Nota técnica
3/2024

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funcas

Junio 2024

Edita: Funcas
Caballero de Gracia, 28, 28013 - Madrid

ISSN: 3020-7436

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Abstract

This article examines gender gaps in higher education in Spain from 1985 to 2023 in the context of technological advancements, particularly digitalization and artificial intelligence (AI). We identify significant disparities, with women overrepresented in health-related fields and underrepresented in STEM disciplines. This imbalance is concerning as STEM fields offer better employment prospects and higher salaries. We analyze university degrees' exposure to technological change through Routine Task Intensity (RTI) and AI exposure indices. Our findings show that women are more enrolled in degrees with high RTI, prone to automation, and less in degrees with high AI exposure, likely to benefit from technological advancements. This suggests technological change could widen existing labor market gender gaps. To address this, we recommend policies to boost female participation in STEM fields and adapt educational curricula to reduce routine tasks and enhance AI complementarities, ensuring equitable labor market outcomes amid technological change.

Key words: Gender Gaps, Artificial Intelligence, Higher Education, STEM, Technological Change, Self-actualization.

* The opinions and analyses are the responsibility of the authors and do not necessarily reflect those of the Federal Reserve Bank of St. Louis or the Federal Reserve System. José Ignacio Conde-Ruiz acknowledges the support of the Research Project of the Ministry of Science and Innovation PID2019-105499GB-I00. Juan José Ganuza acknowledges the support of the Barcelona School of Economics and the Research Project of the Ministry of Science and Innovation PID2020-115044GB-I00.

1. INTRODUCTION

We are witnessing one of the most significant transformations in both the educational system and the labor market in history, driven by technological advancements, particularly digitalization and artificial intelligence. These new technologies will drastically impact pedagogical tools and alter the supply and demand for education, especially at the university level.

This article focuses on the demand for university studies within the context of technological change from a gender perspective. Our objectives are twofold: first, we want to highlight current gender gaps in higher education and their potential implications for employability and wages in the face of technological advancements, especially Artificial Intelligence (AI). Secondly, we want to provide policy recommendations to address the potential challenges and opportunities arising from technological change, aiming to reduce these gender gaps and improve higher education studies in general.

We begin with a descriptive analysis of the evolution of the demand for higher education over the last three decades in Spain. To do so, we combine Eurostat data and data from the Spanish Ministry of Education. The data reveal several interesting aggregate results. Firstly, Spain has one of the highest percentages of young people with university degrees in Europe, particularly among women. The demand for higher education shows significant gender differences. While there are no significant disparities in social sciences and humanities, there is a notable gap in engineering and architecture studies, where men are overrepresented, and in health-related fields, where women predominate. This analysis of 100 university degrees demonstrates a lack of convergence in higher education demand between genders and no significant progress in reducing the gender gap in STEM studies over the past 20 years.

The second part of the article uses the methodology of Conde-Ruiz *et al.* (2024) to analyze the degree of exposure of university degrees to technological change. By combining information on employment patterns of different university degrees from the Spanish "Survey of Labor Market Insertion of University Graduates (EILU)" (National Statistics Institute [INE], 2019) and the indices constructed by Schotte *et al.* (2023) and Webb (2020) that measure the exposure of each occupation to technological change, we obtain indices measuring the degree of technological exposure of university degrees.

We build two indices that allow us to rank university degrees based on two factors related to occupations: Routine Task Intensity (RTI) and exposure to AI. A university degree with a high RTI index means that the students are likely to end up in occupations with a high proportion of routine tasks and consequently, a high risk of being replaced by technology. On the contrary, a university degree with a high index of exposure to AI means that students are likely to work in occupations that are complements to AI, which can lead to an increase in their productivity and better labor outcomes. We show that these indices significantly explain the employability of university degrees and expected salary differences.

From a gender perspective, it is revealed that women are overrepresented in degrees with a higher Routine Task Intensity (RTI) index while they are underrepresented in degrees with a high index of exposure to AI. This is concerning, since, as mentioned before, these indices are very informative on the future labor outcomes of new graduates. Our results indicate that technological change may widen the current labor-gender gaps. Composition effects may be significant, as university degrees vary greatly in terms of the number of students. To address this, we aggregate our indices for each university degree by the population of students and define an aggregate gender gap for each index. Our initial results are confirmed; after aggregation, we show that females study more degrees with a high RTI index and are less enrolled in degrees with a high exposure to AI index. We also show that these gender gaps are persistent over time, with very small improvements in recent years.

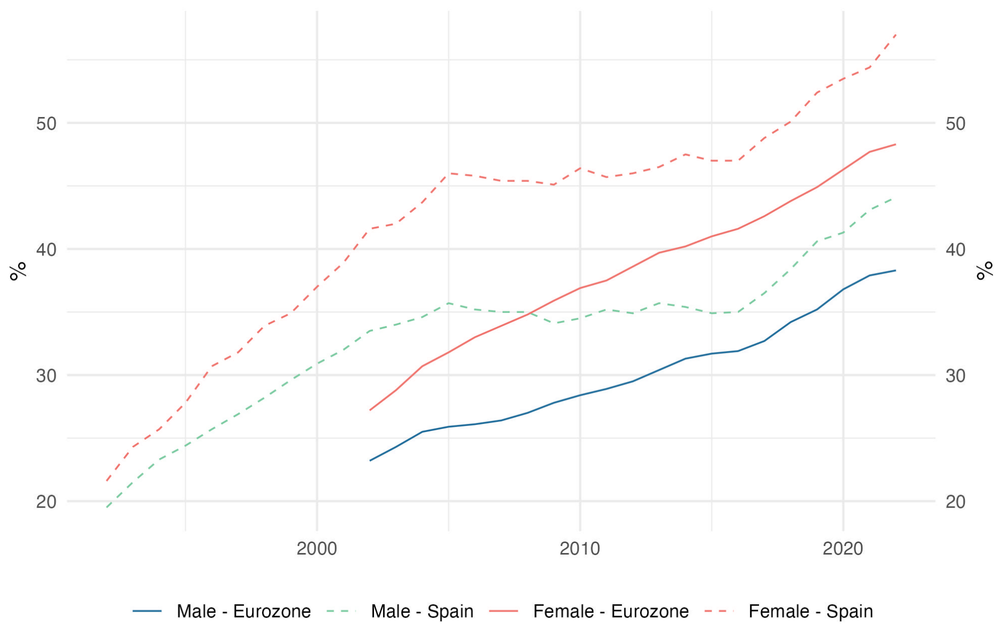
The article is structured into six sections. Section 2 presents a descriptive study of the evolution of the Spanish demand for university degrees from 1985 to 2023. Section 3 introduces the indices we have constructed to measure the degree of exposure of university degrees to technological change. Section 4 uses these indices to explain gender differences in labor market outcomes. Section 5 analyzes the relationship between the proportion of females in various degrees and our indices, defining two gender gaps related to the exposure of university degrees to technological change. Finally, Section 6 presents conclusions and policy recommendations.

2. SPANISH HIGHER EDUCATION DEMAND AND GENDER GAPS

We start by analyzing the evolution of the demand for university studies in recent decades by gender. Figure 1 illustrates the percentage of individuals aged 25-34 with tertiary education across genders, showing a positive gender gap with a higher presence of women in higher education.

This positive gender gap mainly arose in the 1990s, coinciding with a significant increase in university attendance. This pattern is not exclusive to Spain but is also observable in Eurozone countries. OECD reports from 2021 and 2023 support this observation, suggesting that the gap may be attributed to a higher premium for women obtaining a university education in Spain compared to men. For instance, in terms of employability, the difference between having a high school or university education is minimal for men (6% unemployment versus 5%), whereas it is more significant for women (reducing from 9% unemployment to 6%). The data also shows that Spain holds a prominent position within the Eurozone concerning the percentage of university graduates. The upward trend in the demand for university studies in Spain over the last three decades is a common pattern across all nations.[1]

Figure 1. PERCENTAGE OF THE POPULATION (25-34 YEARS) WITH TERTIARY EDUCATION, BY GENDER



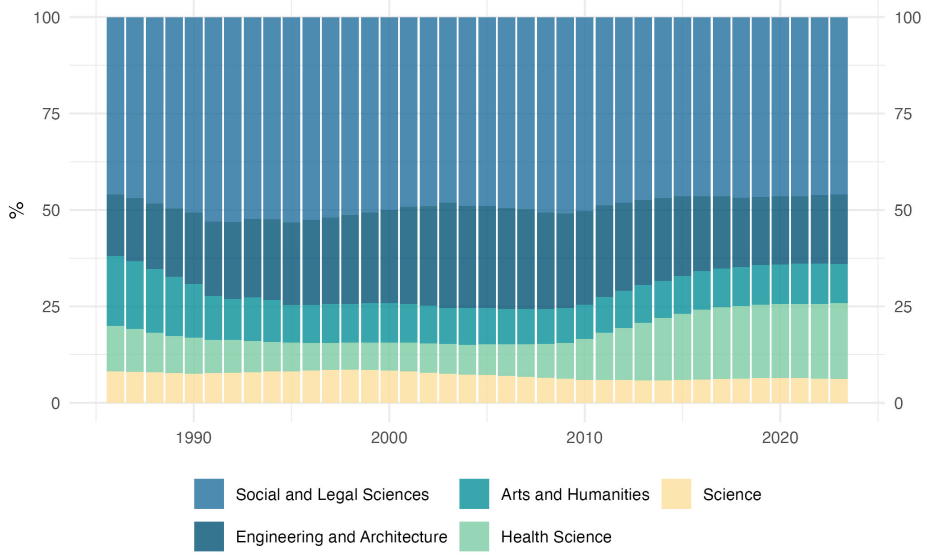
Source: Eurostat.

Now, we focus on the specific demand for university degrees in Spain. Figure 2 illustrates the evolution of the distribution of enrolled students across fields of study.

Social sciences are the most demanded field of study, commanding nearly 50% of the market share. Sciences and humanities maintain a smaller yet relatively stable market share over time. Conversely, engineering and architecture experienced a significant decline in market share following the economic crisis and have struggled to recover. This decline has been compensated by the rise in demand for health sciences. This could be explained by the emergence of new disciplines driven by innovation in this area, as well as the aging of the population.

[1] In Spain, specifically, the proportion of young adults (aged 25-34) with tertiary education has increased from approximately 20% to 50%. This places Spain among the higher-ranking countries in our region, alongside France, surpassing the Eurozone average. However, Spain falls short of the levels observed in Luxembourg (64%) and Norway (60%) within Europe, or in Canada (73%) and South Korea (76%) globally (OECD, 2021).

Figure 2. DISTRIBUTION OF ENROLLED STUDENTS, BY FIELD OF STUDY

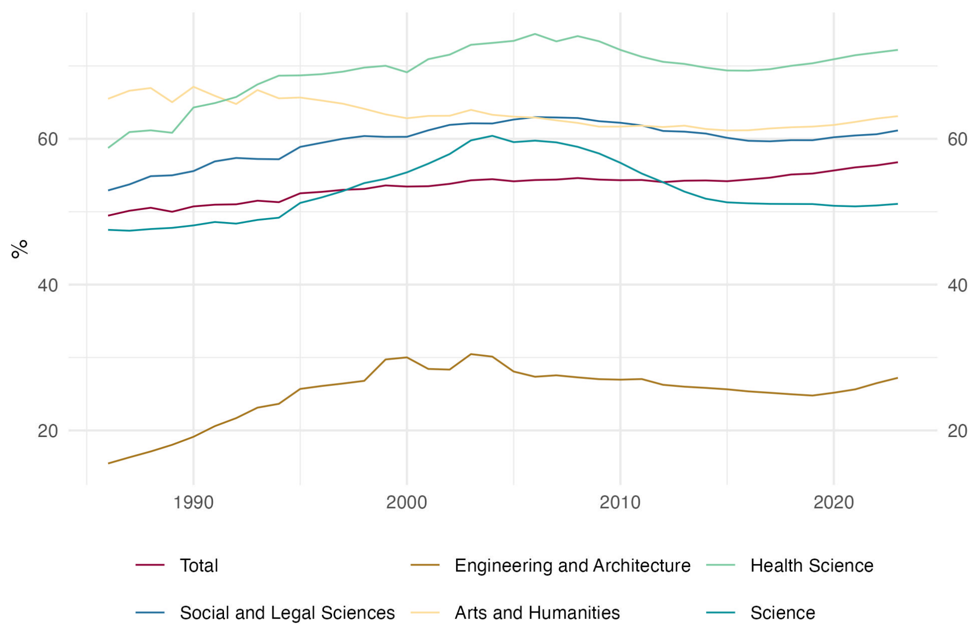


Source: *Sistema Integrado de Información Universitaria (SIIU).* Secretariat-General of Universities.

Despite these trends, demand across fields of study differs and has evolved disparately between genders. Figure 3 displays the evolution of female enrollment across various fields.

Notably, health sciences exhibit a high feminization rate, while engineering and architecture have stagnated below 30% representation of women since the late 1990s.

Figure 3. SHARE OF WOMEN OVER-ENROLLED STUDENTS, BY FIELD OF STUDY



Source: *Sistema Integrado de Información Universitaria (SIIU).* Secretariat-General of Universities.

Table 1 presents university degrees in STEM fields ordered by female representation. Focusing on STEM studies, we observe that, except for those degrees related to health, women are significantly underrepresented. The table reveals a stark overrepresentation of women in disciplines related to Biology and an underrepresentation in fields like Physics, Mathematics, and Engineering.

Table 1. SHARE OF WOMEN ENROLLED IN STEM UNIVERSITY DEGREES

(Percentage)

Degree	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	2021-2022	2022-2023
Biomedicine	77	76	75	75	76	76	77	79
Biochemistry	65	65	65	66	66	68	69	70
Food Science and Technology	69	68	68	67	67	67	66	66
Biology	62	62	62	62	62	62	63	63
Biotechnology	60	60	61	61	61	62	62	63
Marine Sciences	55	58	56	57	58	56	57	58
Architecture	49	49	50	50	52	53	55	57
Chemistry	53	53	53	54	54	54	54	55
Industrial Design and Product Development Engineering	47	47	47	47	48	49	50	51
Environmental Sciences	47	48	48	48	49	49	49	50
Industrial Chemical Engineering	47	46	46	47	47	47	47	47
Statistics	43	43	45	45	46	46	46	45
Technical Architecture	38	38	38	39	39	40	42	44
Geology	41	41	41	40	40	41	40	39
Materials Engineering	24	25	25	29	33	36	38	37
Mathematics	38	38	38	37	36	35	36	36
Agrarian and Agroalimentary Engineering	36	36	34	33	33	33	33	33
Agricultura, Farming and Rural Environment Engineering	33	32	31	31	30	32	31	31
Civil Engineering	29	29	29	28	28	29	29	30
Sound and Image Engineering	25	25	27	26	28	29	30	30
Industrial Organization Engineering	25	26	27	27	28	30	29	30
Physics	26	25	26	27	27	27	28	28
Mountains and Forestry Engineering	26	27	25	25	26	26	28	27
Industrial Technologies Engineering	23	23	24	24	24	25	26	26
Energy Engineering	29	28	28	27	27	26	26	26
Geomatics, Topography and Cartography Engineering	31	31	29	28	28	26	29	26
Aeronautical Engineering	23	23	24	24	25	25	26	26
Mining and Energy Engineering	26	26	27	27	24	24	24	24
Horticulture and Gardening Engineering	31	39	26	27	16	21	23	23
Telecommunications Engineering	21	20	21	21	21	22	22	22
Naval and Oceanic Engineering	19	19	20	20	20	21	21	22
Electronic Engineering	16	17	17	17	17	17	18	19
Industrial Electronic and Automation Engineering	14	14	15	15	16	16	16	16
Electric Engineering	13	14	14	14	15	15	15	15
Software and Application Development	11	11	12	12	12	13	14	14
Computer Science	12	12	12	12	13	13	14	14
Mechanical Engineering	13	13	13	13	14	14	14	14
Computer Science Engineering	10	10	11	10	11	11	12	12
TOTAL STEM	31	32	32	32	32	32	33	34

Source: *Sistema Integrado de Información Universitaria (SIIU)*, Secretariat-General of Universities.

Therefore, women are around ⅓ of STEM students. The gender gap in STEM studies is not unique to Spain. The OECD report (2023) shows that, to a greater or lesser extent, this gap exists in all developed countries. However, it is concerning that despite efforts to promote STEM studies among girls and adolescents, little progress has been made in the past two decades. Moreover, given that the labor market rewards mathematical knowledge, this gap in STEM profiles may contribute to the wage gap between men and women, as highlighted by Hanushek *et al.* (2015) and Rebollo-Sanz and De la Rica (2022). As we will analyze in detail in the following sections, STEM graduates could be better equipped than students of other disciplines to deal with technological change, potentially exacerbating the wage gap between genders

In the appendix we provide detailed information on female representation in approximately 100 university degrees within the science field, reinforcing the conclusions drawn from Figure 3. Women are overrepresented in degrees related to health, social work, and teaching, which we could call the “care economy”. In the social sciences and humanities, although there are differences in representation, these are generally smaller. Finally, in STEM degrees, except for those degrees related to health, women are significantly underrepresented. To give a sample of this pattern, Table 2 selects, from the overall analysis of all grades, the 10 studies in which women are most represented and those 10 in which they are least represented.

Table 2. UNIVERSITY DEGREES WITH LOWER AND HIGHER SHARE OF WOMEN ENROLLED

(Percentage)

Degree	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	2021-2022	2022-2023
Computer Science Engineering	10	10	11	10	11	11	12	12
Mechanical Engineering	13	13	13	13	14	14	14	14
Computer Science	12	12	12	12	13	13	14	14
Software and Application Development	11	11	12	12	12	13	14	14
Electrical Engineering	13	14	14	14	15	15	15	15
Industrial Electronics and Automation Engineering	14	14	15	15	16	16	16	16
Electronic Engineering	16	17	17	17	17	17	18	19
Naval and Ocean Engineering	19	19	20	20	20	21	21	22
Physical Activity and Sport	19	19	20	20	20	21	21	22
Telecommunications Engineering	21	20	21	21	21	22	22	22
Translation and Interpreting	80	80	81	81	81	80	80	80
Conservation and Restoration	78	77	76	77	78	80	81	80
Nursery	78	77	76	77	78	80	81	80
Social Education	81	81	81	81	81	81	82	82
Social Work	81	81	81	81	81	81	82	82
Pedagogy	83	83	83	83	84	83	84	84
Occupational Therapy	83	83	83	83	84	83	84	84
Protocol and Events	88	89	89	88	86	86	87	88
Logopedics	88	89	89	88	86	86	87	88
Early Childhood Education	93	93	93	93	92	92	91	91

Note: 10 fields of study with lower and higher shares of women enrolled in course 2022-2023 are included.

Source: *Sistema Integrado de Información Universitaria (SIIU),* Secretariat-General of Universities.

3. HIGHER EDUCATION EXPOSURE TO TECHNOLOGICAL CHANGE

Technological change has radically transformed the landscape of occupations. The rapid evolution of technology has created new job opportunities in some fields while displacing or modifying roles in traditional industries. This shift may be leading to an increased demand for technical and digital skills, thereby driving the need for constant adaptation and updating of labor competencies.

In this section, we will classify different university degrees based on the level of exposure they have to technological change. To do this, we will use the methodology developed by Conde-Ruiz *et al.* (2024) to estimate an index for each university degree. Firstly, they relate each university degree to different occupations. Secondly, they use information on the degree of exposure of each occupation to technological change. Finally, they assign a technology exposure index to each university degree. The following outlines the procedure for obtaining these indices schematically.

Figure 4. METHODOLOGY FOR OBTAINING THE EXPOSURE INDICES OF UNIVERSITY DEGREES TO TECHNOLOGICAL CHANGE

Source: Conde-Ruiz *et al.* (2024).

To obtain the correspondence between occupations and university degrees, we use data from the "Survey of Labor Market Insertion of University Graduates (EILU)" prepared by the National Statistics Institute (INE) for Spain for the year 2019. This survey includes information on the cohort of graduates in the 2013-2014 academic year (with a sample of 31,500 students) and information on the occupation in which they have managed to find employment five years after completing their degree. From this information, we calculate the distribution of occupations for each university degree, *i.e.,* the percentage of graduates from each degree program who are working in each occupation.

Exposure indices of occupations to technological change have been extensively analyzed in the academic literature.

On the one hand, a line of literature (see Dorn [2015]; Acemoglu and Restrepo [2022]; Autor [2019]; Autor and Dorn, [2013]; Autor and Katz [1999] and Conde-Ruiz and Ganuza [2023], among others) attempts to anticipate which occupations will be most affected by the new digital economy, paying special attention to the possibility that the digital economy may automate those routine tasks within each occupation. Basically, they argue that technological change will not have a large differential impact on workers according to their levels of education, but according to the content of the tasks of their occupations (Task Biased Technological Change). Thus, three types of tasks are distinguished: routine, abstract and manual. Routine tasks involve the repetition of predetermined processes (as in car assembly lines or administrative tasks). Abstract tasks are those that involve problem-solving, intuition, persuasion, and leadership skills, as well as creativity. Manual (non-routine) tasks are those that require personal interactions, adaptability, visual recognition and language. It seems clear that routine tasks are easy to perform by automation technology, while abstract and manual tasks are much more difficult. The former is because they are clearly complementary to technology and the latter is because they are too expensive to be replaced by it. With this argument, a classification of the main tasks in each occupation is made. The most widely used database is O*NET (Occupational Information Network), which provides a direct linkage between tasks and occupations.

On the other hand, more recently, another line of research (Agrawal *et al.* [2018]; Ford [2015]; Susskind [2020], and Acemoglu and Restrepo [2020] or Acemoglu [2024], among others) focuses on new digital advances (Artificial Intelligence, Machine Learning, Generative Artificial Intelligence, and Large Language Models) that go beyond the automation of routine tasks and open the possibility that technology can replace human labor in virtually all occupations and tasks, but it can also complement some particular skills.

To analyze occupations threatened by the automation of routine tasks, we use the Routine Task Intensity (RTI) Index constructed by Lewandowski *et al.* (2022) and Schotte *et al.* (2023). This RTI index is a synthetic measure of the relative intensity of routine tasks within each occupation. Thus, occupations with a higher content (or proportion) of non-routine (analytical and personal) tasks will have a lower value of this metric, while those occupations with a higher content of routine tasks will have a higher value. This index is, therefore, a measure of the routine aspect of the occupation and, therefore, indicates the probability of being replaced by technology.

To analyze occupations exposed to technology beyond the degree of routinization, we use the Artificial Intelligence (AI) Index constructed by Webb (2020) and recently used by Albanesi *et al.* (2023). This AI Index constitutes a measure of the exposure of tasks and occupations to new developments in AI. Specifically, the AI index obtained from Webb (2020) is calculated by measuring the textual overlap (verb-noun pairs) of patents (taken from Google Patents Public Data) with job occupation descriptions from O*NET. We can interpret the AI index as a proxy for the potential impact of Artificial Intelligence on each occupation. It is important to point out that this index measures the degree of exposure of each occupation to AI advances, but we do not know if this impact will end up being positive (complementary) or negative (substitutive). All of this makes the interpretation of the AI index substantially more complex than that of the intensity of routine tasks of the RTI Index.

We classify all occupations using each of these two indices (RTI, artificial intelligence –AI– exposure index) and assign these indices to each university degree based on the occupations in which the students of each degree end up working. Each of the metrics is calculated as the weighted average of the indices of the different occupations.

The tables 3 and 4 show the university degrees most and least exposed to each of the two indices created.

The RTI index indicates that the higher the index, the greater the risk that the occupation will be replaced by technology. Therefore, those university degrees with a higher RTI are at the same risk, as it would indicate that recent graduates in that degree are being hired in occupations that are going to be threatened by technology.

Conversely, the rankings of university degrees using the AI exposure index have a different interpretation. If they have a high index, it means that students pursuing these degrees enter occupations that are exposed to artificial intelligence. In this case, if university education is complementary to the advancement of technology, students pursuing these degrees are not at risk in terms of the occupations they will perform in the future. In any case, it is interesting to point out that all careers with high rates of exposure to AI should update their contents and curricula, paying special attention to technological progress.

Table 3. DEGREES WITH THE HIGHEST AND LOWEST VALUES OF THE ROUTINE TASK INTENSITY INDEX

Low	High
Computer Science Engineering	Information and Documentation
Computer Science	Marine Sciences
Software and Application Development and Multimedia Engineering	Applied Modern Languages
Mathematics	Criminology
Aeronautical Engineering	Humanities
Telecommunications Engineering	Human Nutrition and Dietetics
Physics	Fine Arts
Materials Engineering and Textile Engineering.	Labour Sciences
Industrial Technologies Engineering	Geography
Architecture, Urbanism and Landscape	Engineering of Horticulture and Gardening
Sound and Image Engineering	Nautical and Maritime Transport
Electronic Engineering	History of Art
Biomedical and Health Engineering	Finance and Accounting
Energy Engineering	Public Management and Administration
Primary Education	Tourism

Sources: Own elaboration (*Sistema Integrado de Información Universitaria* and Schotte *et al.,* 2023).

Table 4. DEGREES WITH THE HIGHEST AND LOWEST VALUES OF THE ARTIFICIAL INTELLIGENCE EXPOSURE INDEX

Low	High
Early Childhood Education	Electronic Engineering
Primary Education	Geomatics, Topography and Cartography Engineering
Spanish Languages and Dialects	Computer Science
English Language	Telecommunications Engineering
Pedagogy	Computer Science Engineering
Public Management and Administration	Industrial Chemical Engineering and Environmental Engineering
Literature	Civil Engineering
Music and Performing Arts	Industrial Electronics and Automation Engineering
Teacher Training (Others)	Electrical Engineering
Classical Languages	Mechanical Engineering
Foreign Languages (Others)	Energy Engineering
Archaeology	Shipping and Ocean Engineering
Finance and Accounting	Industrial Technologies Engineering
Applied Modern Languages	Architecture, Urbanism and Landscape
Protocol and Events	Aeronautical Engineering

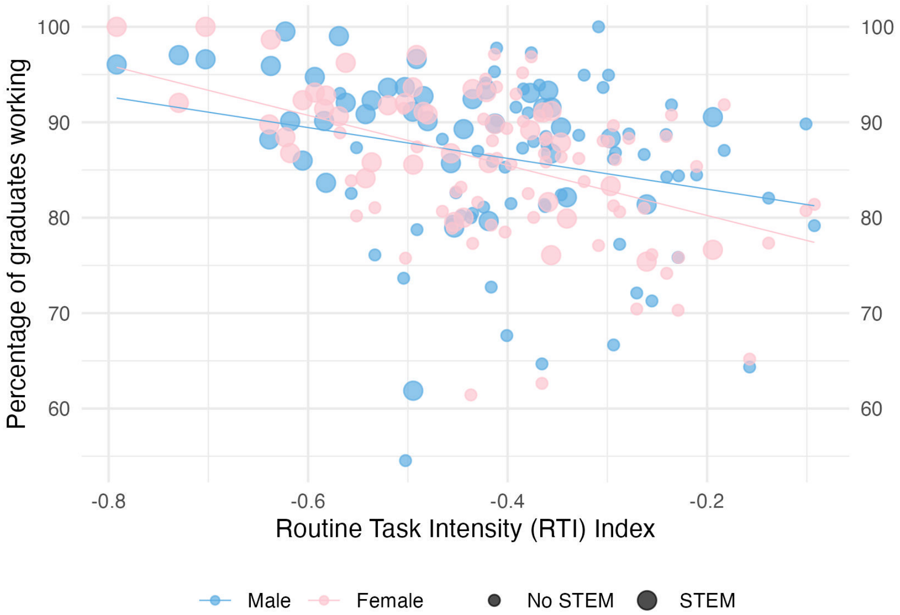
Sources: Own elaboration (*Sistema Integrado de Información Universitaria* and Webb, 2020).

4. GENDER LABOR OUTCOMES IN HIGHER EDUCATION BY RTI AND AI INDICES

In this section, we will analyze the labor outcomes (employability and salaries) of each university degree according to the RTI and AI indices, considering the gender of each graduate.

The Figures 5 and 6 show the percentage of university graduates who are working 5 years after completing higher university studies according to the indices defined in the previous section. As can be seen in Figure 5, there is a negative relationship in the case of the RTI index, indicating that those degrees where students end

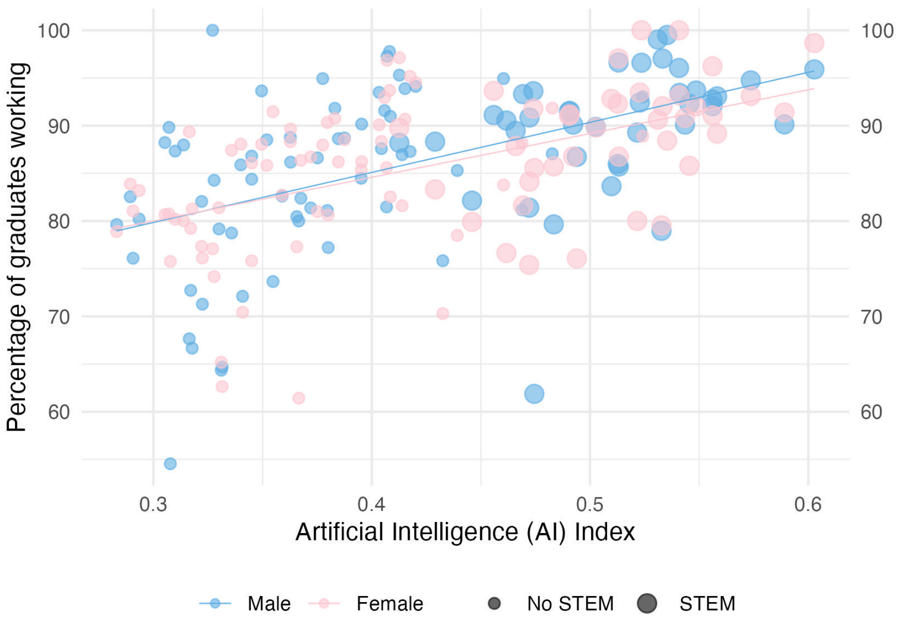
Figure 5. ROUTINE TASK INTENSITY (RTI) INDEX BY UNIVERSITY DEGREE AND EMPLOYABILITY



Source: Own elaboration.

up in occupations with a higher percentage of routine tasks have a lower percentage of graduates working. This negative relationship is not surprising since, as we mentioned above, it is precisely routine tasks that are the easiest to replace with digital technology.

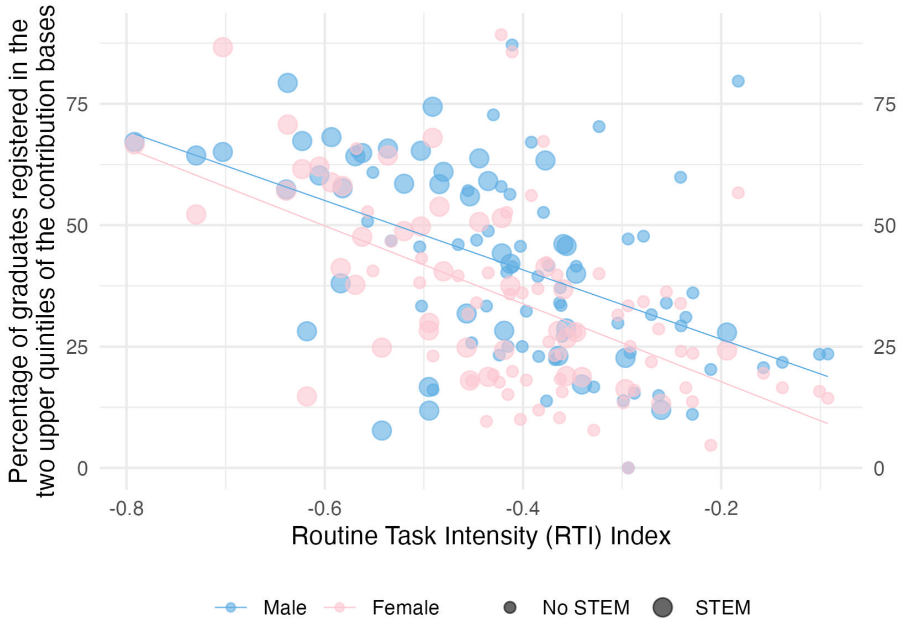
Figure 6. ARTIFICIAL INTELLIGENCE (AI) INDEX BY UNIVERSITY DEGREE AND EMPLOYABILITY



Source: Own elaboration.

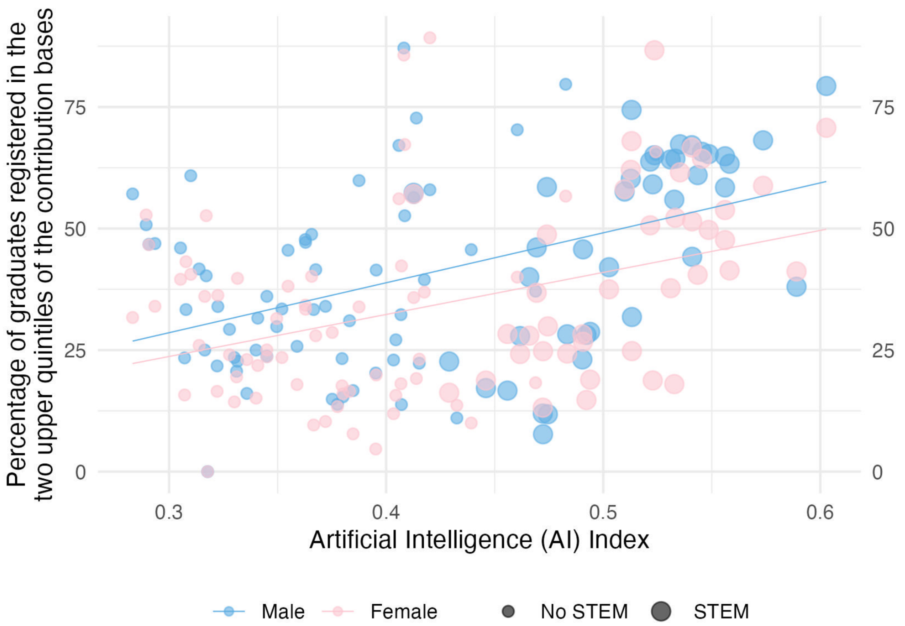
In contrast, in Figure 6, we find that the relationship between the indices of exposure to technology and employability is positive. That is, we find that those university degrees with greater exposure to AI have a higher percentage of graduates working.

Figure 7. ROUTINE TASK INTENSITY INDEX BY UNIVERSITY DEGREE AND WAGES



Source: Own elaboration.

Figure 8. ARTIFICIAL INTELLIGENCE (AI) INDEX BY UNIVERSITY DEGREE AND WAGES



Source: Own elaboration.

In the Figures 7 and 8, we see the relationship between the rates of exposure to technology for each university degree and a metric related to the salary obtained by graduates five years after completing their studies. Specifically, we use the percentage of graduates of each university degree who are working (*i.e.,* affiliated to Social Security as employees) and who have a wage in the top two quintiles of the salary distribution (*i.e.,* of social security contribution bases distribution) as a measure of salary level. We obtain results like those obtained previously. Figure 7 shows a negative relationship in the case of RTI, indicating that those degrees where students end up working in occupations with fewer routine tasks have higher salaries. In the case of exposure to AI, Figure 8 shows a positive relationship, indicating that those degrees with greater exposure to AI have a higher percentage of graduates in the highest wage quintiles (*i.e.,* higher wages).

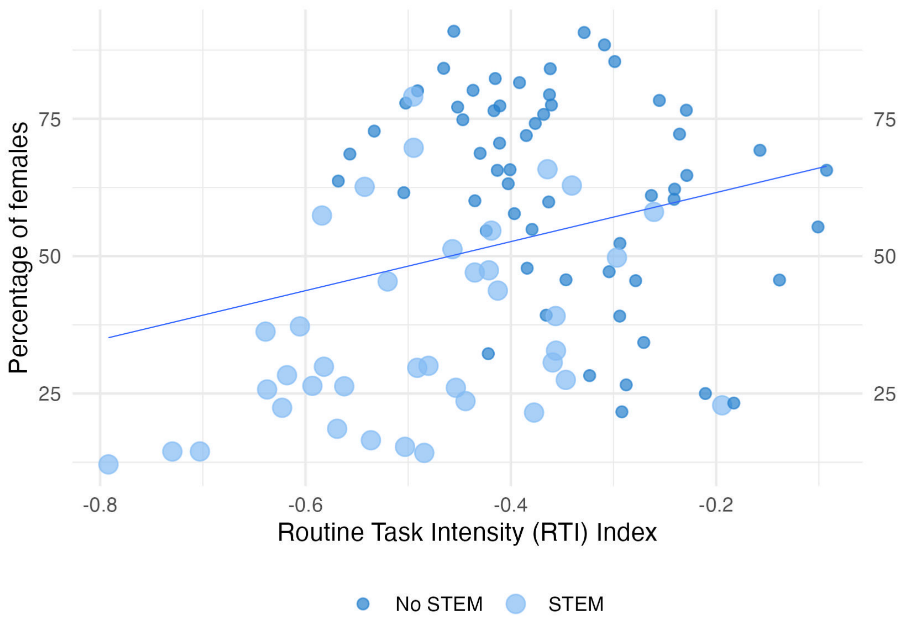
In short, we have found that the employment outcomes of students in higher education degrees with a lower RTI index or a higher AI exposure index are better. The results obtained in this section are in line with the results of Albanesi *et al.* (2023), which, using the same AI index developed by Webb, found that on average, employment has increased in occupations more exposed to AI for a set of 16 European countries over the period 2011-2019.

5. HIGHER EDUCATION GENDER GAPS: ROUTINE TASK INTENSITY AND AI EXPOSURE INDICES

We have seen that in Spain, as well as in most European countries, there is a positive gender gap in the attendance of women to higher education. However, to have the full picture, we also have to analyze the specific patterns of studies undertaken by women. We have shown that there are important differences between women and men regarding the demand for university studies. Women are overrepresented in health-related studies and, more broadly, in fields encompassing care economics, while they are underrepresented in scientific, engineering, and architectural degrees.

Looking toward the future, it is important to analyze how the studies chosen by women will be affected by technological change. To do so, we analyze how the proportion of women in the studies is related to our indices

Figure 9. ROUTINE TASK INTENSITY INDEX BY UNIVERSITY DEGREE AND PROPORTION OF WOMEN

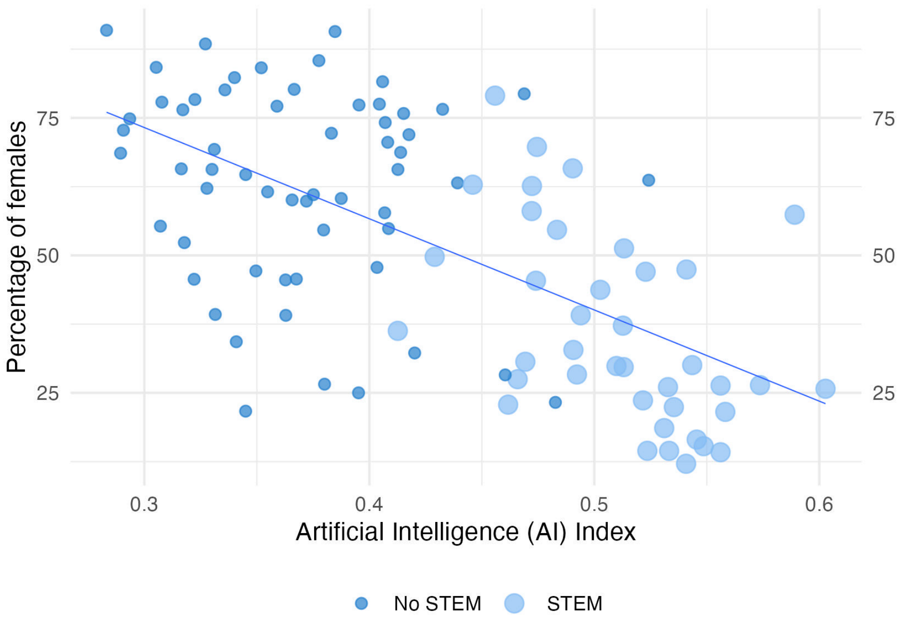


Source: Own elaboration.

of intensity of routine tasks (RTI) and exposure to artificial intelligence (AI) that have been shown to be very informative about labor outcomes. In Figure 9, we plot the proportion of women in a particular university degree with respect to the RTI index of the degree.

It is concerning the positive relationship between the proportion of women and the RTI index, since it shows that studies with an overrepresentation of women may have a higher risk of being replaced by new technologies. Similarly, in the Figure 10, we plot the proportion of women in a particular university degree with respect to the AI Index of the degree.

Figure 10. ARTIFICIAL INTELLIGENCE (AI) INDEX BY UNIVERSITY DEGREE AND PROPORTION OF WOMEN



Source: Own elaboration.

We have shown before a positive relationship between our AI Index and labor outcomes since AI may enhance the productivity of some professions and skills. For this reason, the negative relationship between the proportion of women and the AI Index is a concern, as we can interpret this result to mean that studies with an overrepresentation of women may have fewer complementarities with new technologies.

These two results indicate that technological change may exacerbate gender differences in the labor market and degrees through the channel of the observed horizontal differences between females and males regarding the demand for university studies. However, we must point out that to make this statement, we must also control for the weight of a particular degree in the population. It could be possible that some degrees with an overrepresentation of women may have few students, and they are driving the results.

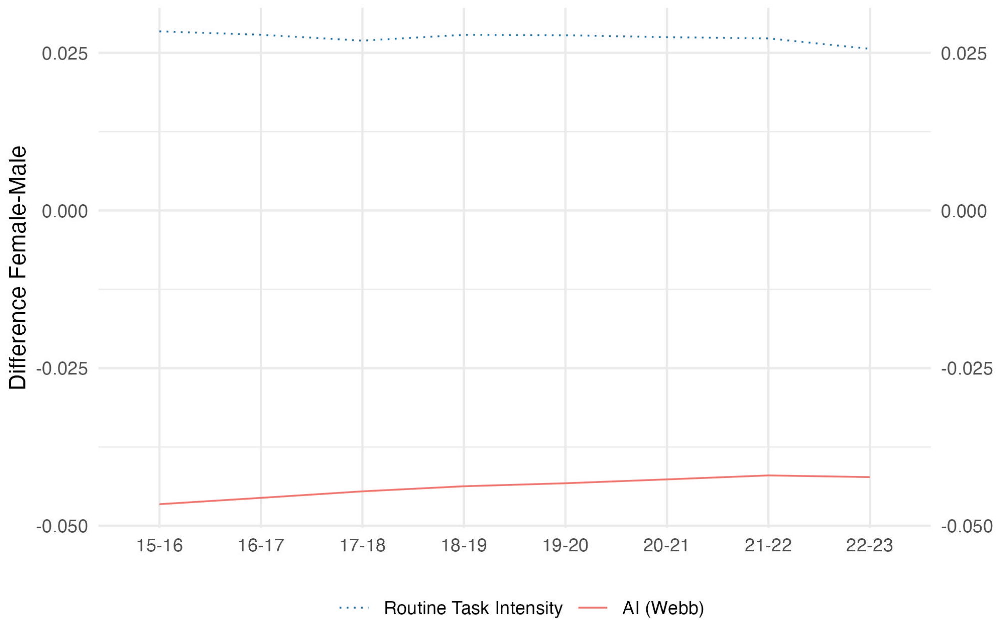
For controlling that we construct weighted (by the number of students) indexes for the two measures of routine task intensity and exposure to AI, for women and men. We multiply the index of a particular grade by the number of students in this grade, then we aggregate this for all the grades and divide such sum by the total number of students. We can compute this weighted average for every year of our sample to capture possible changes in the number of students in the grades. Therefore, we calculate the indexes using the following formula, for each gender (g) and year (t):

$$I_t^g = \frac{\sum_i \; n_{i,t}^g I_i}{N_t^g} \quad [1]$$

where i is the indicator of a particular degree and g is either f or m. Thus, I_i represents the index (RTI and IA) of a particular degree i, $n_{i,t}^g$ is the number of (male or female) students in a specific degree i in year t, and N_t^g is the total number of (male or female) students in a given year.

These aggregate gender indexes in isolation are difficult to interpret, however, the difference between both $I_t^f - I_t^m$ indexes, is a measure of a new gender gap that captures the differences in the intensity of routine tasks (RTI) and exposure to artificial intelligence of the studies chosen by females and males. Figure 11 plots these gender gaps over time.

Figure 11. AGGREGATE GENDER GAP IN RTI AND EXPOSURE TO IA



Source: Own elaboration.

The conclusion is that when aggregating the positive (negative) relationship between the proportion of female students and our RTI (exposure to AI index) index for the whole population, we obtain new gender gaps that are persistent over time, although they have a very small but positive evolution.

6. CONCLUSIONS AND POLICY RECOMMENDATIONS

In this paper, we have analyzed the differences in demand for university studies by gender in an environment characterized by technological uncertainty and the rise of artificial intelligence. Our analysis provides empirical results from which important public policy recommendations can be drawn. Through a descriptive analysis of the demand for university studies in Spain over recent decades, we have uncovered significant insights regarding gender disparities. Women are predominantly represented in health-related fields and generally in disciplines within the care economy, whereas they are notably underrepresented in science, engineering, and architecture degrees. This underrepresentation of women in STEM fields is concerning as it has remained stagnant over the past two decades. Given the advantages of STEM studies in terms of job placement and future salaries, this disparity likely contributes to and potentially exacerbates gender gaps in the labor market.

The second part of the article aims to understand the impact of these horizontal differences in the demand for higher education in the face of technological change. To this end, the first step is to analyze how the different university degrees and their employment opportunities will be affected by new technologies and artificial intelligence. To do this, we follow the methodology of Conde-Ruiz *et al.* (2024) and use two indices for each of the degrees (Routine Task Intensity index and Artificial Intelligence exposure index). These indices are very informative in explaining both the labor market outcomes of the different degrees and the expected salary of their graduates. In particular, the degrees with the highest routine task intensity index (with a high percentage of routine tasks) are the ones that present the greatest danger that their job opportunities will be reduced by the replacement of new technologies. Conversely, degrees with high exposure to artificial intelligence demonstrate higher employability and salary prospects. While artificial intelligence will displace certain occupations, it will also enhance the productivity of others, resulting in varied impacts on different fields of study.

Using these two indices, we analyze the differences in demand in degrees between men and women, and we show that degrees with higher female representation have a higher degree of routinization and lower complementarity with respect to AI. These differences give rise to a gap when we aggregate the entire population, a gap that is persistent over time.

The possible consequences that could be drawn for public policies go fundamentally in two directions. On the one hand, there is a need to encourage women's access to studies that generate less substitutive and more complementary profiles with new technologies, such as STEM degrees. Our analysis of the demand for university studies in Spain shows that this objective is difficult to achieve, because, despite policies to promote STEM studies in Spain, there has been no significant progress in the last two decades. A complementary and perhaps more feasible strategy is to modify undergraduate studies, in general, to adapt them to technological change and to adapt those with an overrepresentation of women to change professional profiles, reducing routinization and increasing complementarity with new technologies, especially with AI.

Finally, it is important to highlight some of the limitations of the present study and, therefore, to introduce caution in the conclusions we have just presented. The methodology for constructing the indices of exposure of university degrees to technological change is pioneering but depends on both the database of the employability of degrees and the indices of exposure of occupations to technological change. Regarding degree employability patterns, it is important to note that they are endogenous and will change with the introduction of new technologies. They are also aggregate patterns that should vary, not only at the level of the individual (qualifications, languages spoken, etc.) but also at the level of the university (quality, location, etc.). Finally, the rates of exposure of occupations to technological change capture the state of the art but should vary as technologies evolve.

To summarize, this paper suggests that the interaction of gender differences in the demand for university studies and technological change may widen gender gaps in the labor market. It is somewhat of a static snapshot given the current state of technology and degree employability patterns, but the result is clear and should give us pause for thought.

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APPENDIX

GENDER GAPS IN HIGHER EDUCATION (STEM VS NO STEM): RTI AND EXPOSURE TO AI INDICES

Degree	% Women (22-23)	RTI	IA (Webb)	STEM
Early Childhood Education	91	-0,46	0,28	No
Logopedics	91	-0,33	0,38	No
Protocol and Events	88	-0,31	0,33	No
Occupational Therapy	85	-0,30	0,38	No
Pedagogy	84	-0,47	0,31	No
Social Work	84	-0,36	0,35	No
Social Education	82	-0,42	0,34	No
Nursery	82	-0,39	0,41	No
Conservation and Restoration	80	-0,44	0,37	No
Translation and Interpreting	80	-0,49	0,34	No
Design	79	-0,36	0,47	No
Biomedicine	79	-0,50	0,46	Yes
Applied Modern Languages	78	-0,26	0,32	No
Literature	78	-0,50	0,31	No
Veterinary	78	-0,36	0,40	No
Advertising and Public Relations	77	-0,41	0,40	No
Psicology	77	-0,45	0,36	No
Fine Arts	77	-0,23	0,43	No
Other Foreign Languages	76	-0,42	0,32	No
Optics and Optometrics	76	-0,37	0,42	No
English Language	75	-0,45	0,29	No
Podology	74	-0,38	0,41	No
Spanish Languages and Dialects	73	-0,53	0,29	No
Human Nutrition and Dietetics	72	-0,24	0,38	No
Pharmacy	72	-0,38	0,42	No
Medicine	71	-0,41	0,41	No
Biochemistry	70	-0,49	0,47	Yes
History of Art	69	-0,16	0,33	No
International Relations	69	-0,43	0,41	No
Primary Education	69	-0,56	0,29	No
Food Science and Technology	66	-0,36	0,49	Yes
Classical Languages	66	-0,40	0,32	No
Tourism	66	-0,09	0,33	No
Odontology	66	-0,41	0,41	No
Labor Relations and Human Resources	65	-0,23	0,35	No
Biomedics and Health Engineering	64	-0,57	0,52	No
Communication	63	-0,40	0,44	No

GENDER GAPS IN HIGHER EDUCATION (STEM VS NO STEM): RTI AND EXPOSURE TO AI INDICES

(continued)

Degree	Women (22-23)	RTI	IA (Webb)	STEM
Biology	63	-0,34	0,45	Yes
Biotechnology	63	-0,54	0,47	Yes
Humanities	62	-0,24	0,33	No
Social and Cultural Antropology	62	-0,50	0,35	No
Information and Documentation	61	-0,26	0,38	No
Criminology	60	-0,24	0,39	No
Law	60	-0,44	0,37	No
Sociology	60	-0,36	0,37	No
Marine Sciences	58	-0,26	0,47	Yes
Audiovisual, Image and Multimedia	58	-0,40	0,41	No
Architecture	57	-0,58	0,59	Yes
Public Management and Administration	55	-0,10	0,31	No
Marketing	55	-0,38	0,41	No
Chemistry	55	-0,42	0,48	Yes
Journalism	55	-0,42	0,38	No
Archaeology	52	-0,29	0,32	No
Ingeniería en diseño industrial y desarrollo del producto	51	-0,46	0,51	Yes
Environmental Sciences	50	-0,30	0,43	Yes
Phisioterapics	48	-0,38	0,40	No
Industrial Chemistry Engineering	47	-0,42	0,54	Yes
Commerce	47	-0,30	0,35	No
Enology	47	-0,44	0,52	Yes
Politics and Public Management	46	-0,35	0,37	No
Finance and Accounting	46	-0,14	0,32	No
Business Administration	46	-0,28	0,36	No
Statistics	45	-0,52	0,47	Yes
Technical Architecture	44	-0,41	0,50	Yes
Philosophy	39	-0,37	0,33	No
Geology	39	-0,36	0,49	Yes
Economics	39	-0,29	0,36	No
Materials Engineering	37	-0,61	0,51	Yes
Mathematics	36	-0,64	0,41	Yes
History	34	-0,27	0,34	No
Agrarian and Agroalimentary Engineering	33	-0,36	0,49	Yes
Financial and Actuarial	32	-0,42	0,42	No
Agriculture, Farming and Rural Environment Engineering	31	-0,36	0,47	Yes
Civil Engineering	30	-0,48	0,54	Yes
Sound and Image Engineering	30	-0,58	0,51	Yes
Industrial Organization Engineering	30	-0,49	0,51	Yes

GENDER GAPS IN HIGHER EDUCATION (STEM VS NO STEM): RTI AND EXPOSURE TO AI INDICES

(continued)

Degree	Women (22-23)	RTI	IA (Webb)	STEM
Physics	28	-0,62	0,49	Yes
Terrestial Transport Service	28	-0,32	0,46	No
Mountains and Forestry Engineering	27	-0,35	0,47	Yes
Geography and Territory Ordination	27	-0,29	0,38	Yes
Industrial Technologies Engineering	26	-0,59	0,57	Yes
Energy Engineering	26	-0,56	0,56	Yes
Geomatics, Topography and Cartography Engineering	26	-0,45	0,53	Yes
Aeronautical Engineering	26	-0,64	0,60	Yes
Geography	25	-0,21	0,40	No
Mining and Energy Engineering	24	-0,44	0,52	Yes
Nautic and Maritime Transport	23	-0,18	0,48	No
Horticulture and Gardening Engineering	23	-0,19	0,46	Yes
Telecommunications Engineering	22	-0,62	0,54	Yes
Physical Activity and Sport	22	-0,29	0,35	No
Naval and Ocean Engineering	22	-0,38	0,56	Yes
Electronic Engineering	19	-0,57	0,53	Yes
Industrial Electronics and Automation Engineering	16	-0,54	0,55	Yes
Electrical Engineering	15	-0,50	0,55	Yes
Software and Application Development	14	-0,70	0,52	Yes
Computer Science	14	-0,73	0,53	Yes
Mechanical Engineering	14	-0,48	0,56	Yes
Computer Science Engineering	12	-0,79	0,54	Yes

Note: In green (red), those Degrees with a higher (lower) share of women enrolled. In green (red), those degrees with a lower (higher) value of the RTI index. And in green (red), those degrees with a higher (lower) exposure to AI, as it is correlated with higher wages and employment levels.

Sources: Schotte et al. (2023) y Webb (2020).