Pro-environmental behavior and its determinants: evidence for Mato Grosso do Sul

Comportamento pró-ambiental e seus determinantes: evidências para Mato Grosso do Sul

Comportamiento proambiental y sus determinantes: evidencias para Mato Grosso do Sul

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Abstract: This article investigates the importance of individual characteristics, including a proxy for testosterone levels (using the biological marker 2D:4D ratio as proxy), to explain students' pro-environmental behavior. We employ machine learning modeling from artificial neural networks. We elaborate an environmental score based on 13 questions related to the environmental impact generated by the individuals. We analyzed which profile variables are most important to explain pro-environmental behavior. The results are in line with the literature, which proves the importance of the 2D:4D ratio as a predictor of pro-environmental behavior (testosterone levels), gender, and age. These results suggest evidence for elaborating public policies to preserve and reduce environmental degradation based on individuals' characteristics and biological markers.
Keyword: ANN; digit ratio; pro-environmental behavior; consumption behavior.

Resumo: Este artigo investiga a importância das características individuais, incluindo uma proxy para os níveis de testosterona (usando a relação do marcador biológico 2D:4D como proxy), para explicar o comportamento pró-ambiental dos alunos. Empregamos modelagem de aprendizado de máquina a partir de redes neurais artificiais. Elaboramos uma pontuação ambiental baseada em 13 questões relacionadas ao impacto ambiental gerado pelos indivíduos. Analisamos quais variáveis de perfil são mais importantes para explicar o comportamento pró-ambiental. Os resultados estão de acordo com a literatura, que comprova a importância da relação 2D:4D como preditor de comportamento pró-ambiental (níveis de testosterona), sexo e idade. Esses resultados sugerem evidências para a elaboração de políticas públicas de preservação e redução da degradação ambiental com base nas características dos indivíduos e nos marcadores biológicos.
Palavras-chave: ANN; razão de dígitos; comportamento pró-ambiental; comportamento de consumo.

Resumen: Este artículo investiga la importancia de las características individuales, incluido un indicador de los niveles de testosterona (utilizando el indicador biológico 2D:4D como indicador *proxy*), para explicar el comportamiento proambiental de los estudiantes. Empleamos modelos de aprendizaje automático a partir de redes neuronales artificiales. Elaboramos un puntaje ambiental basado en 13 preguntas relacionadas con el impacto ambiental generado por los individuos. Analizamos qué variables del perfil son más importantes para explicar comportamiento proambiental. Los resultados están en línea con la literatura, lo que demuestra la importancia de la relación 2D:4D como predictor del comportamiento proambiental (niveles de testosterona), género y edad. Estos resultados sugieren evidencia para la elaboración de políticas públicas para preservar y reducir la degradación ambiental basadas en las características individuales y los marcadores biológicos.
Palabras clave: ANN; ratio de dígitos; comportamiento proambiental; comportamiento de consumo.

1 INTRODUCTION

In recent years, concern about sustainability and environmental preservation has gained prominence in various sectors of society. Education, as a fundamental pillar for the formation of

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conscious citizens, plays a crucial role in promoting pro-environmental attitudes and behaviors. In this context, the university environment emerges as a privileged space for the development of sustainable practices among young people and adults. This article aims to investigate the importance of individual characteristics, including a proxy for testosterone levels (using the 2D:4D ratio as a biological marker), to explain the pro-environmental behavior of undergraduate students in the state of Mato Grosso do Sul.

Understanding the determinants of pro-environmental behavior among university students is essential, as they represent a significant portion of the young population and have the potential to influence positive changes in society. Furthermore, universities, as centers for the production and dissemination of knowledge, can play a central role in training leaders and professionals committed to sustainability.

Our article aims to provide empirical evidence on the strength of the association between digit ratio and pro-environmental behavior. Empirical evidence supporting such an association would provide additional support in the literature with a biological basis for preferences and attitudes. Since individuals' behavior is a relevant variable to the theme of environmental sustainability, we analyzed a homogeneous group of 544 volunteers based on 13 variables on a Likert scale that make up the pro-environmental score.

This experiment aimed to measure individual characteristics and the influence of testosterone exposure (2D:4D ratio) concerning pro-environment behavior. The research included undergraduate students, and the sample consisted of 544 volunteers, 266 men, and 278 women. We used analysis based on Machine Learning modeling to present the estimated layers. We also analyzed the algorithms of Garson and Olden to investigate the importance of variables in the pro-environmental score.

To achieve this goal, we employ machine learning modeling using artificial neural networks (ANN). This innovative approach allowed the analysis of complex data and the identification of patterns that can explain the relationship between individual characteristics and pro-environmental behaviors. Through this methodology, we seek to offer a more in-depth understanding of the biological and psychological factors that influence the ecological attitudes of university students.

To achieve the objectives, this article was divided into this introduction, the next section that addresses the literature and main concepts, the methodology that defines the experimental design, the analysis of results and conclusions.

2 CONCEPTUAL DEVELOPMENT

Experiments with individuals who relate environmental sustainability and human behavior are still scarce in the literature. Van Bellen (2004) conducted a study with professionals linked to the topic and identified the Ecological Footprint Method (EFM) as the most cited among a set of possibilities.

The ecological footprint measures the environmental impact of consumption, measuring the use of the planet's natural resources to meet humanity's consumption demand Scarpa and Soares (2012). The calculation considers the area's measure, in global hectares that includes land and water, necessary to meet the consumption presented by man; the greenhouse gas emissions resulting from this; and air, water, and soil pollutants. The ecological footprint is not unanimous among those who work and debate sustainable development, identifying weak points that need improvement.

For Fiala (2008) there are many problems as a measure of sustainability, with the direct use of other measures being better than the footprint. Jóhannesson, Davidhsdottir and Heinonen (2018), in turn, in a more recent study, points out that there are distortions in footprint studies in economies of less than a million people, which is a problem for it to be considered as a universal metric. Yusliza *et al.* (2020) examined the role of environmental commitment, environmental awareness, green lifestyle, and green self-efficacy influence pro-environmental behavior using partial least squares (PLS) technique.

The results revealed that environmental commitment, environmental consciousness, green lifestyle, and green self-efficacy positively influenced pro-environmental behavior. Kollmuss and Agyeman (2002) State that the question of what shapes the pro-environmental behavior is so complex that it can not be viewed through a single structure or analysis diagram should incorporate new variables and the consumption and new biases.

The ecological footprint and work of Yusliza *et al.* (2020) and Kollmuss and Agyeman (2002) does not assess cognitive and biological biases. The Hand (2020) survey proposed an environmental index measured through a list of 11 activities, adapted from the survey conducted by the UK Government's Department for Environment, Food and Rural Affairs (DEFRA). The list contains nine items of pro-environmental behavior and two behaviors that waste resources.

We propose 13 variables that measure consumption behaviors and attitudes for and against the environment to create an environmental score and measure the effects on these indicators.

2.1 Pro-Environmental Behavior and the 2D Ratio 4D

The behavior of individuals is one of the determinants of the planet's environmental sustainability. The way people relate, how they interact with each other and how they seek to achieve their goals reflects their personalities. It impacts other human beings and their respective quality of life; on the greater or lesser efficiency in the use of existing resources, and on the environment in which they operate, with a greater or lesser impact in terms of environmental degradation.

The sustainable practices of individuals and societies are highlighted by World Commission on Environment and Development (WCED, 1987), and Hák *et al.* (2018), Todorov (2012) and Furtado (2018). These authors consider the responses that the subjects present to the interactions they establish with the environment in which they are inserted and imply minimal negative impacts as sustainable behavior.

The choices of individuals, according to the Expected Utility Theory (TUE), are not based only on rationality but also on behavioral biases Tversky and Kahneman (1991). Biases are a systematic tendency not to adopt a theoretically predominant form of rationality, distorting or limiting the ability to make rational decisions Sternberg (2010). Individuals know the probabilities of possible results to happen and calculate those that favor Tversky and Kahneman (1991). While rationality probably induces sustainable consumption, biases can lead to unsustainable consumption behavior, in which results tend to be more favorable individually, to the detriment of the collective.

Research in behavioral economics inserted the effects of testosterone exposure in the analysis using the biological marker ratio 2D:4D. They are applied in studies from the most diverse areas of knowledge, whose purposes are to establish relations of influence of exposure to the hormone on their study objects.

Manning *et al.* (1998), demonstrated the existence of a relationship between the ratio of the length of the index (2D) and ring (4D) fingers and the individual's exposure to the hormone testosterone during the period in which he remained in the uterus. Da Silva *et al.* (2020) and Rinella *et al.* (2019) present results of the importance of the 2D:4D ratio in risk behaviors by individuals in different situations. Constantino *et al.* (2018) present a broad description of studies developed using the 2D:4D ratio and demonstrate the feasibility of using the marker and established relationships and growing relevance and use in scientific research.

High prenatal exposure to testosterone, as indicated by a low proportion of the length of the second to fourth finger (2D:4D), is related to a more aggressive/hostile behavior of low 2D:4D, especially in challenging situations. How much people are prone to having green behavior is determined by sociability and personality trait, that is, their profile.

Behavioral biases can be analyzed by gender, according to Hand (2020) research on gender and environmental concern reveals that women tend to have higher levels of environmental concern than men Davidson and Freudenburg (1996); Xiao and Hong (2018); Hunter, Hatch and Johnson (2004). Although several possible hypotheses have suggested explaining this difference, only one, the risk issues, has received consistent support Davis and Holt (1993b)[3] and Friedl, Neyse and Schmidt (2018).

We investigate a non-linear relationship between pro-environmental behavior, individuals' characteristics, and the 2D:4D ratio. As suggested by Hand (2020), we evaluated whether gender is essential in environmentally correct behavior based on a supervised neural network model.

3 MATERIALS AND METHODS

3.1 Experimental procedure and sample

The survey was conducted during the years 2018-2019. The sample consisted of 544 volunteers, 266 men, and 278 women, students of the first, second, third, and fourth year of the undergraduate courses in the face-to-face modality. The volunteers were not evenly distributed in the analyzed rooms due to the very diversity of factors that influence students' enrollment and permanence during the courses.

We took some measures to avoid impacts of variables that could disturb the development of the experiment. Our control measures follow Davis and Holt (1993a), with the instruments' application during regular school hours. Therefore, close to their routine. We also ask participants to turn off any electronic device, such as cell phones, that could provide any external noise that could compromise the responses. We delivered instructions to each participant at the beginning, which were also read aloud.

Upon reading the instructions, the respondents signed Terms of Informed Consent (TCE), having the freedom to choose not to continue their participation if they disagreed. The study was approved by the Research Ethics Committee (CEP) of Universidade Católica Dom Bosco (UCDB), protocol number CAAE 66113617.8.0000.5162.

We collect data related to pro-environmental behavior using a questionnaire, which included thirteen questions and covers four dimensions: (i) transportation; (ii) water and electricity; (iii) attitude; and (iv) trend. We also collect data for the participant's profile, with the variables year in course, course, race, sex, age, and professional experience. To collect the hands' image, the camera of a smartphone model iPhone 6 Apple® was used, with a resolution of 3264 x 2448 pixels.

[3] See also Grou and Tabak (2008) and Tabak and Fazio (2010).

We use the images obtained from the left and right hands to measure the index (2D) and ring (4D) fingers of the respondents, with the indicators being divided by that of the ring fingers, thus obtaining the 2D:4D ratio. We use the Automatic 2.2 software to measure finger length and calculating ratios based on the images obtained.

3.2 Variables for the composition of the pro-environmental score

Table 1 presents the 13 variables that make up the dependent variable, and they were collected from the questionnaire developed, and their answers have a Likert scale.

Table 1 – Pro-environmental behavior variables

Variables	Format	Answer Scale
Type of Transportation You Use	1-5	Car to bicycle
Use of Bicycle	1-5	Never- Always
Bath Time (+ 15 minutes)	1-5	Always- Never
Car wash frequency	1-5	Always- Never
Air Conditioning Use	1-5	Always- Never
Web Payments	1-5	Never- Always
Garbage collection	1-5	Never- Always
Concern for the environment	1-5	Never- Always
Electric car (without ipva)	1-5	Disagree- Agree
Exit Paris Agreement	1-5	Agree- Disagree
Your level of pro-environmental behavior	1-5	None- Committed
Access to information	1-5	Never- Always
Family Orientation	1-5	Never- Always

Source: Elaborated by the authors.

Responses to pro-environmental behavior items have been recorded so that a higher number indicates that the activity described is performed more frequently. The original coding for hostile items to the environment has been maintained, so a high value indicates never performing this activity. We obtain a score for each respondent by adding their responses and dividing by the number of responses given. This provides an index of environmental behavior. The higher the value, the greater the involvement with pro-environmental behavior.

We describe the data used to assess the effects or explain the pro-environmental score in Table 2.

3.3 Data

We present the descriptive statistics of the data in Table 2. The dependent variable is each individual's environmental score according to their answers to the 13 questions listed in the questionnaire. The independent variables result from the 2D:4D ratio for both hands, age, and age squared to assess nonlinearity, length of experience in the labor market, gender, and civil status at the survey time.

Table 2 – Descriptive statistics

Variables	Mean	Std Deviation	Minimum	Maximum
Dependent variable				
Environmental score	3.1525	0.0144	1	5
Independent variables				
Left hand digit ratio	0.9741	0.0018	0.81	1.13
Right hand digit ratio	0.9525	0.0017	0.82	1.10
Age	21.48	0.1743	17	50
Age2	478.05	9.5630	289	2500
Experience	2.4577	0.1617	0	34
Gender	0.4889	0.0214	0	1
Civil status	0.0827	0.0131	0	1

Source: Elaborated by the authors.

From the organization of the data, we elaborate the estimation of the model from artificial neural networks using the nnet, Venables and Ripley (2002) package, from the programming language R.

3.4 Modeling of Artificial Neural Networks (ANN)

We use Neural Network modeling to estimate the importance of variables. Weights in a neural network are similar to parameter coefficients in a regression model and help describe relationships between variables. Besides, estimating weights is advantageous because it makes neural networks very flexible to model non-linear functions with multiple interactions.

To estimate the Machine Learning model based on Neural Networks, we use the example of a neuron in Equation 1, where the inputs (x_1, ..., x_i) are the explanatory variables in Table 2, the model calculates its corresponding weights (w_1, ..., w_i), estimates a bias denoted by (b) and the activation function f estimates the output (environmental score) applying to the weighted sum of the inputs. The f(z) activation function, where z is Equation 1:

$$f(b + \sum_{i=1}^{n} x_i w_{i)} \qquad (1)$$

which results in (output layer), that is, an output neuron, where the final decision is made by the machine and returns the environmental output- score.

To analyze each variable's importance, we use the algorithm described in Garson (1991), which identifies the relative importance of the explanatory variables for a single response of variables in a supervised neural network, deconstructing the weights of the model.

Identifying all weighted connections between the nodes of interest might help assess an explanatory variable's relative relevance (or strength of relationship). We identify all weights that connect the specific input node that passes through the response variable's hidden layer. We repeat this for all other explanatory variables until we obtain a list of all weights specific to each input variable.

The steps to obtain the relative importance are:

1. The absolute value of the connection weight between an intermediate i neuron and an output neuron is increased by the absolute value of the connection weight between the same

neuron concealed and an input neuron for each intermediate i neuron. This calculation must be done for all j–nth neurons in the input layer. Then the P_{ij} product is obtained by:

$$P_{ij} = w_{ij} \times w_{io}$$

2. P_{ij} is divided by the total of all Pij for each input neuron to yield Q_{ij} (for each hidden neuron):

$$Q_{ij} = \frac{P_{ij}}{\sum_{j=1}^{n} P_{ij}}$$

3. The values Q_{ij} are added to obtain S_j (for each input neuron):

$$S_j = \sum_{i=1}^{n} Q_{ij}$$

4. We divide S_j by the sum of S_j, and obtain the relative importance R_j:

$$R_j = \left(\frac{S_j}{\sum_{j=1}^{n} S_j} \right) \times 100 \qquad (2)$$

The Garson algorithm uses absolute values of the weights of the connections for calculating the variable's contribution, not allowing an analysis of the direction of the changes that occurred in the output variable when there is a change in the input variables Garson (1991).

For the analysis of Olden, Joy and Death (2004), the algorithm evaluates the analysis of the connection weights of hidden inputs and raw hidden outputs in the neural network, different from the Garson approach, and for the author provides another methodology to quantify with precision the importance of the variable.

The architecture of a neural network model demonstrates how two or more inputs are transformed into an output. The transformation is given in the form of a learning algorithm.

The algorithm follows the same steps as Garson but transforms equation (2) in a matrix form into:

$$Input_x = \sum_{Y=Ai=1}^{E} Hidden_{XY} \qquad (3)$$

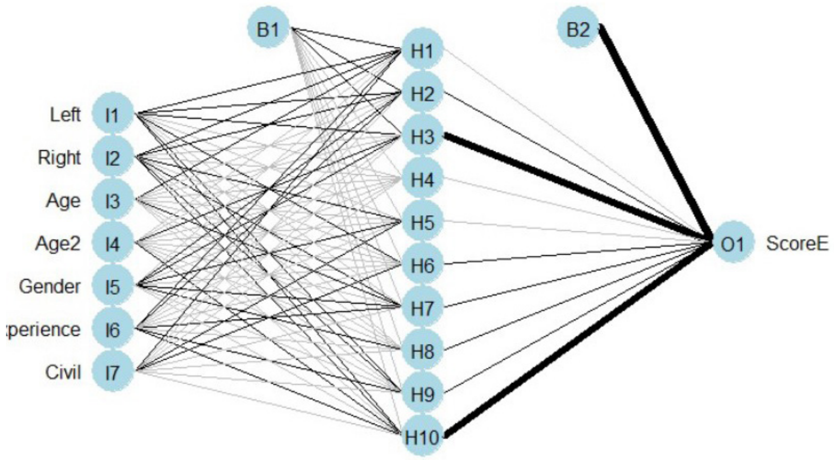
The Garson (1991) and Olden (2004) algorithm are techniques widely used to interpret the importance of input neurons in artificial neural networks. They provide methods for decomposing the weights of a neural network, making it easier to understand how each input variable contributes to the output. These methods provide a systematic way to interpret neural networks, making them more transparent and allowing a deeper understanding of the individual contributions of input variables.

For more details, see Zhang *et al.* (2018). The two approaches for Neural Network present a single value that is obtained for each explanatory variable which specifies the model's connection with the response variable. Machado (2018) used ANN for the recognition of behavioral patterns, which for the author is one of the essences of human behavior, and for that they collected information over time and transformed evident patterns into knowledge. The study revealed that with the evolution of information technology, able to collect much more information than we can understand naturally.

4 RESULTS

The results of the experiment provide a comparison between which variables are essential to predict pro-environmental behaviors. The first step was the Machine Learning modeling from the Artificial Neural Networks (ANN) model with seven explanatory variables and one response variable, and the estimated model presents the ANN in Figure 1.

Figure 1 – Result of the Artificial Neural Network Model

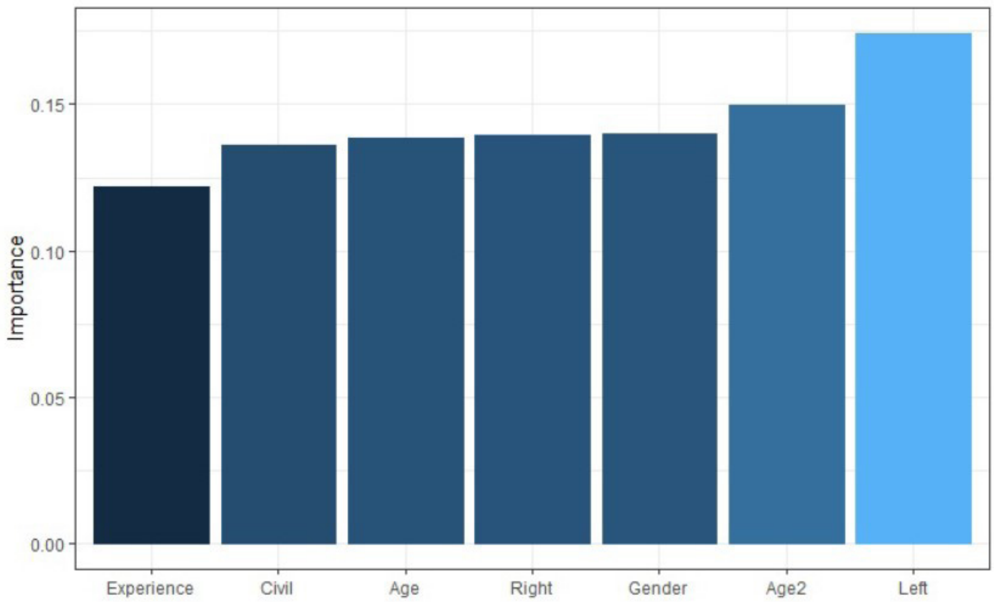


Source: Elaborated by the authors.

The model presents the explanatory variables, the hidden layers, the B coefficients, and the estimated environmental score. From this appropriate model to calculate the importance of the variables, we used two methodologies to quantify the variables' contributions in artificial neural networks.

The first algorithm we analyze is Garson's, which makes a ranking of the most critical variables. The results are in Figure 2.

Figure 2 – Result of the Garson Analysis



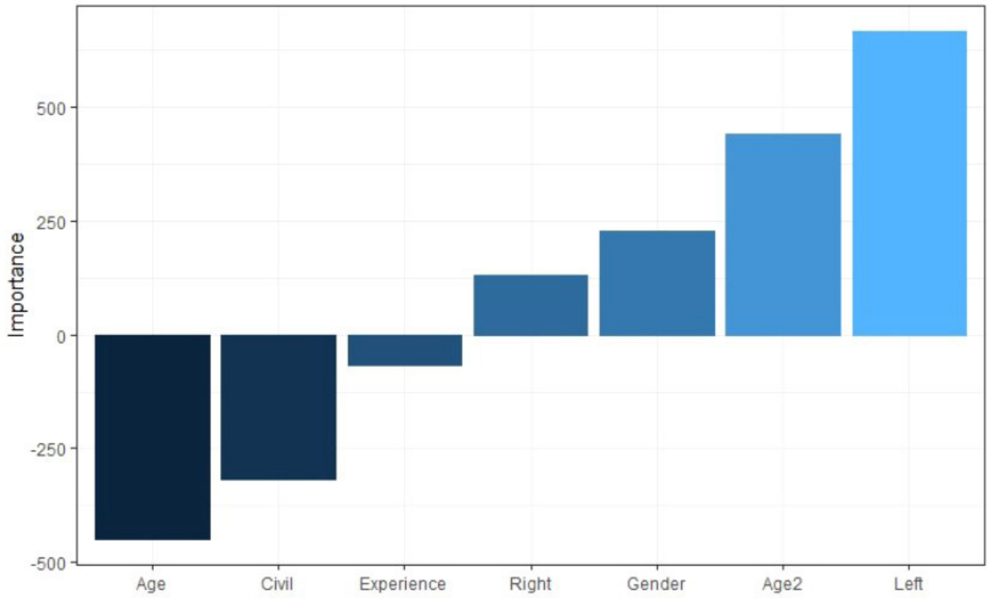
Source: Elaborated by the authors.

The 2D:4D ratio of the left hand is the best-ranked variable followed by age squared. The others remain very similar, and experience is the least important variable to explain pro-environmental behavior. We find that the 2D:4D biological marker helps explain pro-environmental behavior. The less testosterone an individual, has, the more he cares about the environment. This result seems tobe in line with other studies in other areas that find that testosterone is related to greater risk-taking, for example.

This result is essential to show that individual characteristics influence environmental decisions, and even older age can improve pro-environmental behavior. As volunteers have little experience because they have little time in the job market, this variable was of low importance within the group. We find that age and age squared are significant to explain pro-environment behavior and are positively correlated. This suggests that policies aimed at protecting the environment through investments in environmental education, for example, could focus on younger people.

The second algorithm we analyze is due to Olden, which starts from the same logic as Garson. However, it makes the construction of the model weights more flexible (Linnerud *et al.*, 2019).

Figure 3 – Result of the Olden Analysis



Source: Elaborated by the authors.

The 2D:4D ratio of the left hand and age squared remain the most important, along with gender and right hand. However, experience, civil status, and age were of negative importance. This result would be similar to having a negative coefficient in a regression, which suggests that age would have a negative effect on pro-environmental behavior. However, the effect of variable age squared is essential and positively influences this behavior, suggesting that older respondents are pro-environmental.

Both approaches showed similar results in the set of variables. Testosterone has an important role in the environmental behavioral context, age is fundamental, and gender also matters when evaluating pro-environment decisions. The latter result is following Hand (2020) and Xiao and Hong (2018) about the importance of gender in behavioral studies using 2D:4D ratio. The results also corroborate with the use of the 2D:4D ratio in behavioral studies as advocates Manning *et al.* (1998) da Silva *et al.* (2020) Rinella *et al.* (2019) among others.

Using both approaches, we find that gender explains pro-environmental behavior, with men being more pro-environmental in our sample. This result suggests that public policies developed in order to reach specific groups may be more effective. For example, developing different campaigns involving different aspects in order to increase environmental awareness.

In our questionnaire, we explicitly ask if the person is interested in helping the environment. Most respondents answer yes (something expected). However, when answering the other questions, we find that they make a series of decisions that harm the environment and do not behave more consciously. Our results suggest that some individual characteristics are relevant to explain this more selfish behavior that is less concerned with environmental issues.

Several cognitive biases can explain these results. Some respondents may be prey to the status quo bias in which they have difficulty changing their present behavior (Linnerud *et al.*, 2019). Others may have hyperbolic discount rates and a great deal of concern for immediate pleasure and little concern for the future (present value bias)[4]. Others may incorrectly believe that their peers do not have pro-environmental behavior- they understand that the social norm would not worry about the environment (Bergquist, Nilsson and Schultz, 2019).

These cognitive biases can be countered with specific public policies that seek to remove these biases (or mitigate). For example, there is a need for campaigns explaining that there are people in that community who take pro-environmental actions that positively affect the environment.

5 CONCLUSIONS

This study sought to investigate the importance of individual characteristics, including a proxy for testosterone levels (using the 2D:4D ratio as a biological marker), to explain the pro-environmental behavior of undergraduate students. Through the application of machine learning models, specifically artificial neural networks, it was possible to analyze complex data and identify relevant patterns that relate biological factors and ecological behaviors.

The results obtained indicate that individual characteristics play a significant role in shaping university students' pro-environmental attitudes and behaviors. In particular, the 2D:4D ratio, used as a proxy for testosterone levels, proved to be a relevant indicator, suggesting a link between biological factors and the predisposition to ecological actions.

The Artificial Neural Networks model collaborates with the discussion in the literature of non-linear predictive models for behaviors. Our results follow the literature, which shows the importance of the 2D:4D ratio as a predictor of pro-environmental behavior. It also corroborates with the studies that also present gender as relevant for analyzing behavior.

The use of behavioral insights could be useful to raise environmental awareness. For example, respondents may suffer from availability bias. Thus, if examples of the effects of human behavior on creating environmental problems are not available in their minds, they tend to ignore these effects. More research can be done by conducting experiments to test which campaigns

[4] See Wu *et al*. (2016) for a discussion on how present bias value is correlated to irrational behavior.

could be most effective in making economic agents more pro-environment. Our results suggest that several characteristics – including biologic – are relevant and should be considered when designing public policies in this regard.

Our results show that young people do not yet have concerns about the environment and adopt harmful behaviors to the environment. Therefore, it is essential to implement public policies that raise environmental awareness. The focus on the younger audience seems to be crucial to increase the effectiveness of these policies.

Finally, this study paves the way for future research that can further explore the relationship between biological, psychological and behavioral factors in the context of sustainability. Continuing this line of investigation can provide an even deeper understanding and contribute to the construction of a more sustainable future.

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