Diversity in computing majors: how gender, sociability and personality can affect team performance?

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Abstract. *For teams of students to perform most effectively, it is important to understand the patterns related to group formation, including diversity factors. In majors related to computing, this is especially relevant since those are typically less diverse in factors such as gender and social background. This paper explores the association between academic performance and diversity in the context of gender, sociability, and personality. Data on in-class social connections, gender, cross-sectional emotions, team formation, and grades were collected from 15 classes (n = 634) of graduate and undergraduate students of Information Systems, Computer Engineering, and Master's degree in Applied Computing. The influence of each diversity aspect was assessed using linear regression models. Statistical data analysis shows performance improvement for social and personality diversity in teams. The analysis was inconclusive regarding the contribution of gender diversity to the performance of teams.*

1. Introduction

According to the social development theory of Vygotsky (also called Vygotsky's Sociocultural theory) [Vygotsky 1980], the individual develops significant learning potential when interacting with others. Forming teams in the classroom provides opportunities for learning in several dimensions, including technical and social aspects. However, for the teamwork potential to be fully realized, it is necessary to understand several factors that might influence group dynamics. Diversity, in its multiple facets, plays an essential role in effective teamwork, as stated in the Team-Based Learning (TBL) methodology [Michaelsen and Sweet 2008].

Many definitions agree that diversity refers to the distinct differences between individuals noticed in their group interactions. For example, Van Knippenberg and Schippers [Van Knippenberg and Schippers 2007] define it as differences between individuals in any attributes that might lead to the perception that another person is different. However, this concept can be extended as a group attribute rather than an individual one by considering diversity as "the distribution of differences among the members of a unit with respect to a common attribute" [Harrison and Klein 2007] (page 1200). Two forms of diversity influence the behavior of teams: the visible one, that is, the one related to observable characteristics such as age, ethnicity, religion, and sex; and non-visible diversity, which encompasses intrinsic characteristics such as cultural, knowledge, and intellect diversity [Oramas 2016].

An important aspect of visible diversity concerns gender, especially in majors related to computing, in which the composition of teams often presents an unbalanced proportion of male students. This has been observed by the statistical data compiled by the

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Brazilian Computing Society: between 2009 and 2019, the proportion of female students in these majors was 14.6% (± 1.4%) [SBC 2019]. In the teaching practice, one might seek to promote gender diversity in teams. However, due to the low number of female students, even the most diverse teams are usually composed chiefly of male students.

As for invisible diversities, they can influence the behavior of the team as a whole, affecting communication, strategies, and intermediating conflict resolution. With regard to the interaction between students, many studies indicate that sociability plays an important role in academic performance (e.g. [Gomes-Jr 2019]). However, the dynamics of sociability can be group-dependent, i.e., groups with more sociable individuals may not necessarily enjoy the same benefits observed for individual performance. Therefore, it is important to consider the diversity of sociability – an invisible aspect – in the context of teams and how it affects performance.

Another invisible aspect refers to the diversity of personalities in the team. Different personalities can express different mixes and intensities of emotions, which can also influence team dynamics. With data collected from 79 teams from companies in South Korea, a questionnaire-based study assessed the impact of emotional intelligence on conflict resolution and team effectiveness. This study revealed that team emotional intelligence reduces negative impacts on conflict resolution and is positively related to effectiveness, such as performance, innovation, and team cohesion [Lee and Wong 2019].

The aim of this work is to analyze how the diversity of individual characteristics, namely gender, sociability, and personality, affects the performance of teams as a whole, either negatively or positively. Furthermore, the interplay between different aspects of diversity can be context-dependent. For that reason, the results of this work may shed light on the role of these aspects of diversity in the context of computing majors.

The applied methodology (Section 3) combines two datasets, the first focusing on self-reported in-class social connections, which was used to assess the diversity of sociability. The second dataset contains multiple cross-sectional, self-reported emotions collected using a questionnaire. These data were aggregated, and students were clustered according to the reported emotions. The clusters were used as proxies for individual personality traits. To assess the influence of gender diversity, the two datasets were combined. The statistical analysis (Section 4) shows significant positive associations between the diversity of sociability and performance, and between the diversity of personality and performance. The analysis of gender diversity has not achieved statistical relevance for the dataset used.

2. Related work

Several studies emphasize the plurality of variables relevant to the academic performance of individuals, such as marital status, type of high school institution (public or private), course hours, income, scholarship, incentive policies for college admission, etc. These variables significantly influence academic performance and may vary depending on the area of study (exact sciences, humanities, health, among others) [Rocha et al. 2018, Bordim et al. 2019, Lopes et al. 2020]. Diversity adds another dimension to this type of analysis, surfacing emerging phenomena in group dynamics that may differ from the interpretation of individual characteristics.

The concept of diversity in teams has been studied in the field of organizational behavior and management. Research has shown that diverse teams, including those diverse in terms of gender, race, and ethnicity, can bring a range of unique perspectives and experiences to problem-solving and decision-making processes, leading to improved performance and productivity.

The formation of study teams and the performance of their members is a source of discussion in several academic papers. According to [Ciampone and Peduzzi 2000], a team is constituted by a group of people who gather in a particular space and place, having a common objective. By working in teams, students can deal with various aspects they may or may not be used to, such as gaining familiarity with people from different genders and social backgrounds, different ideas and strategies to solve problems, etc. In summary, teams expose students to aspects that could have been previously unfamiliar by choice or lack of opportunity. Among the relevant factors in analyzing the quality of group formation, this article highlights social, gender, and personality/emotional diversity. The literature review sought to understand how different levels of diversity can influence the performance of teams in academic or professional settings.

Diversity is defined as the result of the interaction between people with different identities in the same social context [Fleury 2000]. Assessing these differences is a fundamental concern that helps make more assertive choices [Myers 2003]. In this sense, effective collaborative learning must have diversity as one of its foundations since a plurality of experiences improves the potential contribution from individual students [Brindley et al. 2009]. Diverse teams can draw on a broader range of experiences and perspectives, leading to improved problem-solving and decision-making abilities. In the context of academic performance, diverse teams may be better equipped to tackle complex challenges and generate innovative solutions, leading to improved productivity and success.

2.1. Academic performance and gender diversity

Despite considerable attention being paid to the correlation between gender and performance in activities related to programming, there is still no clear consensus on whether gender is an influencing factor in computing skills. This conflict exists due to studies that indicate that girls need more time to develop computational thinking skills [Atmatzidou and Demetriadis 2016], as well as studies that contradict the idea that girls tend to develop computational thinking faster or better than boys [Sun et al. 2021], or even studies that indicate indifference between genders [Zhong et al. 2016]. These conflicts motivate investigations that consider the gender factor combined with others, such as the study by [Sun et al. 2022] that explores the correlation between the individual's attitudes (boys and girls) towards teaching computational thinking and programming experience. For the study, the authors used responses from online questionnaires from three junior high schools in China, totaling 1180 responses (612 from boys and 568 from girls). The questionnaire collected background information, programming experience, and programming attitudes (composed of a scale of factors: programming self-efficacy, programming utility, social needs, perception of programmers, and programming interest). The analysis showed that girls developed more computational thinking skills compared to boys, despite presenting more negative programming attitudes, which may affect their continued skill development. Even though the study did not consider gender diversity in groups, it shows that observing gender combined with other factors can improve understanding the disparities between genders in computing majors.

One of those disparities is reported by the study [Greenberg-Lake 1994] that concerns how boys and girls develop their self-esteem and satisfaction differently. It has been observed that girls may experience a decrease in self-esteem and satisfaction with their abilities from the age of 9 on average [Greenberg-Lake 1994]. This change in the perception of their self-confidence can signal many aspects of the academic life of girls that can even impact their choice and permanence in classes attended mainly by boys.

Teamwork, the object of this paper, is one of those factors to be analyzed in the context of gender. However, evaluating the trajectory of boys and girls in school education is a challenge, mainly due to the still limited academic production on educational inequalities from the perspective of gender [Sousa 2017]. Moreover, it is necessary to develop studies not only in the children's academic context but also in higher education, especially in the STEM area (Science, Technology, Engineering, and Math), in which the challenge of avoiding dropouts is more prevalent. Vieira et al. [Vieira et al. 2017] studied a community created and attended exclusively by women in the technology field. Using a questionnaire answered by 82 women aged between 18 and 34, this work shows that 72% feel comfortable at a maximum level on the scale in groups restricted to women. Meanwhile, among the 72% of women who also participate in other mixed groups, 45.8% feel comfortable at this same level. On the other hand, the benefits of girls participating in mixed team activities are well established. Curseu et al. [Curşeu et al. 2018] followed the performance of 118 teams of students in a first-year undergraduate course. The authors showed that a significant part of girls' contribution to team performance is mediated by higher quality in group discussions. Such benefits were also observed in [Resende et al. 2020], in which girls' participation in teamwork was evaluated, and it was observed that the female presence increases academic performance.

Therefore, there might be opposing forces influencing the participation of female students in majors with unbalanced proportions of male students. STEM majors, such as computing-related ones, require special consideration.

2.2. Academic performance and diversity of sociability

Among the factors of interaction between the group members, it is important to understand how each person expresses their interest and pre-disposition in interacting. For Cheek and Buss [Cheek and Buss 1981], sociability is an attribute opposite to shyness, in which people avoid being with others. In this way, sociability promotes an inclination to gather together in a community rather than the need to remain secluded.

A benefit from having a broader network of connections has been identified in [Gomes-Jr 2019]. In studies by Burt et al. [Burt et al. 2005], the formation of teams with a greater diversity of social ties provides access to more resources than groups with redundant social connections. The authors define social capital as "the advantage created by a person's position in a structure of relationships" and that "groups and people that perform well are the best connected". This analysis indicated that the performance (aspects related to innovation, positive evaluation, compensation and profit) is maximized when the *network closure*, which occurs when there is a network of contacts that are strongly connected in itself, is high and the members of the network around them have diverse perspectives, skills, and resources. In contrast, this paper considers the diversity of the individual levels of sociability among team members. Therefore, diversity is measured within the team, focusing on whether there is a benefit in having groups mixing shy and extroverted individuals.

2.3. Academic performance and diversity of personality

The influence of certain types or manifestations of personality in group dynamics is well established. For example, emotional intelligence is a critical point in developing teamwork, improving performance levels. Collective intelligence, which is the ability of a group to perform a wide variety of tasks, has been studied by Chikersal et al. [Chikersal et al. 2017]. Their research attempts to relate well-known predictors of collective intelligence, such as group composition and members' perceptions of social diversity, to the mechanisms underlying their effects. In an experiment administered in 120 pairs, a Collective Intelligence Test was answered, and group satisfaction was evaluated. Sensors were used to capture the synchrony in facial expressions, as well as electrodermal skin activity and heart rate. By measuring the statistical variability of team members on a specific characteristic, a positive relationship was found between collective intelligence and synchrony in facial expressions, which confirms the importance of non-verbal visual cues among team members.

Cognitive diversity by itself can be a factor influencing team dynamics. Arazy et al. [Arazy et al. 2011] analyzed this influence in articles produced by groups of Wikipedia editors. The authors developed and tested a theoretical model to explain how factors related to cognitive diversity (mental models shared by group members) and conflict moderation influence the quality of the article. The authors found that members with cognitive diversity tend to produce higher-quality articles when dealing with task conflicts.

Other works (and this paper) focus on measuring the diversity of personality traits within teams. The hypothesis is that diverse teams could have a broader set of resources to draw ideas and resolve conflicts. The main challenge in this context is collecting data and characterizing the personality spectrum. Lim et al. [Lim and Bentley 2019] approached the problem with an agent-based strategy. The authors modeled collaboration between agents to solve an optimization problem. The teams were composed of individuals classified into different personality types using the Myers-Briggs Type Indicator (MBTI). The MBTI is a personality inventory based on Jung's theory of psychological types. Each agent's MBTI type influences its decision-making. For example, the type *extroverted Thinking* is more influenced by the results from its peers. The authors confirmed the hypothesis that heterogeneous teams perform better than homogeneous teams.

Also using MBTI, Pieterse et al. [Pieterse et al. 2018] analyzed the influence of the diversity of personality in student teams during short-lived software development projects. The personality types were determined based on questionnaires where peers assigned members to different personality traits. The authors did not use traditional metrics to measure diversity. The results were inconclusive but showed a slightly positive association between diversity and performance.

This paper considers the diversity of personality, intermediated by self-reported emotions, and its influence on academic performance. As the strategy employed involves emotions associated with teamwork, it is worth knowing other works that investigate emotion as a factor in team performance. The study developed by Gerbeth et al. [Gerbeth et al. 2022] carried out a systematic review of the literature to find the relationship between emotional factors and group work. The empirical results of the review concluded that there are positive relationships between emotions and group work, where teams with members who are more sensitive to their emotions and those of others tend to perform better in their activities in the group, facilitating knowledge sharing, collaborative construction, greater engagement, creativity, and decision making.

3. Methodology

Fig. 1 shows the datasets and the steps of the methodology for each of the three aspects of diversity considered in this work: gender, sociability, and personality. The datasets used were derived from two previous research not related to diversity (details in Section 3.1). Having two different data sources, the analysis employed different combinations of the datasets to build the statistical models.

Diversity metrics such as entropy (for gender and personality, detailed in Section 3.4) and coefficient of variation (for sociability, detailed in Section 3.5) were calculated. In the case of personality, a clustering step derived five personality groups to categorize each individual (details in Section 3.6); then, the cluster assignments were used to calculate the diversity (entropy) of each team. In terms of sociability, the coefficient of variation was calculated based on the in-class social network graphs (using the eigenvector centrality metric, details in Section 3.5). Finally, having all the diversity indices calculated, the associations were analyzed using regression methods. The next sections describe the data sources and methodology steps in more detail.

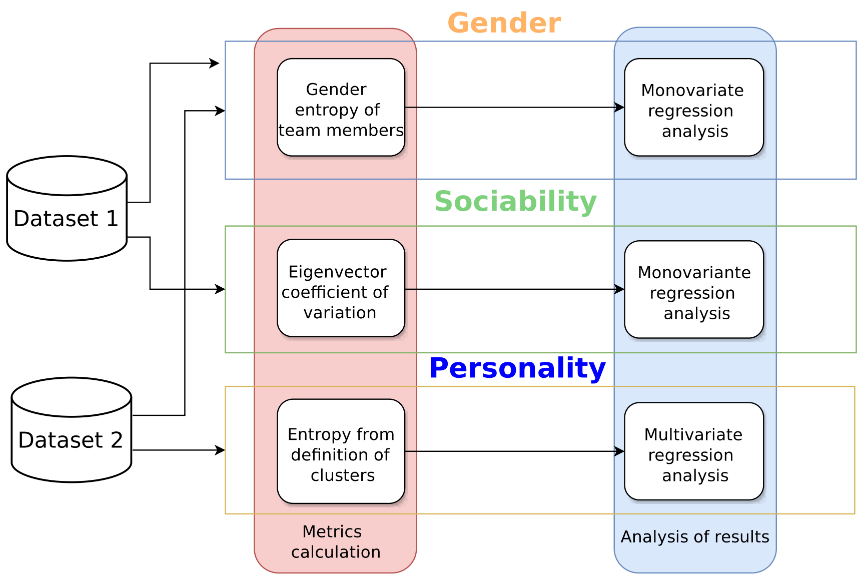

Figure 1. Simplified diagram of the methodology for categorical (gender and personality) and continuous (sociability) variables.

3.1. Data sources

All data were collected in a public university in Paraná, Brazil. The students were aware and agreed that the anonymized data would be used in future research. The data were collected from students in three computing programs (Bachelor of Information Systems, Computing Engineering, and Master's of Applied Computing) taught by two instructors. The assessed classes cover computational thinking, Information Management, Databases, and Data Science. The performance in the team assignment was a major factor in the student's assessment for all classes. The analysis measured performance in terms of final grades for the teams. The grades vary in the interval $[0..10]$.

In the datasets used, there was no information about gender. To obtain this information, a library [Álvaro Justen 2010] was used to infer gender based on first names. First names are a reliable indicator of gender for Brazilian names since names that can be used for multiple genders are rare. Moreover, Brazil has implemented policies for citizens to change their names based on their gender identity. However, the library can only infer binary genders, which does not reflect the real world's diversity.

3.2. Dataset 1

Dataset 1 was initially developed to analyze student sociability questions. As part of a regular class assignment, students were asked to list their acquaintances in the class. Data were collected for the undergraduate Databases classes of mixed computing majors (engineering and information systems). The assignment was proposed at the beginning of the term when the students registered their social connections. The teams were formed freely, without guidance from the instructor regarding the choice of members. The expected size of the teams was three students, but there was a variation due to divisibility and dropouts, with the average of 2.33 students per team. The dataset contains a total of 208 students in 89 teams.

To calculate the diversity index used in the analysis, the eigenvector centrality metric of each student was used, based on the graphs representing their social network. Eigenvector centrality [da F. Costa et al. 2007] captures the connectivity of a node by considering the connectivity of its neighbors recursively. Therefore, this is a good metric to represent the social capital of individuals, which was used as a proxy for sociability.

Academic performance data were then added to this dataset. Table 1 details the variables contained in the dataset.

Table 1. Variables contained in dataset 1

Variable	Description
URI	Student identifier
eigenvector centrality	Metric of the social network for each student
term	The respective term
team	Team name chosen by the members
team grade	Grade from the practical assignment
gender	Male or female

3.3. Dataset 2

Dataset 2 was created from a questionnaire with the aim of capturing elements of students' feelings and emotions throughout the term. This questionnaire was applied to graduate and undergraduate courses in computing (n = 405). The questions addressed the characterization of the students (term, moment of the term, name, id, and subject), as well as aspects related to five emotions. The students were asked to report about their general emotional state at that specific moment, not constrained to their feelings towards the class. To reduce bias related to temporary changes in mood, the questionnaire was applied three times during the semester (at the beginning, middle, and end of the semester).

The ranges of emotions emotions considered were: angry-patient, insecure-safe, depressed-happy, nervous-calm, and exhausted-excited. The emotions were presented on a 5-level Likert scale, in which 1 stands for the most negative emotion and 5 for the most positive. To facilitate the understanding of the scale, facial representations were added as emojis. For this analysis, data on the academic performance of teamwork were also aggregated, resulting in the variables shown in Table 2.

Table 2. Variables contained in dataset 2

Variable	Description
class year	Year
timestamp	Date and time pf the submission of the responses
id	Academic Id
term	The corresponding term
moment of term	Start, middle or end
angry_patient	Likert Scale, where 1 is more irritated and 5 is more patient
insecure_secure	Likert scale, where 1 is more insecure and 5 is more secure
depressed_happy	Likert scale, where 1 is more depressed and 5 is happier
nervous_calm	Likert scale, where 1 is more nervous and 5 is calmer
exhausted_lively	Likert scale, where 1 is more exhausted and 5 is more excited
team	Which team the student belongs to
team grade	Grade obtained by the team
gender	Male or female

3.4. Gender diversity analysis

The gender analysis assesses the influence of gender diversity on team performance. The analysis used a combination of datasets 1 and 2, totaling 634 students and 193 teams where the average number of members per team is 3.28.

To measure diversity, the Shannon entropy (applied to the gender ratio) was used. Shannon entropy is often used to measure the diversity of a set of discrete items. Shannon entropy can be understood as a measure to quantify the uncertainty of the observations of a population. For a random variable X with values in a finite set χ, Shannon entropy is defined as [Shannon 1948]:

$$H = -\sum_{i=1}^{M} P_i \, log_2 \, P_i \tag{1}$$

where P_i is the probability of observation i in a sample and M is the number of distinct observations. Observations in the context of this paper refer to gender (M or F) of team members. The equation produces $H = 0$ for a team with no diversity (e.g. all male students) and $H = log_2 M$ represents a set with maximum diversity (which equals 1 for gender, since $M = 2$).

The diversity index measured by entropy was then used in a linear regression analysis, with the final grade of the assignment being the dependent variable of the model (Section 4.1).

3.5. Sociability diversity analysis

The coefficient of variation applied over all members' eigenvector centrality was used to measure the sociability diversity of each team. The coefficient of variation (*CV*) is defined as a proportion:

$$CV = s/\overline{x} \tag{2}$$

where *s* represents the sample standard deviation and $\overline{x}$ the sample arithmetic mean.

The coefficient of variation is a normalized version of the standard deviation, capturing the tendency of the sample to deviate from the average value. In this setting, the greater the coefficient of variation is, the greater the variation in terms of extroversion (or social capital) in the team – i.e., there is a mix of introverted and extroverted members. The diversity index was then used for the linear regression analysis, with the final grade of the team as the dependent variable of the model.

3.6. Personality diversity analysis

Sentiment data reported in dataset 2 were used to derive proxies of student personality traits. The assumption is that different aspects of an individual's personality would be manifested in the answers to the questionnaire. To unify the responses of each student and reduce bias, the average of the responses for each feeling throughout the semester was calculated, generating a single list with five measurements of emotions per student.

To identify personality profiles, students were clustered based on their measurements of emotions. The clustering approach employed was hierarchical clustering, using the *ward* distance method [Blum et al. 2017]. The resulting dendrogram and the chosen cut-off point can be seen in Fig. 2. From the cut-off point used, the five personality clusters portrayed in Figure 3 were formed.

An informal interpretation of Figure 3 characterizes the *cluster 1* as made up of good-natured but exhausted people, the *cluster 2* of people with more positive feelings, the *cluster 3* is composed of people with a greater range of feelings (intra-cluster variance = 0.58) and thus possibly less constant, the *cluster* 4 are people with neutral moods but more exhausted and finally the *cluster 5* being constant people (intra-cluster variance = 0.11) but less calm.

From the classifications of the individual profiles, Shannon entropy was used in a similar way to that described in Section 3.4 and thus served as an index of team diversity. In a similar way to the analysis performed for gender and sociability, this index was used later in linear regression analysis, with the final grade of the team as the dependent variable of the model. To control for personality diversity mediated by gender, gender diversity was also included as a variable.

Figure 2. Dendrogram of the personality clusters with cut-off line.

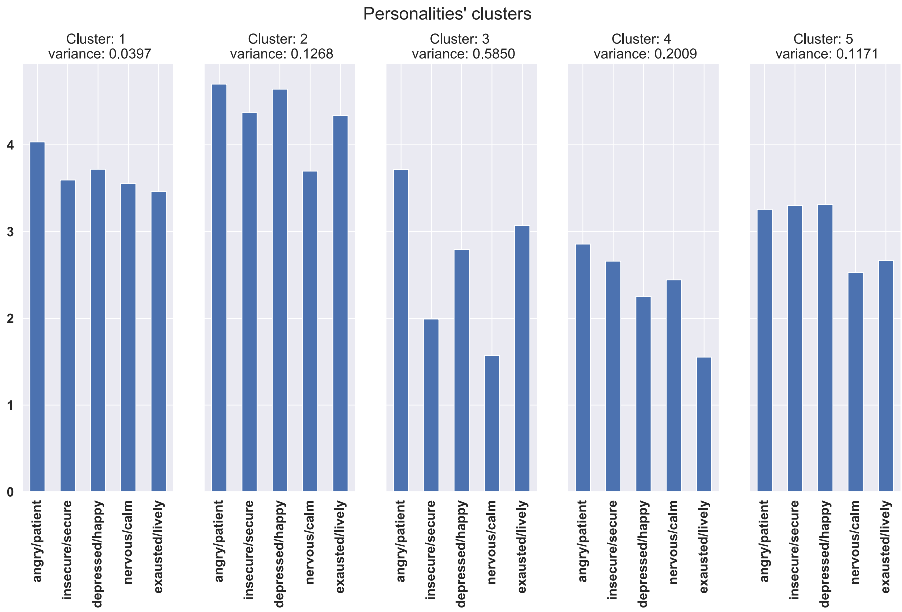

Figure 3. Means of emotions in the personality clusters and their respective variances (at the top of each cluster).

4. Results and discussion

This section presents the results of the analysis for the attributes: gender, sociability, and personality, following the methodology described in Section 3.

4.1. Gender diversity

To measure the influence of gender diversity on team performance, the following regression equation was used:

$$\text{grade}_i = \alpha + \beta \text{gender\_entropy}_i + \epsilon_i \quad (3)$$

where *grade_i* is the final grade, *gender_entropy* is the gender entropy for team i.

The R^2 obtained was 0.002 and the other values are shown in Table 3. As the p-value equals 0.549, this model does not reach statistical significance for the variable assessed. Therefore, based on the data and model used, gender diversity cannot be associated with better performance for teams. A reasonable explanation for this result is the lack of data (too few teams with female members). Another possibility is that of high variance associated with other factors (such as an oppressive environment for minorities).

Table 3. Variables and coefficients of the gender regression model

Variable	Coefficient	Std Error	p-Value
intercept	8.069	0.174	< 0.01
gender_entropy	-0.2757	0.46	0.549

4.2. Sociability Diversity

To measure the influence of sociability diversity on team performance, the following regression equation was used:

$$\text{grade}_i = \alpha + \beta \text{cv\_sociability}_i + \epsilon_i \tag{4}$$

where *grade_i* is the final grade for team i, and *cv_sociability* is the coefficient of variation of the eigenvector centralities of team i's members.

The R^2 for the model was 0.048 with coefficient values shown in Table 4. The positive and statistically significant coefficient for the variance of sociability indicates a benefit from having groups that mix students with different degrees of extroversion. The estimated gain in grade for the most diverse teams (with a diversity index greater than the third quartile) compared to the less diverse teams (those whose diversity index is lower than the first quartile) is equivalent to 1.41 grade points.

The estimated interquartile improvement is high. This could be a result of omitted variables or confounding variables. Specifically, some personality traits could be directly influencing sociability and other beneficial behavior expressed in the teams. A longer and more detailed study would be necessary to identify individual contributions for different traits.

Table 4. Variables and coefficients of the sociability regression model

Variable	Coefficient	Std Error	p-Value
intercept	7.24	0.328	< 0.01
cv_sociability	1.111	0.532	0.04

4.3. Personality diversity

To measure the influence of personality diversity on team performance, the regression equation used was as follows:

$$\text{grade}_i = \alpha + \beta \text{personality\_entr}_i + \delta \text{gender\_entr}_i + \epsilon_i \tag{5}$$

where *grade_i* is the final grade, *personality_entr* is the entropy of personality, and *gender_entropy* is the gender entropy for team i.

The R^2 for the model was 0.198. The values for the coefficients are shown in Table 5. Gender entropy does not have a significant p-value, confirming the results from

Section 4.1. Personality entropy has a positive and significant coefficient, indicating a benefit from having teams mixing the personality clusters. According to the model, the estimated gain of grades for the most diverse teams (with a diversity index above the third quartile) compared to the less diverse teams (those whose diversity index is lower than the first quartile) is equivalent to 1.43 grade points (with *gender_entropy* fixed as the average).

The estimated contribution (interquartile improvement) is also high. In this case, the improvement is justifiable by a more detailed characterization of the variable into distinct clusters. This is a good indicator of the importance of this type of diversity.

Table 5. Variables and coefficients of the personality regression model

Variable	Coefficient	Std Error	p-Value
intercept	7.5287	0.351	< 0.01
personality_entr	1.3717	0.388	0.001
gender_entropy	-0.6083	0.659	0.361

5. Conclusion

Academic performance is complex to define as it is influenced by factors such as the student's background, the relationship between instructor and student, assignments and tests applied in the classroom [Fagundes et al. 2014], etc. For teamwork and classroom discussions, diversity is one of the factors influencing student performance, since it can provide a favorable environment for the emergence of ideas and ways to solve problems. This study sought to identify the influence on academic performance of the diversity factor represented by the attributes of gender, sociability, and personality.

An important question raised by this research refers to gender, as the predominance of boys in the majors studied is well documented [SBC 2019]. The analysis, however, was not conclusive regarding the benefits of gender diversity in teams. More data and control variables that could capture the subtleties of the dynamics are necessary to understand the behavior and performance of the teams.

With regards to personality diversity and sociability, the gains in assignment grades in different teams compared to less diverse teams are expressive, something that encourages further investigation of hypotheses such as: how is the connection between sociability and personality; which personalities could mediate in the resolution of group conflicts; which personalities are associated with good and bad academic performance; what is the best association of these personalities in the composition of teams.

The research presented in the paper represents a step toward better understanding the complex role of diversity in computing majors (which is probably related to other STEM areas). Even though diversity seems beneficial in general, there might be circumstances where this benefit can be constrained by other aspects of the course, such as the significant imbalance in gender. In such cases, these factors should be addressed. Regarding practical recommendations, administrative personnel should foster diversity in admissions and guarantee that students with different personality traits feel comfortable in the department. As for instructors, randomly assigning students into teams or mixing teams midterm could improve diversity and maximize the benefits identified in this research. It is worth mentioning that the analyzes of this work regarding gender will be openly available on the ELLAS (ellas.ufmt.br) platform (which collects and integrates diverse data about women in STEM courses), thus contributing to open science.

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