obvious strong centrality in the other four networks.

Significantly, these six sketches are obtained by visualizing the questionnaire data. In each graph, students are connected with the students they selected in the corresponding questions. For example, in the cooperation network, one student is linked to students whom he selected in the question "Whom you would like to go for cooperation?".

C. Prediction Analysis

To verify the significance of facial features and actual academic performance in the social centrality prediction, we implement three different prediction methods: KNN, LR, and SVM. Notably, we predict the degree centrality of students in each educational network based on both facial perception and actual academic performance. We conduct the prediction methods as a binary classification problem, which means that a node will be detected as the node with a higher degree centrality or not. We implement three groups of experiments. One group only uses GPA as the features, one group only uses the facial features, and then one group uses both. In each group, we also implement two experiments to evaluate the training performance. Specifically, we use 90% and 80% of the sample as training sets, and the testing sets occupy 10% and 20%, respectively.

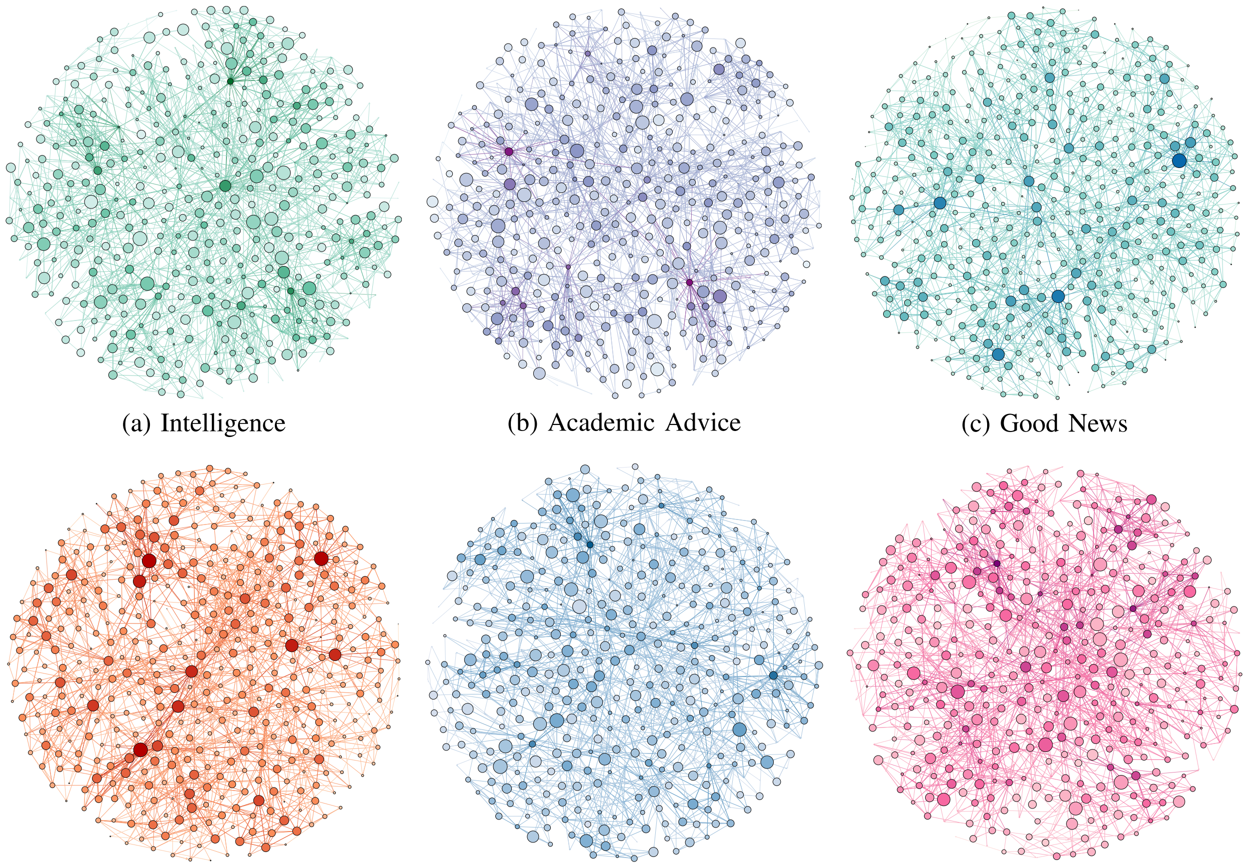
Fig. 7 shows the results of our experiments. In each figure, the horizontal axis represents the different networks, and the vertical axis shows the prediction accuracy. The curve of 10%-All means the experiment results of the group using all features and the test set is 10% of the whole sample. Similarly, 20% indicates that the test set is 20% of the entire sample. Facial and GPA denote the experiment groups using only facial features and using only GPA as the features, respectively.

As shown in Fig. 7, in general, the prediction results of the academic advice network are the best, while the results of the support network are relatively worse. Interestingly, regardless of which method we use, the prediction results of the experiment group using all the features are the best. Therefore, it can indicate that students' educational network positions are influenced by their facial traits and academic performance. Furthermore, compared with facial features, the results of the experiment group having only the feature of GPA are better. Thereby, although the perceived facial traits of students can influence their position in the educational networks, the main impact factor is their ability to study.

VI. CONCLUSION

In this paper, we investigate how facial appearance, as compared to actual academic performance, could affect the social centrality of students in various educational networks. This paper first analyzes the dual effect of facial perception and actual academic performance on the social centrality of students. Then, a novel facial perception and actual academic performance based network situation prediction framework is proposed. We predict students' positions in the educational networks based on both their academic performance and facial traits.

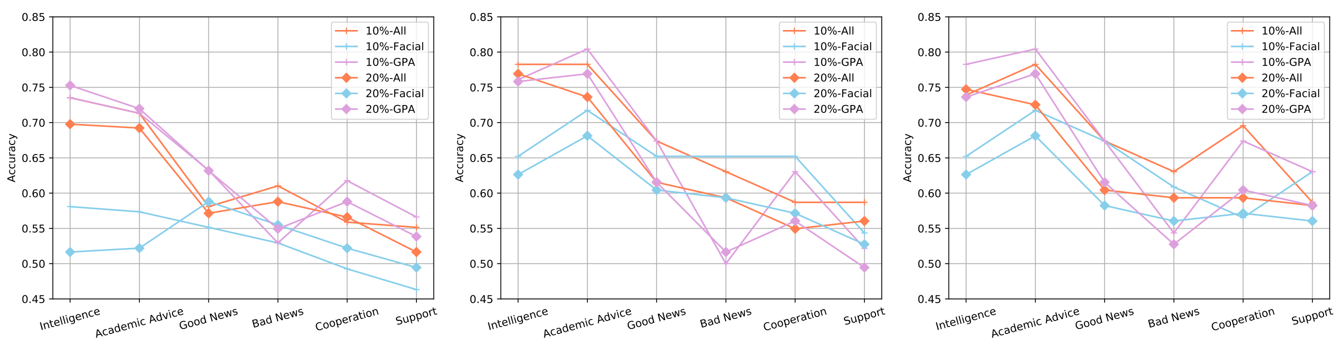
This research can bring a variety of benefits and be applied to various fields. Firstly, this study can be used to analyze the effect of facially perceived biases on the social centrality of students. For example, in the election of student cadres,



(a) Intelligence (b) Academic Advice (c) Good News

(d) Bad News (e)Support (f) Cooperation

Fig. 6. Sketches of six educational networks.



(a) KNN (b) LR (c) SVM

Fig. 7. Prediction results of three methods.

the method proposed in this paper can predict the influence of students' facial bias on the election results in advance, so as to take timely measures to stop the unfair results caused by appearance bias. Then, the comprehensive analysis of the correlation between facial traits and social centrality can contribute to a foundation for future works using psychological features. In psychology, the social centrality of one person is often studied through his personality. However, the method proposed in this paper can also consider the facial traits of people.In addition, a unique and valuable dataset of a relatively large size is created, and it will be released to the public with privacy protection.

The experimental results suggest that both facial perception and academic performance correlate with the social centrality of students in the educational networks. In addition, the actual academic performance is more indicative than students' facial traits. Therefore, we can conclude that although students' facial appearance can influence their position in the school, the most important impact factor is their study abilities. It suggests that people should pay more attention to improving their actual abilities.

Our future work will focus on the effect of facial perception on different social networks. For example, the proposed method can be extended to explore the influence of people's facial appearance on their positions in a company. It is also possible to compare the influence of facial traits in the work environment and the educational environment.

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