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Assessing the effects of gender stereotype in STEM in a Brazilian university

Camila Alvarenga and Cicero Braga
Departamento de Economia Rural, Universidade Federal de Vicosa, Vicosa, Brazil

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Abstract

Purpose – In Brazil, over 4.7 million women enrolled in university in the year 2017. However, Brazilian women have been consistently overrepresented in humanities and care majors and underrepresented in science, technology, engineering and mathematics (STEM). Given that observed gender differences in math-intensive fields have lasting effects on gender inequality in the labor market, and that observed gender variations do not necessarily associate with differences in innate ability, in this paper we explore the paths of societal gender bias and gender differences in a Brazilian university.

Design/methodology/approach – We conduct a social experiment at a University in Southeastern Brazil, applying the gender-STEM Implicit Association Test.

Findings – We found that women in STEM are less likely to show gender-STEM implicit stereotypes, compared to women in humanities. The results indicate a negative correlation between implicit gender stereotyping and the choice of math-intensive majors by women.

Originality/value – The stereotype-congruent results are indicative of the gender bias in Brazilian society, and suggest that stereotypes created at early stages in life are directly related to future outcomes that reinforce gender disparities in Brazil, which can be observed in career choices.

Keywords Gender gap, Gender bias, Experiment, STEM, University, Tertiary education

Paper type Research paper

1. Initial remarks

Nowadays, women represent most of the students in tertiary education (colleges and universities) around the world, according to the United Nations Educational, Scientific and Cultural Organization (United Nations Educational, Scientific and Cultural Organization (UNESCO), 2020). This fact is illustrative of Brazil – in 2017, over 4.7 million Brazilian women enrolled in university to pursue an undergraduate degree, corresponding to 57% of total enrollments (Instituto Nacional De Estudos E Pesquisas Educacionais Anísio Teixeira, 2019). Among the 20 most popular majors, women constitute most students in no less than 14 of them, featuring Pedagogy (92.5%), Social Services (90.1%), Nutrition (85.2%), Nursing (84.0%) and Psychology (80.5%) [1]. On the other hand, men prevail in majors such as Mechanical Engineering (89.7%), Civil Engineering (69.5%), Production Engineering (65.0%), and Entrepreneurship (52.4%). (Instituto Nacional De Estudos E Pesquisas Educacionais Anísio Teixeira, 2019).

In addition, the share of Brazilians aged from 25 to 34 years who completed tertiary education grew 10 percentage points (p.p.) between 2009 and 2019, reaching 21%. Decomposing for gender, the percentage of young women achieving a tertiary degree was

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25% in 2019, compared to 18% of their male peers (OECD – Organisation For Economic Co-Operation And Development, 2020). Data demonstrates that enrollments in science, technology, engineering and mathematics (STEM) majors increased during the last decades (Nascimento & Gusso, 2015) and that STEM professionals tend to be more often employed in the formal market and run more businesses than the overall average of people with higher education (Maciente, Pereira, & Nascimento, 2014). So why are Brazilian women so overrepresented in humanities and care majors, and so underrepresented in STEM courses?

Choices of higher education tend to reflect expectations about the returns to additional education, as well as innate ability and earlier educational attainment (Altonji, Blom, & Meghir, 2012). For example, some evidence connects the gender gap in mathematical achievement with gender differences in major choices and, consequently, with the gender gap in future income (Bharadwaj, Giorgi, Hansen, & Neilson, 2016). Additionally, Levine and Zimmerman (1995) demonstrate that additional math and science courses taken by women during secondary school are associated with the choice of technical majors and therefore with an increase in the proportion of women in math-related jobs [2].

Nonetheless, choices – and performances – in higher education also have implications for economic outcomes that increase gender gaps. For example, Waitkus and Minkus (2021) show that wealth gaps by gender vary within and between classes, creating certain occupation classes in which men benefit more than women. Additionally, Espino, Alma, Isabella, Leites, and Machado (2017) show that there is a substitution effect between wage increases and labor supply for women, meaning that increases in relative wages reflect female labor force participation. Therefore, engagement in better-paid jobs tends to incentive women to enroll in paid work.

Another significant fact to consider is that Brazilian women work, on average, 7.5 more hours than Brazilian men every week, accounting for both paid and unpaid labor. Moreover, between 1995 and 2015 the proportion of women in the labor market in the country has stagnated around 55%, despite the rise in average years of education, relative to men (Fontoura, Rezende, Mostafa, & Lobato, 2016). This gender disparity is still persistent nowadays, and according to Macedo and Pinheiro (2022), during the pandemic of Covid-19 women were more prone to be unemployed than men, and had higher participation in unpaid domestic work.

The stagnation of the labor market structure seems to reflect both the fact that the ratio of female to male students in math-related areas diminishes as the level of education increases (Nosek, Banaji, & Greenwald, 2002; Di Tommaso, Maccagnan, & Mendolia, 2021), and the persistence of domestic and care work as female occupations (England & Folbre, 1999; Jesus, Turra, & Wajnman, 2022), which in turn may keep women from paid activities (Perrons, 2000). In Brazil, over 90% of women perform unpaid household chores, while the proportion of men is 53% (Fontoura *et al.*, 2016; Melo, Morandi, & Mensurar, 2021). Complementarily, the specialization of women as paid care professionals is substantiated by the overrepresentation of women in care-related majors, as we have pointed out.

Therefore, the fact that care work is associated with women (England & Folbre, 1999; Hirata, 2020) while math-related jobs are connected to men seems to relate to the maintenance of gender inequality in Brazil. According to Jesus (2018), unpaid reproductive work in Brazil represents approximately 10% of the GDP, which corresponds to a great amount of missing financial inclusion for women. Indeed, Brazil is one of the most gender-unequal countries in Latin America: although ranking in the 57th position of the overall Gender Gap Index (GGI), ranks in the 86° and 73° position respectively in the economic participation and opportunity, and the educational attainment sub-indexes in 2023 (World Economic Forum, 2023).

With the understanding that observed gender differences in math-intensive fields have lasting effects on gender inequality in the labor market, and that observed gender variations do not necessarily associate with differences in innate ability, but often with prescribed gender roles (Sent & Staveren, 2019), in this study we explore the relationship between one of the main aspects of societal gender bias – gender stereotypes – and gender differences in fields of major in a Brazilian university.

Gender stereotypes are defined as beliefs that men and women are differentiated by a set of attributes (Ashmore & Boca, 1981) and they can be thought of as stemming from social roles, that is, "the tendency of perceivers to observe women in lower status roles than men" (Eagly & Steffen, 1984). Related, implicit stereotypes are automatic associations that people make between a group (for example, men) and an attribute or domain (like math). It differs from an explicit stereotype in that it is unconscious and involuntary (Greenwald & Banaji, 1995).

We conduct a social experiment in a public university in Southeastern Brazil, by adapting and applying an instrument that captures the implicit gender stereotype at an individual level – the gender-STEM Implicit Association Test (IAT). We depart from the approach of Smeding (2012) by designing the so-called gender-STEM IAT to fit the idiosyncrasies of tertiary education in Brazil, as well as by analyzing the results using a discrete, qualitative method.

The IAT, proposed by Greenwald, Mcghee, and Schwartz (1998), is commonly used within social-psychological experiments, and it has demonstrated that men are more implicitly associated with math and science while women are more often linked to arts and humanities (Nosek *et al.*, 2002; Charlesworth & Banaji, 2019; Dunlap & Barth, 2019). In a similar approach to the one of this research, Smeding (2012), found that "female engineering students held weaker implicit gender-math and gender-reasoning stereotypes than female humanities". We did not find in the Brazilian literature studies that used this approach, and the evidence about gender gaps in STEM, especially considering its underlying factors, is still scarce.

To the best of our knowledge, Traferri (2011) and Lemos (2019) are the only studies that investigate the theme of gender differences in college major choice in Brazil, although the authors employ different data and methods for their assessments. Traferri (2011) studies gender differences in major choices in a Brazilian University using data from the admission test. The author finds that men are more likely to choose majors associated with mathematics. Additionally, gender differences in choice for majors that require higher grades – such as Engineering and Architecture – are explained by entrance probability (Traferri, 2011). Using data from Enem and Sisu – part of a unified college admissions system – Lemos (2019) uses a discrete choice model to evaluate the effect of gender on choice of major in Brazil, finding that women are less likely than men to choose a STEM major by 4.5 p.p. Complementarily, the author finds that being a woman increases the probability of choosing a non-STEM major by 11.84 points. Moreover, the author indicates that the gender-specific component "could not only be capturing the effect of gender differences in willingness to compete and in risk aversion levels, but also the impact of social norms related to society's expectations about which programs women should be pursuing in college" (Lemos, 2019).

Using a different approach, our main objective in this paper is to assess if implicit gender-STEM stereotypes negatively correlate with the (already given) choice of math-intensive majors by women in a Brazilian university. We expect to shed light on this behavior to contribute to policies that focus on reducing gender disparities in the labor market in the early stages. We also expect to build evidence on how "gender culture" (Hinton, 2017) may be shaping Brazilian women's major choices.

2. Gender, implicit stereotype and STEM performance

As stated by Lave (1988), "cognition observed in everyday practice is distributed – stretched over, not divided among – mind, body, activity and culturally organized settings (which include other actors)". The introspective process that occurs within conscious experience does not correspond to what goes on inside one's mind (Nosek, Hawkins, & Frazier, 2011). For that reason, it is common that explicit reports of one's social perception do not accurately describe such perception, even when the individual is fully motivated to answer honestly and in a state of conscious awareness.

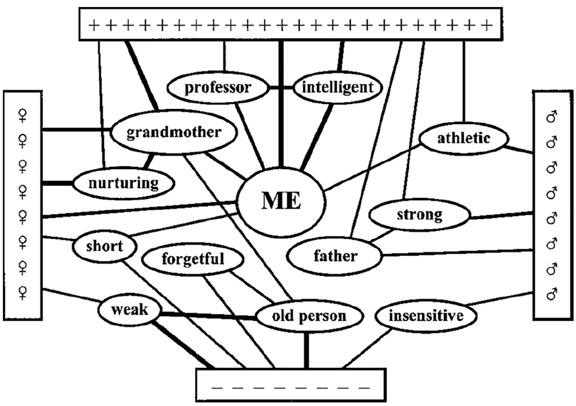
In social psychology [3], implicit measures of social-psychological constructs have been extensively used in the field due to their "practical value for predicting human behavior" (Nosek *et al.*, 2011). In this work, we focus especially on four key concepts of this field: attitudes, stereotypes, self-esteem and self-concepts.

These four concepts are the key hypothesis of the theory of balance (Heider, 1946) [4], and it states that interconnections among concepts like attitudes, stereotypes and self-concepts organize themselves in such a way that a cognitive balance is achieved, i.e. these concepts become mutually consistent (Cvencek, Meltzoff, & Greenwald, 2011). For example, the stereotype "math is for boys" combined with the gender identity (self-concept) "I am a girl" balance each other and influence the self-concept "Math is not for me" (Cvencek *et al.*, 2011).

From the empirical application of Heider's (1946) assumptions, Greenwald *et al.* (2002) proposed the unified theory of implicit social cognition. The theory integrates essential cognitive and affective constructs of social psychology, and the theoretical definitions of such constructs stem from the association among concepts.

In the case of cognitive constructs, namely stereotype and self-concept, societal self-concepts are associated with one or more non-valence attributes, that is, with characterizations of a social group (stereotype) or an individual (self-concept) that do not involve valences like positive/negative or good/bad. On the other hand, affective constructs, namely attitude and self-esteem, are associations of social group/object and self-concepts with valence attribute concepts. For example, a person who associates the self with *positive* valence is likely to have high self-esteem. In the same spirit, the association of the attribute trait *intelligent* with *positive* valence characterizes an attitude.

Figure 1 is a diagrammatic representation of a social knowledge structure (SKS) in the psyche of an elderly female academic from Greenwald *et al.* (2002). Nodes represent concepts and lines represent associations. The thickness of lines represents the strength of association. Note that the self-concept is represented by links of the *me* node to non-valence attributes such as *professor*, *intelligent*, *athletic* and *nurturing*. Likewise, self-esteem consists of the direct link of the *me* node to the positive valence attribute, as well as the indirect associations of the *me* node to valence attribute concepts through components of the self-concept, e.g. *me–professor–positive*. Stereotypes are all links of group concepts like *old person* and *male* with



Source(s): Greenwald *et al.* (2002)

Figure 1.
The social knowledge structure of an elderly female academic

attribute concepts, e.g. *male – strong*. Finally, attitude is the combination of links of social group concepts to valence concepts, which may or may not be mediated by components of stereotype, e.g. *professor – positive* and *female–grandmother–positive*.

Three principles of the theory in Greenwald *et al.* (2002) govern the associative strengths of relations among the described constructs of the SKS. They are defined as follows:

(1) *Principle 1:* Balance-congruity. When two unlinked or weakly linked nodes share a first-order link, i.e. when they are both linked to the same third node, the association between these two links should strengthen.

(2) *Principle 2:* Imbalance-dissonance. The network resists the formation of new links that would result in a node having first-order links to both of two bipolar-opposed nodes, i.e. nodes that have fewer shared first-order links than expected by chance.

(3) *Principle 3:* Differentiation. Pressured concepts, i.e. concepts that develop links to both of two bipolar-opposed nodes, tend to split into sub-concepts, each linked to a different one of the pressuring bipolar-opposed nodes.

As an illustration, each link can be read theoretically as follows. Principle 1 tends to reinforce links like *me – male*, given that both concepts are linked to STEM courses, that is, they share a first-order link. Principle 2 avoids the production of links among all pairs of nodes that otherwise would occur by Principle 1. Using the same example as before, Principle 2 resists the formation of the link *me – male*, given that there already exists the association *me – female* and that *male* and *female* are bipolar-opposed nodes. Finally, Principle 3 eliminates pressures toward change driven by Principle 1 and that are prevented by Principle 2, avoiding imbalanced configurations (Greenwald *et al.*, 2002).

Empirical evidence shows that gender gaps are observed in the early stages, in both attitudes and outcomes of children. In Italy, for example, girls are less likely to be confident in mathematics subjects and in their ability to perform in the field at higher levels (Di Tommaso, Maccagnan, & Mendolia, 2021). We want to assess these links through an experiment applied to male and female students from a public university in Southern Brazil to understand implicit gender stereotypes that may affect how individuals choose their courses. Following Smeding (2012), we apply the IAT, which accounts for the implicit association between gender and behavior.

3. Experimental design: the Implicit Association Test

The IAT is a widely researched method in experimental social psychology, defined as a "response competition task" (Nosek *et al.*, 2002) or an "individual difference measure" (Fazio, 2001). The test in its various forms [5] has been applied to over a million people around the world and is available at Project Implicit, a non-profit organization, intending to "educate the public about hidden biases and to provide a virtual laboratory for collecting data on the Internet" (Project Implicit, 2011). The framework of the test implementation is available as an online open code, and it was the basis of the experiment developed in this study.

Thus, in the context of this research, the IAT will allow us to observe whether female undergraduates in a public university in Brazil who attend STEM courses display a weaker gender-STEM stereotype, relative to arts and humanities female undergraduates. The evidence will enable the partial verification of the hypothesis of this research, supported by the underlying theory described previously: stereotypical beliefs influence individual self-concepts in such a way that women disidentify with math and, therefore, with STEM majors.

For that assessment, we rely on an implicit measure because of the validity problems often encountered in explicit answers given by individuals [6]. Nevertheless, in this experiment, we compute a self-report measure for the sake of comparison with the IAT results.

3.1 Self-report measure

Before administering the IAT itself (details in the next section) the respondents answer a questionnaire requesting basic socio-demographic information, as well as questions that allow us to obtain an explicit. For that purpose, we apply a thermometer-type score. Respondents are asked to associate the concepts *exact and natural sciences* and *human sciences* with a score varying from 1 to 5, meaning respectively: strongly male, somewhat male, neither male nor female, somewhat female, strongly female. The thermometer measure is given by the difference between the scores. Adapting from Greenwald, Nosek, and Banaji (2003), the thermometer items are as follows:

Please rate how much you associate the following domains with males or females.

(1) Exact and Natural Sciences

(2) Human Sciences

3.2 The Implicit Association Test (IAT)

The IAT does not rely on introspective experience but on the existence of "well-established associations" within one's mental operations. It consists of a thought experiment in which an individual's implicit attitude is measured by the strength of association between concepts and attributes (Greenwald *et al.*, 1998). For this study, the concepts are *male* and *female* and the attributes are *exact and natural sciences* and *human sciences*, and the main measure of implicit attitude is the implicit gender-STEM stereotype [7]. This is measured, roughly, by the differential time it takes for a person to complete stereotype-congruent and stereotype-incongruent computer assignments.

Stereotype-congruent assignments in the IAT design are those in which *male* names share a computer key with *exact and natural sciences* words, while *female* names share a computer key with *human sciences* words. Stereotype-incongruent tasks pair *male* names with *human sciences* words and *female* names with *exact and natural sciences* words (Cvencek *et al.*, 2011). The principle is that people with stronger implicit gender-STEM stereotypes should take longer to respond to stereotype-incongruent tasks than to stereotype-congruent ones [8].

The predictive power of the IAT in the assessment of stereotypes and attitudes relies on the fact that one concept is assessed relatively to the other, as in the pair *exact and natural sciences* and *human sciences*. In line with our theoretical framework, we state that stronger implicit STEM-male stereotypes imply more negative math and science attitudes toward women, which are reflected in some women's difficulty in associating themselves with math [9] (Nosek *et al.*, 2002).

3.3 Subjects

To comply with the objectives of our study, Greenwald *et al.* (2003) suggest a sample of at least 39 subjects. Although such a sample would not grant any external validity, it should be enough to yield consistent results, internally. Furthermore, we need a balanced composition of male and female subjects from both STEM and humanities courses. A strategy used by Nosek *et al.* (2002) in their experiment was to give the IAT to their students in fulfillment of course credit.

In the present study, we use institutional e-mail to send alerts to all students enrolled in the university, inviting them to take the test. This task is simplified by the fact the gender-STEM IAT is hosted on a server and is available online by clicking on the link informed in said e-mail. We acknowledge that this strategy may lead to some selection bias since students who are more engaged in gender studies may be more interested in participating. However, we believe that by sending this e-mail repeatedly (highlighting its importance) and considering that this is a common practice in the university, we were able to gather a representative and almost-random sample (see Table 2 for sample characteristics).

3.4 Procedure

Adapting from Nosek *et al.* (2002) and Nosek, Greenwald, and Banaji (2005), the IAT is applied following seven blocks:

(1) *Learning the concept dimension*: Respondents sort stimuli words from *exact and natural sciences* and *human sciences* concepts into their superordinate categories. They use the left key of the computer keyboard for *exact and natural sciences* concepts and the right key for *human sciences* concepts.

(2) *Learning the attribute dimension*: Respondents sort stimuli words representing *male* and *female* trait attributes into their superordinate categories. They use the left key for *male* attributes and the right key for *female* attributes.

(3) *Concept-attribute pairing (practice block):* Sorting tasks 1 and 2 are combined for practice. Respondents use the left key for both *exact and natural sciences* concepts and *male* trait attributes, and the right key for both *human sciences* concepts and *female* trait attributes.

(4) *Concept-attribute pairing (critical block)*: Sorting tasks 1 and 2 are combined for generating critical data. Respondents use the left key for both *exact and natural sciences* concepts and *male* trait attributes, and the right key for both *human sciences* concepts and *female* trait attributes.

(5) *Learning to switch the spatial location of the concepts*: Respondents sort stimuli words from *exact and natural sciences* and *human sciences* concepts into their superordinate categories, as in the first block, but the key assignment is reversed. They use the left key of the computer keyboard for *human sciences* concepts and the right key for *exact and natural sciences* concepts.

(6) *Concept-attribute pairing (practice block)*: Block 3 is repeated for practice. Respondents use the left key for both *exact and natural sciences* concepts and *male* trait attributes, and the right key for both *human sciences* concepts and *female* trait attributes.

(7) *Concept-attribute pairing (critical block)*: Block 4 is repeated, generating critical information. Respondents use the left key for both *human sciences* concepts and *male* attributes, and the right key for both *exact and natural sciences* concepts and *female* attributes.

As suggested above, blocks 4 and 7 are the ones that provide critical information to calculate the IAT effect. Table 1 summarizes the sequence of trial blocks in the gender-STEM IAT.

A list of example stimulus words for the concepts and attributes of our study is provided below, adapted from Nosek *et al.* (2002) [10]:

(1) *Exact and natural sciences*: math, engineering, physics, astronomy, chemistry, geology and statistics.

(2) *Human sciences*: Portuguese, literature, philosophy, history, sociology, pedagogy and journalism.

(3) *Masculine*: brother, father, uncle, grandfather, son, he and him.

(4) *Feminine*: sister, mother, aunt, grandmother, daughter, she and her.

Table 1.
Sequence of trial blocks in the gender-STEAM IAT

Block	Number of trials	Function	Item assigned to the left key response	Items
1	20	Practice	Exact and Natural Sciences concepts	Human Sciences concepts
2	20	Practice	Male attributes	Female attributes
3	20	Practice	Exact and Natural Sciences concepts + Male attributes	Human Sciences concepts + Female attributes
4	40	Test	Exact and Natural Sciences concepts + Male attributes	Human Sciences concepts + Female attributes
5	20	Practice	Human Sciences concepts	Exact and Natural Sciences concepts
6	20	Practice	Human Sciences concepts + Male attributes	Exact and Natural Sciences concepts + Female attributes
7	40	Test	Human Sciences concepts + Male attributes	Exact and Natural Sciences concepts + Female attributes

Source(s): Adapted from Nosek *et al.* (2002) and Nosek *et al.* (2005)

When participants click the e-mail link, they receive a brief explanation of the task they are about to perform and consent to their participation. They are advised to be seated in front of the computer and follow the instructions on the screen. Note that the IAT may be administered on any regular computer with basic software apparatus.

3.5 Scoring procedure: the IAT effect

The IAT effect is calculated using an algorithm that follows nine steps:

(1) Drop blocks 1, 2 and 5. Therefore we use data from blocks 3, 4, 6 and 7.

(2) Eliminate trials with latencies above 10,000 milliseconds, eliminate respondents for whom more than 10% of trials have latency below 300 milliseconds.

(3) Compute the mean of correct latencies for each block.

(4) Compute pooled standard deviation for all trials in blocks 3 and 6; another for blocks 4 and 7.

(5) Replace each error latency with block mean plus 600 milliseconds.

(6) Average the resulting values for each of the 4 blocks.

(7) Compute the following differences: block 6 – block 3, and block 7 – block 4.

(8) Divide each difference by its associated pooled-trials standard deviation.

(9) Average the quotients obtained in the last step.

By dropping unexpected responses (Steps 2 and 7) and the complementary steps, it is expected that possible bias or interruptions be diminished.

3.6 IAT result analysis: ordered probit

After the scoring procedure of the IAT is complete, each respondent gets an objective result, ranging from categories that affirm the stereotypical views of gender and STEM to ones that are contrary to the stereotype. This sort of categorization suggests the use of an ordered response model for the regression analysis of the IAT results. For that reason, we apply an ordered probit model. This is an adequate approach, firstly, because of the ordinal nature of the results – the levels of implicit stereotype vary from stereotype-congruent to stereotype-incongruent, passing by a point of neutrality. Secondly, such measures can be clustered into categories – in this case, a total of three.

In our model, we observe the measure of implicit stereotype, y. As with binary models, we are interested in knowing how changes in the predictors, x', translate into the probability of observing a particular ordinal outcome, which varies from 0 to 2. We begin with a latent variable y^*, that is, the implicit stereotype that is not observed. We define:

$$y = 0\, if y^* \leq \alpha_1$$

$$y = 1\, if\, \alpha_1 < y^* \leq \alpha_2$$

$$y = 2\, if y^* \geq \alpha_2$$

where α_i (for $i = 1,2,3$) is the threshold parameter for y^*. As a result, the measured implicit stereotype, y, will take the value (*stereotype-congruent, neutral or stereotype-incongruent*) associated with the latent implicit stereotype level y^*. Generalizing the model according to Greene (2000), in an ordered model with m alternatives we define:

$$y_i = j\, if\, \alpha_{j-1} < y_i^* \leq \alpha_j$$

Therefore:

$$\begin{aligned} \Pr\left[y_j = j\right] &= \Pr\left[\alpha_{j-1} < y_i^* \leq \alpha_j\right] \\ &= \Pr\left[\alpha_{j-1} < x_i'\beta + \mu_i \leq \alpha_j\right] \\ &= \Pr\left[\alpha_{j-1} - x_i'\beta < \mu_i \leq \alpha_j - x_i'\beta\right] \\ &= \mathrm{F}\left(\alpha_{j-1} - x_i'\beta\right) - F\left(\alpha_j - x_i'\right) \end{aligned}$$

where μ_i is the error, F is the cumulative density function of the error and β represents the coefficients to be estimated, so that we can infer the probability of observing a given implicit stereotype measure (as a function of the probability of a given interval of latent implicit stereotype). In this study, as well as in Braga and Costa (2022), we assume that y^* can be fitted into a linear regression model, such that $y^* = x_i'\beta + \mu_i$, and the errors are normally distributed. Consequently, the maximum likelihood estimation results in ordered probit parameters.

We are also interested in measuring the marginal effects, given by:

$$\frac{\partial \Pr\left[y_j = j\right]}{\partial x_i} = \left\{F'\left(\alpha_{j-1} - x_i'\beta\right) - F'\left(\alpha_j - x_i'\right)\right\}\beta$$

By computing the estimates for the marginal effects, it is possible to measure the percentage points associated with each measure of observed implicit stereotype, for each independent variable in the model.

4. Experiment results

The gender-STEM IAT, designed to measure the implicit gender stereotype in STEM fields, was made available to all students at a public University in Southern Brazil in November of 2019. They accessed the test through a link sent to the institutional e-mail of each student, accompanied by a short description of the scope of the research and the instructions to complete the test. The test was preceded by a questionnaire where students filled out information such as their gender and their course, and responded to questions about their perceptions of gender stereotypes. Those responses were used to construct the explicit measure of gender-STEM stereotypes.

Subsequently, the respondents were introduced to the IAT and received specific instructions to complete the test. Their responses were computed according to the algorithm presented in the Methodology section, and categorized into 1 of 9 groups, corresponding to levels of stereotype, ranging from congruent to incongruent. This constitutes the implicit measure of gender-STEM stereotypes. All incomplete tests were dropped.

Although the methodology allows to correct possible biases in explicit measures – such as those results derived from observed data and characteristics – it is possible that individuals have benefited from incentives in early-life stages – such as parental education – that cannot be controlled. Therefore, the results here presented should be interpreted cautiously. The results section is organized into two parts – descriptive analysis and ordered probit analysis.

4.1 Descriptive analysis

We received 552 complete responses to both the questionnaire and the IAT. We dropped 175 observations, 161 of which correspond to graduate students (not in the scope of the analysis); 6 correspond to undergraduate courses that are not taught at this university and 8 had either filled out the age box incorrectly or were outliers (which can be a source of bias). Therefore, our analysis is based on responses from 377 undergraduate students in the university. We grouped the students according to knowledge fields given by the Coordination for Higher Education Staff Development (CAPES), an organization connected to the Brazilian Ministry of Education. The distribution is presented in Table 2, below, along with the distribution by reported gender:

According to Table 2, the areas with the higher proportion of women respondents, relative to male respondents, are Human Sciences, Applied Social Sciences, Health Sciences, Agricultural Sciences and Biological Sciences. We did not consider Arts and Language because it has only one observation. Overall, 54.6% of respondents are women, and they represent around 37% of students in Engineering and Exact Sciences. To avoid working with small groups, we clustered related areas – biological sciences with health sciences, human sciences with arts and language, and engineering with exact sciences (broadly, the STEM field), so that we are left with five fields.

4.1.1 Explicit stereotype measure. When asked about the intensity of their association between *exact and natural sciences* with *men* and *women*, respondents chose from a scale that went from *strongly masculine* to *strongly feminine*. Among female respondents, 40.8% said that they do not differentiate, that is, they are neutral. Among male respondents, that percentage was bigger – 49.8%. Not one male respondent associated STEM with *feminin*ity,

Table 2. IAT respondents distributed among scientific fields and reported gender

Scientific field	Female	Male	Total	Female percentage
Agricultural sciences	37	28	65	56.9%
Biological sciences	15	13	28	53.6%
Engineering	31	45	76	40.8%
Exact sciences	13	29	42	31%
Human sciences	32	13	45	71.1%
Arts and language	1	0	1	100%
Health sciences	16	12	28	57.1%
Applied social sciences	61	31	92	66.3%
Total	206	171	377	54.6%

Source(s): Research results

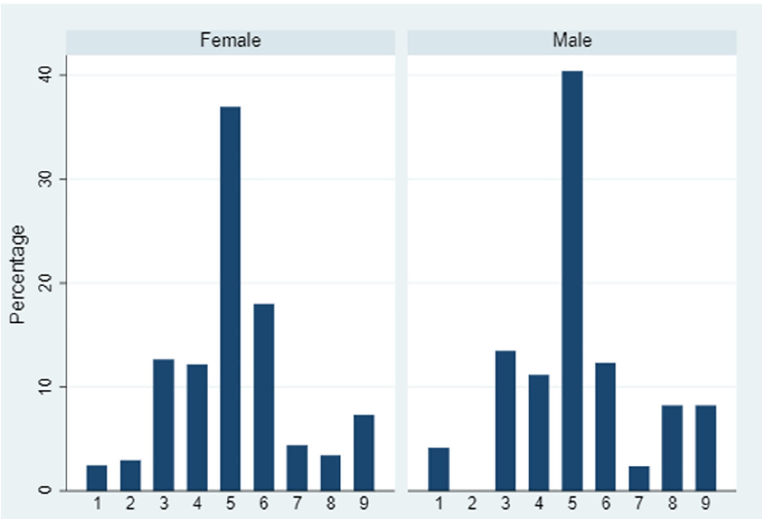
and only 7 (3.4%) of women did so. On the other end of the scale, 55.8% of women and 50.3% of men associated STEM with masculine, slightly or moderately. Therefore, most students, men and women, responded in conformity to the gender-STEM stereotype.

When respondents did the same associations for human sciences, the proportion of neutral associations was higher – 57.8% among women and 63.2% among men. According to their answers, human sciences are less stereotypically perceived than exact and natural sciences are. Nonetheless, the associations between human sciences and the female concept are significant – 35% of women and 31.6% of men think that human sciences are, to some degree, a feminine field. Oppositely, 7.3% of women and 5.3% of men think that it is a masculine field.

The thermometer measure for explicit stereotypes is a combination of the associations above, which are summarized in Figure 2. The more an individual associates STEM with masculine and human sciences with feminine, the more stereotype-congruent the explicit measure is. If the contrary happens, we have a stereotype-incongruent measure. We can also have a neutral position, where a person does not associate either field with masculine or feminine valences. In the present experiment, 67% of the women who participated belong to the latter category (neutral), and the same is true for 63.7% of the men. While there exists some variation between scientific fields, at least half of men and women across all fields fall into this category, except for men in biological sciences, where they represent 48%.

Note that, in Figure 2, the stereotype-congruent categories are the smallest, varying from 1 to 3. The neutral category is represented by the central area of the graph, where respondents are concentrated (4–6). Lastly, the stereotype-incongruent category is on the right side of the chart, from 7 to 9. Overall, we did not observe systematic differences, even controlling for gender and field of study. This is not true for the implicit measure, as we demonstrate in the next session. For that reason, we found a low correlation between explicit and implicit measures, as expected.

4.1.2 Implicit stereotype measure. The following results are based on the codes and respective meanings summarized in Table 3 for the implicit measure of stereotype. These are the results that represent the possible outcomes for each participant who took the IAT. As with the explicit measure, they vary from 1–9, ranging from a stereotype-congruent outcome



Source(s): Research results

Figure 2.
Explicit measure of gender-STEM stereotype at UFV, by gender

Table 3.
IAT codes and results meaning for ordered probit estimation

Code	Meaning
1	You associate men with exact and natural sciences and women with human sciences much more than men with human sciences and women with exact and natural sciences
2	You associate men with exact and natural sciences and women with human sciences more than men with human sciences and women with exact and natural sciences
3	You associate men with exact and natural sciences and women with human sciences a little more than men with human sciences and women with exact and natural sciences
4	You associate men with exact and natural sciences and women with human sciences slightly more than men with human sciences and women with exact and natural sciences
5	You don't associate men with exact and natural sciences any more than you associate women with exact and natural sciences
6	You associate women with exact and natural sciences and men with human sciences slightly more than women with human sciences and men with exact and natural sciences
7	You associate women with exact and natural sciences and men with human sciences a little more than women with human sciences and men with exact and natural sciences
8	You associate women with exact and natural sciences and men with human sciences more than women with human sciences and men with exact and natural sciences
9	You associate women with exact and natural sciences and men with human sciences much more than women with human sciences and men with exact and natural sciences

Source(s): Adapted from Project Implicit (2011)

to an incongruent one. Moreover, Tables 4 and 5 represent the distribution of female and male students from the university among IAT results and scientific fields.

According to Table 4, the 206 female respondents are well distributed among fields, with proportions ranging from 15% (biological) to 30% (applied social courses). Moreover, we see that 45% of all women in the sample are in the most stereotype-congruent category, meaning that they associate men with exact and natural sciences and women with human sciences much more than men with human sciences and women with exact and natural sciences. These respondents are concentrated in the areas of human and applied social sciences.

On the other end of the spectrum, we observe that 11% of female students associate women with exact and natural sciences and men with human sciences much more than women with human sciences and men with exact and natural sciences. That is, they make implicit associations that are contrary to stereotypical views of gender, math and science. The majority of these women are majoring in exact sciences, a find that is expected if it is true that

Table 4.
Distribution matrix of female students according to IAT results and scientific field

	Scientific field					
Code	Agricultural	Biological	Exact	Human	Applied social	Total
1	8%	6%	5%	11%	15%	45%
2	0%	0%	0%	1%	1%	2%
3	1%	2%	2%	1%	2%	9%
4	0%	0%	0%	0%	0%	0%
5	5%	5%	6%	1%	8%	26%
6	1%	0%	1%	0%	0%	3%
7	1%	0%	0%	0%	0%	2%
8	0%	0%	0%	0%	1%	1%
9	0%	1%	6%	0%	2%	11%
Total	18%	15%	21%	16%	30%	100%

Source(s): Research results

Code	Agricultural	Biological	Scientific field Exact	Human	Applied social	Total
1	11%	8%	25%	3%	10%	57%
2	1%	0%	2%	1%	0%	3%
3	1%	1%	2%	0%	0%	4%
4	0%	0%	0%	1%	0%	1%
5	3%	5%	9%	2%	6%	25%
6	0%	1%	0%	1%	1%	3%
7	0%	0%	2%	1%	1%	3%
8	0%	0%	1%	0%	0%	1%
9	1%	1%	2%	0%	1%	5%
Total	16%	15%	43%	8%	18%	100%

Source(s): Research results

Table 5. Distribution matrix of male students according to IAT results and scientific field

gender-STEM stereotypes negatively correlate with the choice of math-intensive majors by women.

Note that the implicit views of 26% of women in the sample are categorized as neutral, which means that they do not associate men with exact and natural sciences any more than they associate women with exact and natural sciences. These respondents occur more in applied social sciences and less in human sciences.

According to Table 5, among the 171 male respondents, the distribution of IAT results is comparable to Table 4, although there is a steeper tendency towards stereotypical views among men, compared to women. Moreover, the general distribution of men in scientific fields displays more variation, ranging from 8% (human sciences) to 43% (exact sciences). Note that among male students with strong stereotypical views (category 1), 44% of them major in an exact sciences course.

4.2 Ordered probit analysis

To test the hypothesis that women in exact sciences have a smaller average degree of implicit stereotype, we conduct an ordered probit analysis for the sample of 206 female undergraduate students. Seeing that few results in Table 4 are not either in the extreme categories or the neutral area, we clustered the less populated categories such that we are left with three groups: 1-2-3, 4-5-6 and 7-8-9. Respectively, these correspond to stereotype-congruent, neutral and stereotype-incongruent clusters.

From the probit model, the dependent ordinal variable is the stereotype cluster, varying from 0 to 2. The independent variables are dummies for knowledge areas, namely Exact, Agricultural, Biological and Human. The variable for applied social sciences is omitted because of collinearity. The results are organized in Table 6.

Scientific field	Coefficient	Standard error
Exact	0.73	0.23
Agricultural	0.05*	0.24
Biological	0.16*	0.26
Human	−0.78	0.30

Note(s): *Denotes coefficients that were not statistical significance at 5%
Source(s): IAT results

Table 6. Ordered probit analysis for IAT results of female students

By looking at the direction of the effects in Table 6, we observe that it is more likely for a student to be in the stereotype-incongruent group if she majors in exact sciences (+). Conversely, there is a higher probability associated with being in the stereotype-congruent category if the student is a human science major (−). We can derive interpretations that are more direct by computing the marginal effects, exhibited in Table 7.

According to Table 7, being in the exact sciences field additively increases the probability of being in the stereotype-incongruent category by 15 p.p. Similarly, the same position decreases the probability of being in the stereotype-conforming group by 26 p.p. Note that being in the human sciences field is associated with almost exactly the opposite result – it additively increases the chance of conforming to the stereotype by 28 p.p. and diminishes the probability of non-conformance to the stereotype by 16 p.p.

Therefore, we have evidence indicating that stereotypical views of women (about STEM) are negatively correlated with the choice of STEM majors by women in a Brazilian University. Note that we cannot derive a causal relationship from our results. Nonetheless, we observe that women in exact sciences are less likely to show gender-STEM stereotypes, compared to women in human sciences [11]. This means that women in the human sciences field implicitly associate men more with STEM and women more with humanities.

The literature suggests that men do the same associations (Nosek *et al.*, 2002), regardless of the field they study. However, the coefficients we estimated were not statistically significant for the sample of men. This result is likely a function of the fact that we do not observe variation between scientific fields – most men in *all* fields associate men more with STEM and women more with humanities, except for men in human sciences, in which the association is strong.

5. Concluding remarks

The objective of this study was to identify the existence and analyze the gendered distribution of gender stereotypes in the STEM field in Brazil. Motivated by that, we conducted a social-psychological experiment at a Brazilian University in Southeastern Brazil, in which we applied the gender-STEM IAT and employed the ordered probit analysis. The main challenge we faced was the sensitivity of the subject – gender stereotypes are complicated both to approach and to measure. Nonetheless, we were able to design an innovative procedure, from the choice and adaptation of the instrument to the qualitative analysis we implemented.

We found that women in STEM are less likely to show gender-STEM implicit stereotypes, compared to women in humanities. In other words, they are more likely to belong to the incongruent stereotype end of the spectrum, while women in human sciences are more likely to implicitly conform to the stereotype. We also show a negative correlation between implicit gender stereotyping and the choice of math-intensive majors by women at the university. We did not find relevant differences in men across scientific fields – in every field, we found that

Table 7. Marginal effects of ordered probit analysis for IAT results of female students

Scientific field	Stereotype congruent	Neutral	Stereotype incongruent
Exact	−0.26	0.11	0.15
Agricultural	−0.02*	0.01*	0.01*
Biological	−0.06*	0.02*	0.03*
Human	0.28	−0.12	−0.16

Note(s): *Denotes coefficients that were not statistical significance at 5%
Source(s): IAT results

men associate men more with STEM and women more with humanities, a stereotype-congruent result. In this sense, the fact that most of our subjects displayed stereotype-congruent results is indicative of the profoundness of gender bias in the setting we analyzed.

On one hand, this is an intriguing result, considering that it is expected that women in human sciences are more prone to question – and acknowledge – gender stereotypes. On the other hand, it shows how implicit concepts may be intrinsic and, therefore, affect future outcomes, such as labor force participation and time spent in unpaid reproductive work, a problem that affects mainly women. In this sense, we can infer that implicit stereotypes are developed before engaging in tertiary education, either in the early stages of schooling or even through parental and daily socialization.

While we cannot say that the instrument we used can predict behaviors, the gender-STEM IAT was useful in demonstrating the correlation between an important aspect of "gender culture" (gender stereotypes) and the gender composition of STEM fields. This gives insight into how individuals assimilate aspects of gender bias into their everyday lives – each to a higher or lower degree.

Such assimilations are very important to be accounted for in future public policies. For future research, we suggest the use of other experiment designs and instruments to help substantiate the findings and apply the same in other career phases, such as in early schooling; with professionals in different fields, especially teachers and others that may influence decisions and with parents and caregivers.

Notes

1. Other courses in which women predominate are Odontology (72.2%), Pharmacy (71.9%), Physiotherapy (79.0%), Human Resources (78.0%), Architecture (66.6%), Medicine (58.2%), Accounting (57.0%), Law (55.3%) and Business (54.9%) (Instituto Nacional De Estudos E Pesquisas Educacionais Anísio Teixeira, 2019). See Nosek *et al.* (2002) and Beede, Julian, Langdon, Mckittrick, Khan, & Doms (2011) for similar distributions of gender across majors, in the USA.

2. This happens because additional math and science courses increase educational attainment (Levine & Zimmerman, 1995). This is substantiated by Rose & Betts (2004), who have found that an additional year of math, raises wages significantly even after controlling for math test scores.

3. Myers & Twenge (2013) define social psychology as "a science that studies the influences of our situations, with special attention to how we view and affect one another". More precisely, it is the scientific study of how people think about, influence and relate to one another.

4. Recent developments and applications of the theory of balance can be found at Krawczyk, Wołoszyn, Gronek, Kułakowski, & Mucha (2019), Chiang, Chen, Chuang, Wu, & Wu (2020), and Goswami (2023).

5. Examples of IAT tests available at Project Implicit (2011) are Age IAT, Race IAT, Sexuality IAT, Religion IAT and others.

6. Individuals may change answers to avoid being seen as discriminatory and, as we have presented, even in cases when people are motivated to answer truthfully, some perceptions we form may not be accessible through introspection.

7. In the context of this research, we use the terms exact and natural sciences and STEM interchangeably, considering that in Brazil the former usage is more widely spread, and because of that it was the term employed in the experiment, with the proper Portuguese translation. On the other hand, the term STEM is widely used in the literature, and it is conceptually adequate for this research.

8. See Cvencek *et al.* (2011) for a complete description of such mechanisms in the context of the math-gender IAT.

9. We also rely on the strength of gender identity for such implications.

10. We use these and other similar stimuli words that are descriptive of the concepts and attributes we are working with, with the proper adaptation to Portuguese.
11. The interpretation of the IAT results as an indicator of implicit stereotypes is supported by the theoretical definition of the construct and the associations between concepts and attributes, such as defined by Greenwald *et al.* (2003) and described in the theoretical framework.

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Corresponding author
Camila Alvarenga can be contacted at: camilaalvarenga89@gmail.com