MACHINE LEARNING APPROACH FOR PREDICTING CORPORATE SOCIAL RESPONSIBILITY PERCEPTION IN UNIVERSITY STUDENTS

Felipe Lillo-Viedma, Pedro Severino-González, Estela Rodríguez-Quezada, Felipe Arenas-Torres and Giusseppe Sarmiento-Peralta

SUMMARY

Corporate Social Responsibility has become an important corporate principle. Perception about the use of this concept is regarded by corporate stakeholders as strategically crucial. The present work explores the use of machine learning models to analyze connections between socio-demographic traits and CSR perception. Three models are tested based on information provided by university students: a Neural Network (NN), Random Forest (RF) and a Gradient Boosted Tree model (GBT). These models consider socio–demographic and perception scores as inputs and output features, respectively. Results indicates that the GBT model makes better prediction about perceptions. Furthermore, the RF model estimates feature importance which shows the income level feature as a main predictor of CSR–perception.

Introduction

Corporate Social Responsibility (CSR) is a topic addressed from different research perspectives and applications fields (Gond *et al*., 2023). Research perspectives focus mainly on analyzing perceptions, behaviors and preferences from CSR stakeholders (Sarfraz *et al*., 2018; Boğan and Dedeoğlu, 2020; Stanco and Lerro, 2020), whereas research in applications fields has lead to developing concepts such as University Social Responsibility (USR), Organizational Social Responsibility (OSR), and (CSR), all of which involving themes related to governance, sustainability, leadership, education, ethics, philanthropy and social well-being (Zhao *et al*., 2018; Kvasničková *et al*., 2020; Janowski, 2020). All these factors contribute to the development of a healthy environment, thanks to the provision of strategies which consider legal elements, complemented by strategies that include ethical and philanthropic aspects, and leading to the provision of legal and socially responsible behavior.

CSR research in university contexts is usually addressed from two perspectives. Firstly, there is the CSR learning perspective, which focuses on student learning and perception of CSR (Teixeira *et al*., 2018; Galvão *et al*., 2019; Silva *et al*., 2020; Severino-González *et al*., 2022). For example, Pätäri *et al*. (2017) proposes CSR learning strategies for students related to the forestry industry. Almutawa and Hewaidy (2020) analyzes CSR perceptions in accounting students.

With this study, we should point out that perception constitutes the representation of reality according to the particularities of the subject and its relationship with the environment. Studies relevant to this research, in terms of research subjects' characteristics, have contributed to findings that reveal statistically significant differences between students' perceptions. Similar findings are presented by Severino-González and Gaete (2019). However, the authors emphasize the importance of socio-demographic variables in CSR perception, because CSR perception constitutes the representation of the strategies that aim to satisfy stakeholders' needs.

Ugwuozor (2020), investigates the role played in university students by ethics and morals for both the understanding of CSR and the construction of a responsible social behavior. Secondly, there is the CSR projection perspective, which extends the university vision, mission and commitment to the community (Lúquez *et al*., 2014). Such extension generates actions, collaboration and aid from universities that improve human well-being (Ramírez *et al*. 2019). Universities should thus articulate their institutional guidelines, teaching and research to attain a

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ENFOQUE DE APRENDIZAJE AUTOMÁTICO PARA LA PREDICCIÓN DE LA PERCEPCIÓN DE RESPONSABILIDAD SOCIAL EMPRESARIAL EN ESTUDIANTES UNIVERSITARIOS

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RESUMEN

La Responsabilidad Social Corporativa se ha convertido en un importante principio corporativo. Las partes interesadas corporativas consideran que la percepción sobre el uso de este concepto es estratégicamente crucial. El presente estudio explora el uso de modelos de aprendizaje automático para analizar las conexiones entre los rasgos sociodemográficos y la percepción de la RSC. Se prueban tres modelos basados en información proporcionada por estudiantes universitarios: una red neuronal (RN), Random Forest *(RF) y un modelo* Gradient Boosted Tree *(GBT). Estos modelos consideran las puntuaciones sociodemográficas y de percepción como características de entrada y salida, respectivamente. Los resultados indican que el modelo GBT hace una mejor predicción sobre las percepciones. Además, el modelo RF estima la importancia de la característica, lo que muestra la característica del nivel de ingresos como un predictor principal de la percepción de la RSC.*

ABORDAGEM DE APRENDIZADO DE MÁQUINA PARA PREVENIR A PERCEPÇÃO DE RESPONSABILIDADE SOCIAL CORPORATIVA EM ESTUDANTES UNIVERSITÁRIOS

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RESUMO

A Responsabilidade Social Corporativa se tornou um importante princípio corporativo. As partes interessadas corporativas consideram que a percepção sobre o uso deste conceito é estratégicamente crucial. O presente trabalho explora o uso de modelos de aprendizado automático para analisar as conexões entre os rasgos sociodemográficos e a percepção do RSC. Teste três modelos baseados em informações fornecidas por estudantes universitários: um red neuronal (RN), Random Forest *(RF) e um modelo* Gradient Boosted Tree *(GBT). Esses modelos consideram as pontuações sociodemográficas e de percepção como características de entrada e saída, respectivamente. Os resultados indicam que o modelo GBT tem uma melhor previsão sobre as percepções. Além disso, o modelo RF estima a importância do recurso, que mostra o recurso de nível de entrada como um preditor principal da percepção do RSC.*

complete CSR education scheme where stakeholders are at the core of strategic decisions (Ali *et al*., 2021).

The two perspectives are the mainstay in CSR education which focuses on the development of both students and professionals committed to common well- being and public service (Coelho and Menezes, 2021; Severino-González *et al*., 2022) This development is achieved by procuring a learning process involving innovative education, environmental awareness and scientific solutions of social problems (Escobar *et al*., 2021). What is the use of machine learning models to analyze the connections between sociodemographic traits and the perception of CSR? The following objective is defined: exploring the use of machine learning models to analyze connections between socio-demographic traits and CSR perception.

It is in this sense that this research seeks to contribute to predicting perception of corporate social responsibility in university students through a machine learning approach, contributing to the design of socially responsible strategies in university contexts (Severino-González *et al*., 2022; Fatima and Elbanna, 2022), which in turn could contribute to the implementation strategies that meet the needs of various interest groups (Figueroa *et al*., 2022; Al-Samhan, 2023).

Corporate Social Responsibility and Strategic Education University

The study of social responsibility has been developed in various contexts, which has made it possible to identify the implications which interest groups have in decision-making (Jeet, 2022; Velte, 2022). These seek to improve quality of life through relationships based on values such as empathy and solidarity, contributing to better conditions of access and possibility for all those who make up society (Kvasničková *et al*., 2020; Janowski, 2020). In particular, its study in educational contexts has led to its approach to the attitudes, perceptions and expectations of the subjects that comprise the educational communities, promoting the design of educational strategies based on organizational policies (Boğan and Dedeoğlu, 2020, Stanco and Lerro, 2020).

One important strategic aspect related to CSR education is the stakeholder perception of CSR; more specifically, how particular stakeholder traits define a view about CSR (Lee *et al*., 2022; Severino-González *et al*., 2022). This problem has important strategic implications, since future CSR implementation scenarios can be predicted based on stakeholder characteristics, which could predict interest in satisfying stakeholders' needs. This work addresses such problems considering socio-demographic traits as potential predictors of CSR perception.

There is a notable body of literature addressing CSR perceptions in various contexts, including CSR in higher education. In particular, this research considers the research subjects' sociodemographic characteristics, specifically the characteristics of university students. For instance, Kleinrichert *et al*. (2013) investigated differences on perceptions in study plans that include CSR courses. The authors found significant differences between student who could pass CSR courses and those who could not. Similarly, Ullah and Manzoor (2021) and Simpson and Aprim (2018) emphasize the relevance in higher education that both CSR subjects and CSR practice have on social responsibility perception. In a particular case, Anand and Singh (2021) analyzed CSR perception in business students, concluding that gender, age and experience significantly explain CSR views. All these factors could contribute to defining the strategic orientations that characterize decision-making processes (Boğan and Dedeoğlu, 2020; Severino-González *et al*., 2022).

From a methodology viewpoint, studies about CSR perception include consumers, workers and businessmen (Jing *et al*., 2022). In particular, research which considers university students (Rodríguez-Gómez *et al*., 2022) mainly applies techniques based on either factor analysis or determination of statistically significant differences (Larrán *et al*., 2018; Sarmiento-Peralta *et al*., 2021; Owan *et al*., 2022). The literature also mainly presents models based on these techniques where gender, working experience and educational level are considered as key CSR perception drivers, somehow demonstrating the importance of stakeholder satisfaction (Galvão *et al*., 2019).

The overall research focus in the literature has mainly been on evaluating CSR perception, leaving aside prediction based on subject traits. As a result, this work follows some ideas presented by Lillo-Viedma *et al*. (2022) and Lee *et al*. (2022) so that an empirical analysis based on machine learning techniques is performed for assessing CSR perception among university students. The study also tackles the relevance of sociodemographic traits for prediction. These factors contribute to the development of competent and socially responsible professionals, which could help to mitigate the lack of talent with the right knowledge of CSR, and could also help to minimize the delays of modern societies.

The practical and theoretical implications of this research are linked to the design of educational strategies and policies that help raise awareness and sensitize university students regarding the problems and challenges of contemporary society (Lillo-Viedma *et al*., 2022; Nave and Ferreira, 2019). This is crucial because it will be the future decision-makers who may promote or limit the design of CSR strategies, which could affect the image of organizations as an entity that satisfies various interest groups' needs (Sarmiento-Peralta *et al*., 2021).

Materials and Methods

A quantitative research approach with a descriptive focus was selected to accomplish the objective. In addition, Primary information is gathered in a cross-sectional manner for the 2019 period. This data is studied via Machine Learning-based techniques.

Population and sample

The study population is comprised of university students in the Maule Region of Chile. There were 24343 university students formally enrolled by 2019 in the Maule region (Servicio de Información de Educación Superior, 2022). This study considers a non-probabilistic convenience sample, which included 204 students; these were directly contacted during November 2019.

Data gathering

Data gathering from the primary sources took place during November 2019 with an instrument composed of three sections: Section 1 identified personal information. Section 2 socio-demographically characterized students by recording personal information which is detailed in Table 1. Finally, Section 3 evaluated CSR perception based on a Likert scale originally designed by Maignan (2001), and whose principles were postulated by Carroll (1991). This scale considers four CSR dimensions to be assessed: Economic, Legal, Ethic and Philanthropic (Table I). Each dimension is addressed by four variables that are measured in a six–level Likert scale. A detailed explanation of the scale appears in Wendlandt *et al*. (2016).

For the application, the instrument was implemented online. Participant access was granted by a link available on a university website between August and December 2019 (Table II).

Analysis techniques

A Machine learning approach is used to assess the relation between socio-demographics and CSR perception. Three specific machine learning regression models (ML-models) are tested: a Neural Network model (NN), a Random Forest model (RF), and a Gradient Boosted Tree (GBT). Figure 1 shows the data pre-processing flow, as well as the procedure applied for the ML-models.

The application of machine learning approaches in different CSR contexts appears in the literature. Works such as Park *et al*. (2018) and Pons *et al*. (2021) use machine learning to predict CSR performance when companies experience crisis and environmental issues, respectively. Similarly, Martínez-Regalado *et al*. (2021) and Thompson and Buertey (2023) apply machine learning techniques to assess the

TABLE I
PERCEPTION OF CORPORATE SOCIAL RESPONSIBILITY

Dimension	Variables
Economic	Va. Maximize profits. Vb. Strictly control production costs. Vc. Planning long-term success. Vd. Always improve economic results.
Legal	Ve. Ensure that employees behavior within legally define standards. Vf. Fulfill contractual obligations. Vg. Avoid infringing the law, even if this helps improve performance. Vh. Always respect the principles defined by regulations.
Ethical	Vi. Fulfill ethics, despite any negative economic performance results. Vj. Ensure that respect for ethical principles outranks economic results Vk. Commitment to well-defined ethical principles. Vl. Avoid compromising ethical standards to achieve corporate goals.
Philanthropic	Vm. Help resolve social problems. Vn. Participate in managing public affairs. Vo. Earmark part of their resources to philanthropic activities. Vp. Play a key role in our society, beyond pure profit generation.

TABLE II
SOCIODEMOGRAPHIC VARIABLES

Dimension	Options	Encoding
Gender (GE)	Female	1
	Male	0
Age group (AG)	18 to 24	1
	25 to 31	0
Occupation (OC)	Student	1
	Worker student	0
University years (UY)	1 to 3	1
	4 to 6	2
	7 to 9	3
Family members (FM)	1 to 2	1
	3 to 4	2
	5 to 6	3
Monthly income level USD(IL)	less than 243	1
	243–486	2
	486.5–729	3
	729.5–973	4
	973.5–1216	5
	Over 1216	6
Living area (LA)	Urban	1
	Rural	0
Volunteering (VO)	Yes	1
	No	0
CSR–knowledge (CSR–K)	Yes	1
	No	0

efficiency of CSR investment decisions. In higher education matters, Amani (2023) study CSR implementation in universities by means of machine learning and statistical techniques, primarily taking stakeholder opinions into consideration. None of these studies tackle either whether sociodemographic traits are CSR predictors or which sociodemographic traits are more determinant of CSR perception.

The corresponding dataset is pre-processed so that all categorical input variables are encoded (label encoding) and normalized by min-max scaler to (0,1) accordingly. Correlations between predictors and target variables are also computed, since ML-models are very affected by collinearity issues. Outliers beyond 4 times the interquartile range (IQR) are identified and removed from analysis as well (4*IQR assures to remove extreme values without significantly altering the data natural variation).

The neural network is constructed by assigning sociodemographic traits as the input layer, whereas the output layer corresponds to perception scores on each CSR dimension. There are 3 hidden layers, and 256 nodes in each layer. The activation function used in these layers is the "Relu" function. A normal kernel initializer is also employed, and "Linear" is used as the activation function of the last layer. The loss function of the NN model is mean squared error (MSE), and the objective function is optimized using Adam optimizer. The mean absolute error is also computed (MAE). 500 epochs are considered as well, and the model is fitted by splitting train and validation dataset in 0.8 and 0.2 (random state= 20), respectively.

RF is an ensemble learning method for either classification or regression, and operates by constructing several decision trees from a training data set (Ho, 1995). RF has the advantages of handling both regression and classification, a small number of tuning parameters, appropriateness for complex problems, avoiding overfitting, as well as visualization of cross-validation, variable importance and suitable for small size problems (Zhang and Ma, 2012). The random forest test performed here has 60 trees (number of estimators). Both Mean squared error (MSE) and Mean absolute error are also computed to compare performance.

Variable importance is computed via Permutation Feature Importance (PFI), which is a method that normalizes a biased measure based on a permutation tree test and returns significance for each feature (Altmann *et al.*, 2010) In this case, the significance is measured by the R2 (coefficient of determination) regression score function.

GBT provides a prediction model as an ensemble of weak prediction models, which are commonly decision trees (Stiglic *et al.*, 2019). A gradient-boosted tree model is constructed in a stage-wise form and generalizes other boosting methods by permitting optimization of an arbitrary differentiable loss function. For implementation purposes, the presented GBT model takes 10 as the maximum tree depth for base learners, while other parameters are set by default from the computational library.

The three ML models are implemented by Keras and Sklearn Python libraries. Likewise, "RandomForestRegressor" and "XBGRegressor" are implemented for RF and GBT models, respectively. Finally, the "PermutationImportance" package is imported to estimate feature ranking in both tree models (scoring = r^2 and number of iteration = 5).

Performance is compared between the regression models by both Mean Squared Error and Mean Absolute Error.

Results

This section presents the main characteristics of university students. In addition, the most relevant findings are presented according to the research objective.

Answer summary

The sociodemographic traits for the 204 students are statistically summarized by Figure 2. We can see that that female students predominate. Students have manly stayed between 4 to 6 years in university, and the majority claim to have no knowledge about CSR. Regarding this factor, some research shows that these perceptions are related to training prior to university education, as well as a lack of formal education in HEIs about aspects related to citizen participation, business ethics, development sustainability, and organizational volunteering (Cox and García, 2021; Rosak-Szyrocka *et al.*, 2022).

Table III and Figure 3 describe sample perception for each CSR dimension. The outlier column shows the percentage of outlier data according to Tukey's fences criteria (4*IQR). These are subsequently removed from the analysis. Results in general show a bias towards higher scores of the Likert perception scale. In particular, legal as well as ethic perceptions score high levels. This indicates that students deem these dimensions important since they are related to norms and principles that ensure healthy working environments (Górny, 2019). On the other hand, the economic dimension scores low, together with the philanthropic. Both dimensions are mainly interrelated with profit maximization and financial corporate management. Nonetheless, the economic dimension features a greater dispersion level, which could be a result of discrepancies among student perceptions.

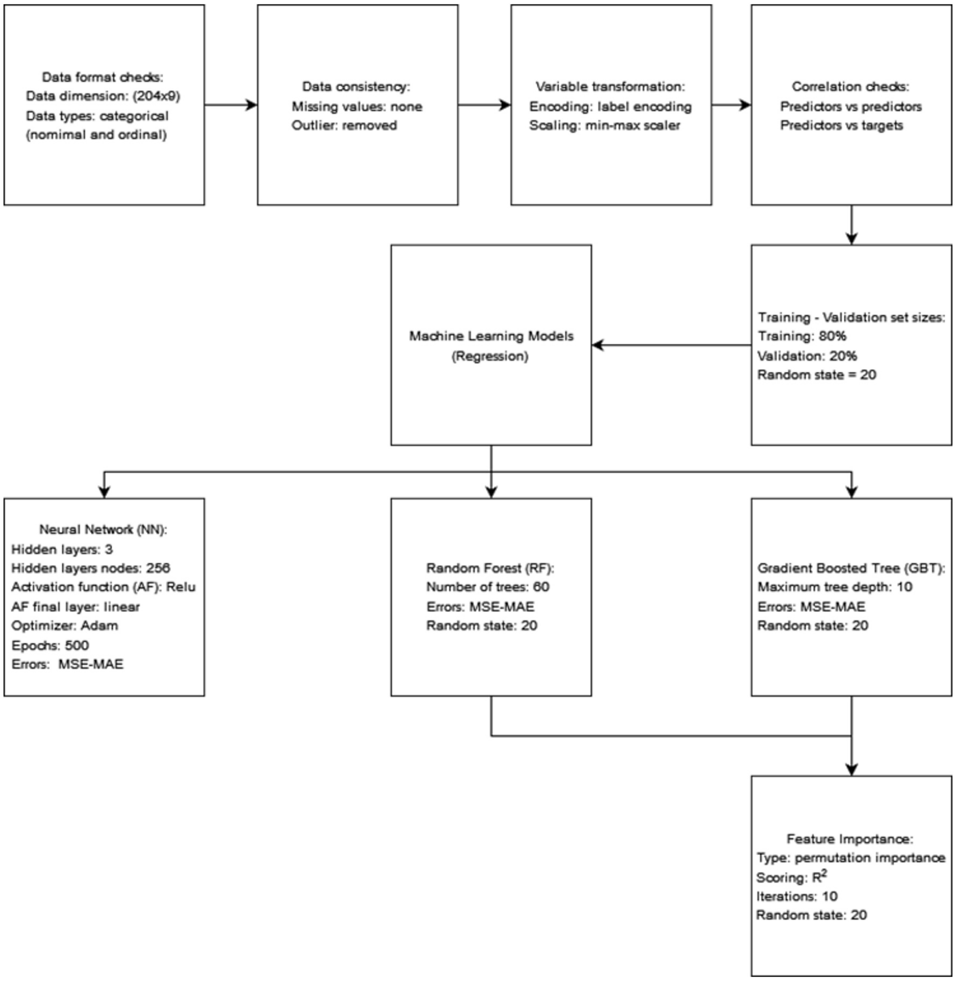

Figure 1. Data processing flow chart.

Two correlation scenarios are estimated to identify collinearity. Table IV checks correlation between independent variables. In general, correlation values are small disregarding multicollinearity. Table V shows correlation coefficients between independent and dependent variables. Low values are noticed in this case as well. The interaction between Income Level (IL) and target variables is interesting, since only positive correlation values are reported.

Machine learning models

Results associated with the machine learning regression models are presented by Table VI. It can be seen that ML tree models outperform the NN model, since their error values are lower. Specifically, the GBT model possesses the best performance on estimating CSR perception scores.

Table VII present a comparison between real and predicted values (normalized values). A sample was randomly extracted from the validation set. Predictions values agree with error levels, which confirms that the tree models have the best performance.

Finally, feature importance is computed from tree models. Figure 4 shows feature importance score for each sociodemographic characteristic based on permutation importance for RF and GBT models. Income level and Family members rank as the most determinant predictive features for each CSR dimension according to the tree regression models. On the other hand, Volunteering turns out to be the worst CSR perception predictor.

Discussion and Conclusions

This paper addressed the estimation of CSR perception from sociodemographic traits. As far as the bibliography is concerned, the use of ML-models to analyze CSR-perception has been scarcely addressed. Three machine learning models were developed and evaluated. ML regression models could reasonably predict CSR perception scores from sociodemographic variables. In general, the models tested in this work showed low error estimates, highlighting the probabilistic tree-based models. The good performance of tree models is consistent with arguments presented by Zhang and Ma (2012) and Herce-Zelaya *et al.* (2020). Specifically, the ability of these models for computing feature importance is a useful aspect when CSR strategies are formulated (Thompson and Buertey, 2023). However, the ML-models can certainly be improved by applying hyperparameter tuning techniques, so that the performance of the models can be maximized. This is a limitation for the study, but it also falls outside its scope, since the authors tackled the research in an exploratory manner (a view of ML-techniques on CSR perception.

From the RF model, feature importance shows Income Level as an important predictor of CSR perception. The importance of income aligns with other studies such as Luo *et al.*

TABLE III
PERCEPTIONS OF CSR–DIMENSIONS

	mean	std	min	25%	50%	75%	max	Outlier (%)
Legal	5.43	0.87	1.0	5.3	5.8	6.0	6.0	3.0
Philanthropic	4.98	0.93	1.3	4.5	5.3	5.5	6.0	0.0
Economic	4.81	0.92	1.0	4.3	5.0	5.5	6.0	0.0
Ethic	5.20	0.92	1.0	4.8	5.5	6.0	6.0	0.0

CSR: Corporate Social Responsibility.

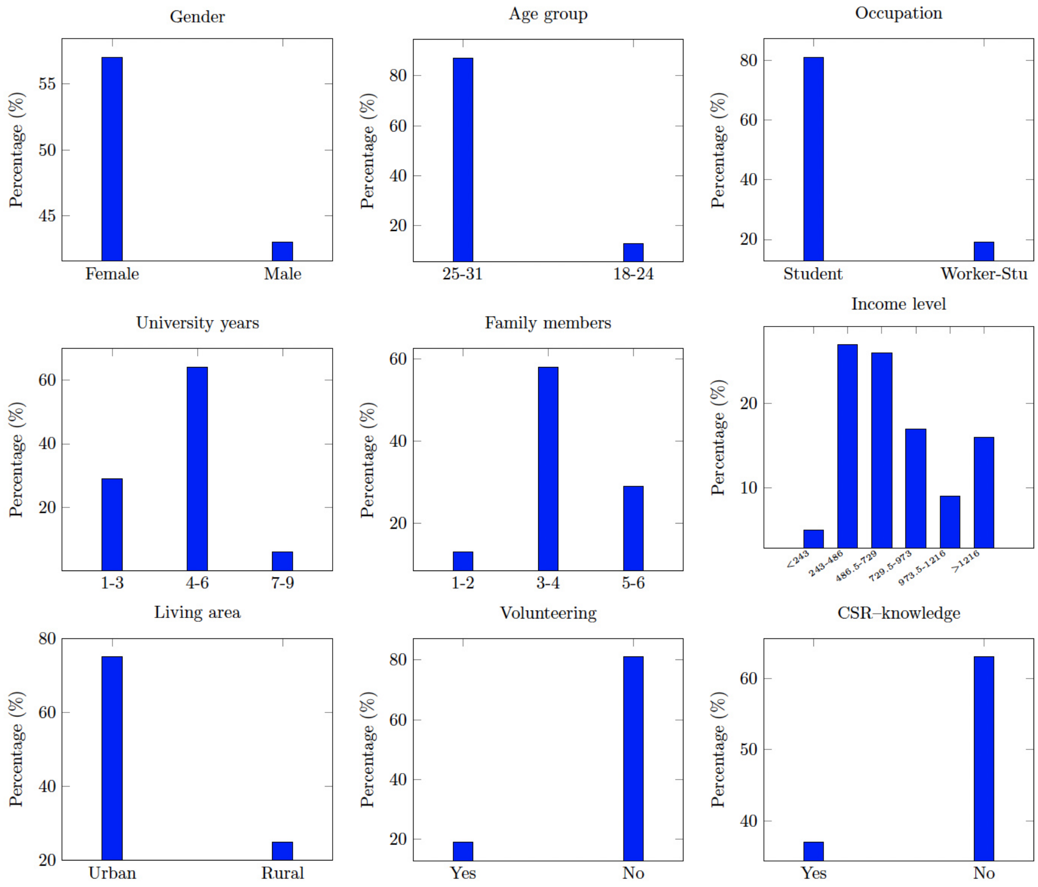

Figure 2. Sample sociodemographic traits description.

(2022) and Severino-González *et al.* (2022). The latter author also has in other study about university students, regarding the influence of family income on both sustainable consumerism and social responsibility (Severino-González *et al.*, 2022). Nonetheless, some research arrives at a different conclusion. For instance, Severino-González *et al.* (2022) shows how from a socio-emotional view, family income has no incidence on socially responsible policies developed by universities. A relation between Income Level and Family members may also affect some results (FM is the second most important feature) since both variables are connected (Zedan, 2011). Further research is needed to clarify such potential relation.

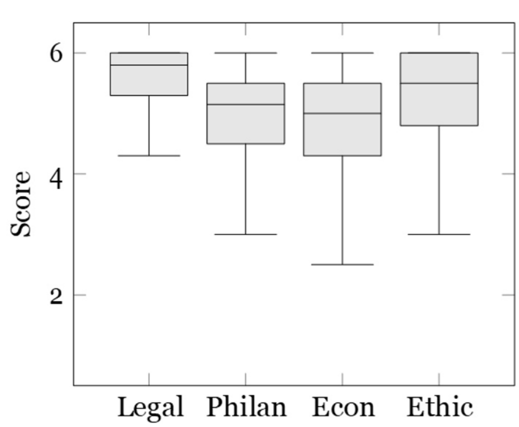

Figure 3. Boxplots for CSR perceptions.

When considering the behavior of the Legal dimension, which features a high mean value as well as low dispersion, we should note that companies' legal responsibilities respond to initial requirements that constitute the basis of interpersonal labor relations, which is present in each socially responsible strategy (An, 2021). Therefore, the feature importance results could suggest that compliance with government policies and ethical behavior are important CSR perception determinants from a stakeholder viewpoint.

When we consider volunteering, studies indicate that universities develop strategies to motivate this concept among students (de Prada *et al.*, 2020; Ortega-Vivanco *et al.*, 2021; Soler and Saneleuterio, 2022). Feature importance describes volunteering as the worst predictor of CSR perception in this research. This result contradicts findings in Sarmiento-Peralta *et al.* (2021) where volunteering positively contributed to CSR perception in Peruvian university students. This could be evidence of a "local effect" driving CSR perceptions. Research supporting the idea of cultural and behavioral traits defining CSR perception is found in several works such as Díaz-Iso *et al.* (2020), Alfakhri *et al.* (2020) and Avazovich (2022). Clearly, more investigation is needed to clarify the role of local surroundings in CSR perceptions.

The socially responsible strategies contained within higher education can be implemented and contribute to the development of competent and socially responsible professionals. These factors contribute to supplying talent with CSR knowledge, which is linked to providing tools that can facilitate decision-making processes in search of simpler, more diligent ways to address old and new challenges of current societies.

Following ideas presented by Fassin *et al.* (2015), future research can integrate views from different social groups about CSR perception. By doing this, the development of a mental model based on sociodemographic features as well as spatial characteristic could be tackled in order to understand the social interpretation of CSR. Furthermore, the development of more tuned Ml-models to improve prediction can certainly assist decision makers in strategic decisions regarding the public view of an organization. This could contribute to designing more efficient strategies, which respond

TABLE IV
CORRELATION VALUES FOR FEATURES

	AG	OC	VO	GE	IL	FM	LA	UY	CSR-K
AG	1.000	-0.018	0.023	0.027	-0.015	-0.105	-0.143	0.078	0.058
OC	-0.018	1.000	-0.129	0.141	-0.236	-0.198	-0.098	0.139	0.069
VO	0.023	-0.129	1.000	-0.128	-0.038	0.055	-0.072	0.043	0.108
GE	0.027	0.141	-0.128	1.000	0.070	0.167	-0.026	0.023	-0.025
IL	-0.015	-0.236	-0.038	0.070	1.000	0.281	0.017	0.049	-0.190
FM	-0.105	-0.198	0.055	0.167	0.281	1.000	0.172	0.006	-0.070
LA	-0.143	-0.098	-0.072	-0.026	0.017	0.172	1.000	-0.083	-0.016
UY	0.078	0.139	0.043	0.023	0.049	0.006	-0.083	1.000	-0.314
CSR-K	0.058	0.069	0.108	-0.025	-0.190	-0.070	-0.016	-0.314	1.000

AG: Age group; OC: Occupation; VO: Volunteering; GE: Gender; UY: University years; IL: Monthly income level USD; FM: Family members; LA: Living area; CSR–K: CSR–knowledge.

to stakeholders' particular needs according to their socio-demographic traits.

On the other hand, it is recommended that future research can expand the sample, which could provide greater support for the findings of this research. Furthermore, it is advisable to develop a study that allows the application of the instrument in real time for the comparison of the results, generating a parallel that considers pre- and post-pandemic, which would provide greater congruence to the problematization, theoretical support, the results. and future lines of work.

It is important for a future study to consider the tie between perception and prediction with regards to the combination of socio-demographic characteristics such as income level and family composition of university students, and also to ensure a gender-balanced sample since it could affect the perception according to the particularities of each CSR dimension.

All these elements could be a determining factor in predicting their perceptions about CSR, especially due to the cross-sectionality of legal responsibility in all types of organizations.

TABLE V
CORRELATION VALUES BETWEEN FEATURES AND TARGET VARIABLES

	Legal	Philanthropic	Economic	Ethic
AG	-0.045	-0.086	-0.090	-0.071
OC	-0.010	-0.100	0.029	-0.041
VO	-0.117	0.027	-0.028	-0.017
GE	0.060	-0.144	0.042	-0.009
IL	0.144	0.028	0.169	0.036
FM	0.121	-0.049	0.049	0.084
LA	0.040	-0.039	-0.105	0.071
UY	0.006	-0.062	-0.037	-0.016
CSR-K	-0.004	0.157	-0.015	-0.008

AG: Age group; OC: Occupation; VO: Volunteering; GE: Gender; UY: University years; IL: Monthly income level USD; FM: Family members; LA: Living area; CSR–K: CSR–knowledge.

TABLE VI
ERRORS FOR ML–MODELS BASED ON SCALED VALUES

Prediction feature	NN		RF		GBT	
	MSE	MAE	MSE	MAE	MSE	MAE
Legal	1.323	0.858	1.111	0.711	1.029	0.682
Philanthropic	1.479	0.913	0.923	0.707	1.062	0.774
Economic	2.305	1.203	1.034	0.806	1.036	0.790
Ethic	1.649	0.988	1.187	0.804	1.486	0.910

NN: Neural Network model; RF: Random Forest model; GBT: Gradient Boosted Tree.

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TABLE VII
PREDICTED VALUES (NORMALIZED)

Dimension	Real Value	Predicted Value		
		NN	RF	GBT
Legal	1.00000	0.946603	0.669905	0.999996
	0.84375	0.932134	0.739022	0.843750
	0.93750	0.672709	0.888021	0.999996
Philanthropic	0.750	0.795119	0.792843	0.691326
	1.000	0.653439	0.699375	0.750000
	0.500	0.912971	0.669429	0.678255
Economic	0.825	0.999705	0.666515	0.669955
	0.625	0.516935	0.579583	0.575004
	0.750	0.846770	0.614763	0.625216
Ethic	0.700	1.073927	0.796736	1.002206
	0.575	0.869081	0.764810	0.559216
	0.700	1.150041	0.913750	0.999995

NN: Neural Network model; RF: Random Forest model; GBT: Gradient Boosted Tree.

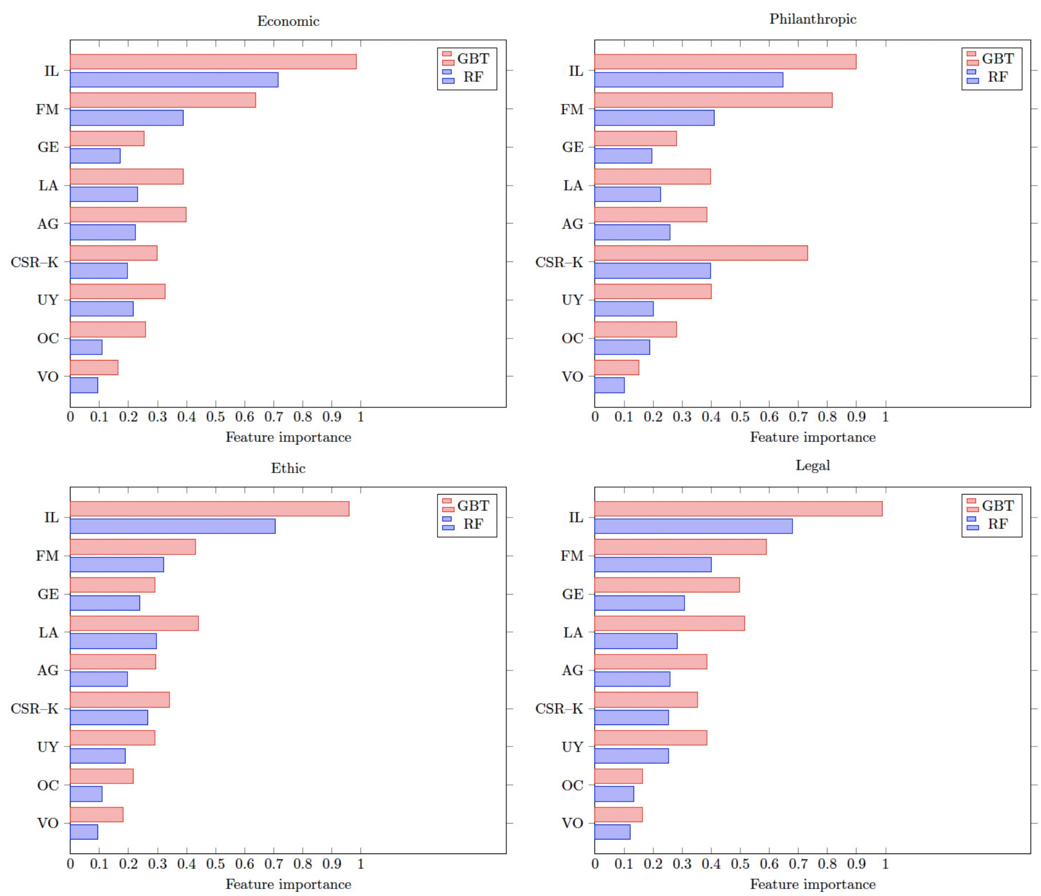

Figure 4. Feature importance for each CSR–dimension according to RF and GBT.

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