Temporal Correlation between Women studying Computing & Human Development Index (30 years of data)

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***Abstract*—This paper explores the correlation between a country's Human Development Index (HDI) and the same country's ratio of women studying computing, over time. Our dataset consists of the ratios of women students enrolled in higher computing education from N=35 countries with data points from a period of about three decades (1990–2020), a total of 513 data points. We use multiple linear regression for statistical modelling. We find a strong negative correlation between the proportion of women students in higher computing education and the HDI, globally, over time. We observe the same trend on a national level across the world. These findings extend the results from previous research on the gender equality paradox in ICT from a 'snapshot' in time to a *temporal* development, both globally, but also nationally. The results do not diminish the complexity of the issue nor discard that initiatives to support and encourage women as well as a more diverse body of students have effect.**

***Index Terms*—Gender, Computing Education, Diversity, Gender Equality, Human Development Index**

I. Introduction

Computer science education suffers globally from a gender imbalance. In fact, computer science is infamously the least equitable of the STEM (Science, Technology, Engineering, and Mathematics) fields [1]. According to a 2017 UNESCO report, women constitute only 30% of all STEM students in higher education globally, and the number is as low as 3% in ICT areas (Information and Communication Technology) [2].

The gender gap in computing education is visible both as a lack of enrollment [3]–[5] and a higher drop out rate of women students [6], [7], both of which bring about an underrepresentation of women in computing and engineering careers [8]. This phenomenon, known as the leaky pipeline of computing education, means that gender diversity decreases from compulsory to post-compulsory computing education and beyond [9], [10]. The gender gap only increases the further one looks up the academic ladder [11], [12].

While the computing education gender gap is an issue for many countries, there are notable differences to be observed globally. European and other developed countries score higher on general gender equality, but this is not associated with greater gender equality in computing education. In fact, the female proportion of students in ICT is much lower in developed countries (for instance, less than 10% of ICT students are women in Belgium and Luxembourg) than in countries that score lower on general gender equality, such as Saudi Arabia and Syria. For instance, the Arab countries have a 40–50% female participation in ICT programmes [13]. This disparity is often called the ICT Gender Equality Paradox, that is:

> Countries that are closest to achieving gender equality overall [...] have the fewest women pursuing the advanced skills needed for careers in the technology sector. Conversely, countries with low levels of gender equality [...] have the largest percentage of women pursuing advanced technology degrees [13].

Most existing research studying the ICT Gender Equality Paradox focuses on a single point in time, examining data from one year only (a snapshot). This research offers a longitudinal analysis: We explore the presence and extent over a prolonged period of time, across a wide range of countries. Initially, we model the global development of the ICT Gender Equality Paradox, over time. Subsequently, we present an analysis of the existence and development within all individual countries. We conduct a multiple linear regression analysis of the ratio of women students in computing education over HDI in 35 different countries, over time. Based on this substantial dataset, we find a stable, negative correlation between a country's HDI and its ratio of women students in higher computing education.

II. Background

This study investigates (the ratio of) ***women students***—as defined by each country's own reports—for lack of richer data. It is worth noting that not all countries necessarily quantify and report this in the same way and that there may be inconsistencies between different countries' reporting (see Section VI). Most countries have not historically kept records of non-binary people enrolled in education, and we do not know to which degree different countries have updated records regarding transgender students. When we look at historical records, we are therefore compelled to consider data which pertains to registers of binary sexes.

The programs included in 'Information & Communication Technology' (ICT) vary across countries. Some subjects which may be viewed as part of ICT, are not categorized as STEM majors by many universities; e.g., digital design, information studies, and science and technology studies (STS). These subjects are often taught by humanities colleges. We therefore use the term **computing education** to describe programs that teach computer science and computational thinking. The programs included in our data are not purely one kind (e.g., Computer Science), but rather computing-related. This is discussed further in the Threats to Validity section (Section VI).

In this research, we compare **two types of data**: (1) the **Human Development Index**, which is considered a relatively stable indicator of a country's social and economic living standards; *and* (2) the **ratio of women students enrolled in university-level computing education**. The first data is publicly available, while the second was gathered and cleaned by the research team, as described in the methodology section.

The Human Development Index (HDI) [14] attempts to quantify national social *and* economic conditions by considering the human development of a country along three dimensions: *health* (citizens leading long and healthy lives), *education* (access to knowledge and education), and *economics* (average wealth). The life expectancy index is determined by life expectancy at birth, and the education index is both considering the mean years of schooling for 25-year-old adults, as well as the expected years of schooling. Lastly, the GNI index measures a nation's yearly wealth [15]. These three dimensions are each referenced by an index that measures life expectancy, education, and Gross National Income (GNI) index, respectively, which altogether sum up to a country's HDI. The HDI ranges from 0.000–1.000 with South Sudan currently at the bottom with an index of 0.385 and Switzerland currently at the top with an index of 0.962, as of 2021 [14], [16]. HDI has been chosen in this study, as it is computed every year for all countries going back more than 30 years. This is not the case for any other indices that measure equality.

III. Methodology

This paper investigates the following research questions:

> **RQ1 (Global Perspective):** How does the trend of the gender equality paradox change globally over time in relation to improvements in HDI?
>
> **RQ2 (National Perspective):** To what extent does the gender equality paradox exist on a national level in relation to improvements in HDI over time?

The approach of this paper is an *exploratory quantitative methodology*. The novelty of this study is that we have data on the gender equality paradox of up to 30 years back and thus can study its development over time as a **global** (country-inspecific) trend as well as **national** (country-specific) trends.

A. Data Collection

The research question requires two types of data for an individual country: its yearly *HDI score* and the *ratio* (or, equilvalently, *percentage*) *of women students admitted in computing education* at the same points in time. Furthermore, both types of data need to exist for numerous different years for the correlational analysis to make sense.

While the HDI of a country is publicly available since 1990, the number and gender of students enrolled in computing education is more challenging to obtain. This data is *not* publicly available for most countries, and we therefore collected datasets from a number of different sources. This involved soliciting data from relevant educational and statistical institutions, ministries, incl. academic scholars via email. Other parts of the gathered data are from portals and websites.

For each country, we set out to collect the *percentage of women* students. (If unable to obtain data on *admitted students*, we accepted data on *enrolled students* as a *proxy* for admitted students. Both metrics ought not to differ substantially in terms of the *ratio of women students* which is ultimately what we are interested in quantifying.) We sought to obtain data from 2020 and as far back as possible (ideally as early as 1990, from whence HDI data is available). The goal was to obtain *enough* data that a meaningful statistical analysis could be performed and our research question could reliably be answered.

Our data collection proceeded according to *three* stages with each stage compensating for any shortcomings of prior stages:

Stage 1 (repository data): We began the data collection accessing *repository* data already available. Informatics Europe[1] has published data from 13 European countries on the admission to Informatics studies according to gender from around 2010 and onward. However, this data included only European countries, so we proceeded to the second stage:

Stage 2 (representative countries): The goal of this stage was a *systematic* approach of reaching out to countries with *representative* variation according to their HDI. Since there are around 200 countries on the HDI ranking, we decided to reach out to *every fifth country* according to the HDI rank (as of 2020). For each of these countries, we contacted the Ministry of Education (or similar) along with three universities. When restricting to responses containing relevant data, the response rate was 9% and yielded data from another 18 countries (11 from Europe, two from each of Asia, Oceania, and North America along with one from South America). These countries, however, were predominantly *developed* countries (HDI ≥ 0.80); correlating with countries with access to organized data. We therefore proceeded to a third stage:

Stage 3 (developing countries): This stage specifically targeted *developing* countries (HDI < 0.80); in particular, the BRICS[2] countries that have undergone recent rapid development. Since we expected a very low response rate, we reached out to ten universities per country rather than three, and also proceeded by sending personal email to our university faculty contacts, possibly via intermediary colleagues. Despite significant effort, this stage added only five new countries (two from Asia, two from South America, and one from Africa), bringing the total to N=35 countries (a total of 513 data points). Among the BRICS countries, we managed to get data from Brazil, Russia, and South Africa; we elaborate on the cases of China and India:

China is not included in our study for two reasons: First, from 1980 to 2015, China had a *one-child policy* [17] which

[1] Non-profit organization aiming to promote, shape and stimulate quality research, education, and knowledge transfer in Informatics in Europe.

[2] BRIC is a union of emerging economies formed in 2009, including: Brazil, Russia, India, and China. In 2010, it South Africa was added; hence: BRICS. (Recently, in 2024, Egypt, Ethiopia, Indonesia, Iran, and UAE were admitted.)

arguably contributed to a distorted (high) ratio of men to women which poses a significant threat to validity for our study [18]. Second, the well-known *media censorship* in China makes it difficult to retrieve data involving sensitive information from decades ago; in particular, the National Bureau of Statistics of China reports annual data, but only from 1999 and onward [19]. (Even so, this data is no longer available.)

India is also not included in our study even though we *did* obtain data from the country. This is because of a number of significant validity threats. Since the data came from so-called IITs (Indian Institutes of Technology), which are expensive elite universities requiring coaching before entering, the data is far from representative of the country. Women participation in CS is about 40% nationwide in 2015–2018; however, this number is very low for IIT's, ranging from only 8 to 14% [20]. Research reports that parents are reluctant to provide such coaching for their daughters (favoring their sons) and desire for their daughters to be educated closer to home, especially in same-sex colleges. The percentage of women students in these universities is thus significantly lower compared to the national average [21].

The global span of countries can be seen in Figure 1.

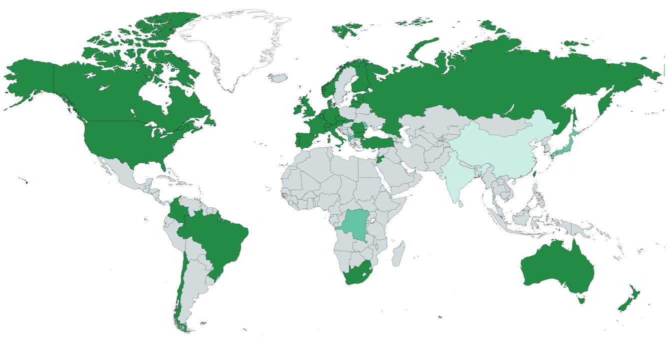


Fig. 1: Map of the countries of the study: ■ *Included* country; ■ *Excluded* country (too small sample); ■ *Excluded* country (due to validity threats). (Map created with MapChart.)

B. Data Characterization

Table I describes the data from the N=35 countries on which our study is based in terms of year range, the percentage range of women students (in the year range considered), HDI range (in the year range), and data source (where the data came from). In the few cases where we had two data sources for a given country, we favored the richer data source (we deliberately did not merge them as they may cover overlapping students). In the following, we clarify the content of each column in the table.

Country: The country column lists the countries included in the study. The N=35 countries correspond to about a sixth (16%) in terms of the number of countries in the world, with an over-representation of larger countries (modulo India & China). All habitable continents are represented albeit with an over-representation of occidental countries.

TABLE I: Characterization of the data from the N=35 countries included in our study according to year range, percentage of women, HDI range, and data source: Informatics Europe, Ministry, national Statistics bureau, or University.

Country	Year range	%Women	HDI range	Data
Australia	2001 – 2019	19 – 26 %	0.90 – 0.94	M
Austria	2000 – 2019	17 – 24 %	0.85 – 0.92	M
Belgium	2010 – 2015	06 – 08 %	0.91 – 0.92	E
Brazil	2000 – 2020	09 – 17 %	0.69 – 0.77	U
Bulgaria	2010 – 2018	27 – 33 %	0.79 – 0.81	E
Canada	1992 – 2018	27 – 40 %	0.86 – 0.93	S
Chile	2012 – 2020	08 – 12 %	0.82 – 0.85	U
Colombia	1990 – 2021	10 – 32 %	0.60 – 0.77	U
Czechia	2010 – 2018	12 – 17 %	0.87 – 0.90	E
Denmark	1992 – 2019	07 – 23 %	0.81 – 0.94	M
Estonia	2006 – 2020	19 – 31 %	0.84 – 0.92	M
Finland	2000 – 2021	15 – 29 %	0.86 – 0.94	M
France	2010 – 2018	08 – 10 %	0.88 – 0.90	E
Germany	2010 – 2018	15 – 21 %	0.93 – 0.95	E
Ireland	2008 – 2017	04 – 23 %	0.90 – 0.96	M
Italy	1990 – 2019	11 – 27 %	0.78 – 0.89	U
Jordan	2010 – 2020	33 – 51 %	0.73 – 0.74	U
Latvia	2015 – 2020	16 – 18 %	0.85 – 0.87	M
Lithuania	2013 – 2018	15 – 20 %	0.85 – 0.88	E
Luxembourg	2005 – 2020	13 – 28 %	0.88 – 0.92	M
Malta	2001 – 2020	17 – 24 %	0.80 – 0.90	U
Netherlands	2010 – 2018	11 – 22 %	0.92 – 0.94	E
New Zealand	2003 – 2019	18 – 28 %	0.89 – 0.93	M
Norway	2010 – 2018	16 – 21 %	0.94 – 0.96	E
Portugal	2010 – 2018	11 – 17 %	0.83 – 0.86	E
Romania	2010 – 2018	27 – 30 %	0.80 – 0.82	E
Russia	2012 – 2021	20 – 26 %	0.77 – 0.82	U
Slovakia	1995 – 2020	13 – 21 %	0.75 – 0.86	M
South Africa	2006 – 2019	14 – 27 %	0.63 – 0.71	U
Spain	1990 – 2020	12 – 30 %	0.76 – 0.91	M
Switzerland	2000 – 2019	06 – 12 %	0.90 – 0.96	M
Taiwan	1991 – 2020	27 – 38 %	0.85 – 0.92	M
Turkey	2010 – 2020	27 – 36 %	0.74 – 0.82	E
United Kingdom	2010 – 2018	15 – 18 %	0.90 – 0.93	E
United States	2012 – 2019	23 – 30 %	0.92 – 0.93	U
35 Countries	**1990 – 2021**	**04 – 51 %**	**0.60 – 0.96**	**–**

Year range: The Year column shows the *earliest* and *latest* year we could obtain data from a given country. The earliest year varies greatly according to the data available, the first data points being 1990 (Colombia, Italy, & Spain); the latest year is typically recent (within the range of 2018 to 2021). Note that there are some cases of data missing for individual years within the interval shown.

%Women: The %Women column gives the *lowest* and *highest* percentage of women students in the data for a given country. The lowest number is 4% in the case of Ireland (in 2008); the highest is 51% from Jordan (in 2017).

HDI range: The HDI column gives the *lowest* and *highest* HDI (with two decimal points) for a country within the year range for which we have access to data about %Women students. Since HDI mostly goes up in times of political peace, the lowest and highest HDI will typically be (close to) the earliest and latest year indicated for the country. The lowest HDI is Colombia with 0.60 (in 1990); the highest HDI is Norway & Switzerland with 0.96 (in recent years).

Data: The data source column shows where the data came from: Informatics Europe, Ministry, national Statistics bureau, or directly from one or more Universities.

C. Data Analysis

Throughout the study, regression is used as a tool in the data analysis for statistical modelling. Linear regression is a statistical method that determines the strength of the linear relationship between a *dependent variable*, y (that you are trying to understand), and one or more *independent variables*, x_i (that you suspect can predict y). In this study we use both multiple linear regression and simple linear regression. A multiple linear regression analysis is determining the *intersection* (aka, *intercept*), a, and *linear coefficients*, b_i, of the formula [22]:

$$y = a + \sum_i b_i \cdot x_i$$

(Simple linear regression analysis considers only *one* variable: $y = a + b \cdot x$; i.e., i=1.) If you have a *family* of observations, as in our case (with observations for each country, c), the formula generalizes to the following, while allowing for a family-dependent contribution (aka, *noise* or *error term*), ϵ_c:

$$y_c = a + \left(\sum_i b_i \cdot x_{ic}\right) + \epsilon_c$$

In our simple linear regression analysis of the inequality paradox, we consider *HDI* as the independent variable, as this has been done in previous studies of the issue.

The multiple linear model is parameterized on the *country* to allow the model to account for cultural variation between the countries i.e., fixed differences (ϵ_c). This will also allow for countries with roughly the same development in HDI to vary in the level of the proportion of women students in computing education, but experience the same *trend* in development. Obviously, *HDI* is considered as an independent variable because of the hypothesis of this paper. We have included the independent variable *year*, to account for the possibility that the ratio of women students simply changes (drop) over time. The variable year also captures if there is a general increase or decrease in the proportion of women in computing studies irrespective of other factors. We also include the interaction of the variables HDI & year; this will give us an indication whether the impact of HDI on the proportion of women in computing studies changes over the years, this can be used to asses if advancement in HDI are becoming more or less effective over time in influencing gender diversity in intake in computing educations. After a (tentative) model has been found, the residuals (the difference between the model and the actual data) and assumptions are checked in order to make any statistical inference. The *outcome* of a multiple linear analysis consists of several values: the intercept (a), the coefficient(s) of the linear relation (b_i), the country-specific baseline offset (ϵ_c), the p-values (p_a and p_{b_i}, for each b_i), the adjusted R-squared (R^2), and the residuals.

The coefficient parameters from the linear regression analysis output indicates whether a linear relation is *positive* or *negative*, along with the strength of the relation. A positive coefficient indicates that when the independent variable, y_c, increases by one unit, the dependent variable, x_{ic} increases by b_i. In contrast, a negative coefficient indicates that when the independent variable increases, the dependent variable decreases. The adjusted R-squared of the analysis (ranging from 0 to 1) relays how much of the variation of the proportion of women students in computing education that can be explained by the model:

$$R^2 = 1 - \frac{\sum_c (y_c - f_c)^2}{\sum_c (y_c - \overline{y})^2},$$

where y_c is the observed ratio of women students in computing education; f_c is the predicted (based on the model) ratio of women students in computing education; and $\overline{y}$ is the average of the observed ratio of women students in computing education.

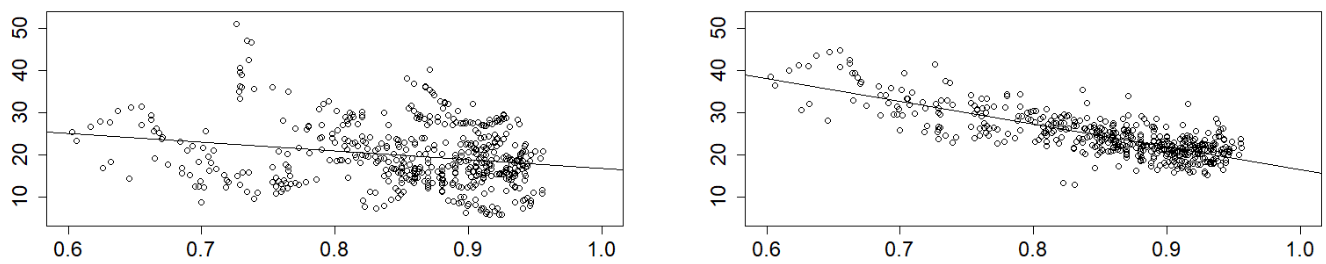
The p-values corresponding to the intercept p_a and independent variable p_{b_i} represent the probability that the data set (or a more extreme data set) could have randomly occurred when there were, in fact, *no* linear correlation between the dependent and the independent variable(s).

It should be mentioned that in order to consider the possibility of serial dependence of the ratio of women students in computing education from one year to the other, we have studied the difference in change between years. However, we see no trends towards serial dependence. In addition, to take into consideration other types of regression, we have also looked at quadratic and logarithmic regression. Unsurprisingly, the quadratic model is a (slightly) better fit, but only because it allows an extra term. A linear regression model is the best fit for our data. We have chosen to use linear regression models despite that over a longer period of time HDI will, in most cases, increase. A linear model will provide a nuanced understanding of how relationships between the variables evolve over time and across different categories, in this case countries. In addition, it can inform on complex dynamics and handle non-uniform data structures.

IV. Results

To answer **research question 1** (global perspective) we consider a model adopted from other studies of the gender inequality paradox, in which *HDI* is considered the descriptive variable and the proportion of women the output variable. The result of the model is visualised in Figure 2a. The HDI-model has a p-value of 5.475×10^{-7} and $R^2 = 4.796\%$. The residual plot does not show any systematic patterns, the QQ-plot of the standardised residuals does not show any significant deviations from the normal distribution, and neither does the frequency plot. We, therefore, conclude that based on this model, the descriptive variable HDI **correlates linearly** with the proportion of women students in computing education (see Figure 2a):

> **OBSERVATION 1 (Global Perspective):** The Human Development Index (HDI) of a country is strongly negatively linearly correlated with the percentage of women students in computing education at the university level.



(a) Linearity plot *without* country-specific baseline offset.

(b) Linearity plot *with* country-specific baseline offset.

Fig. 2: Correlation plots: Human Development Index (x-axis) *vs* the percentage of women studying computing (y-axis).

To answer **research question 2** (national perspective), we now perform a multiple linear regression analysis that investigates *country-specific offset* as well as testing for development over time and variation of the effect of HDI over time. As we are interested in HDI as a predictor of the proportion of women students in computing education, we consider a multiple linear regression analysis with HDI, country, year and the interaction of HDI and year as predictors.

We first check the model: the plot of residuals (the deviations of the observations from the sample mean) against the fitted values is randomly distributed around zero with no trends. Also the density plot of the residuals resembles a normal distribution, and the Q-Q plot is a straight line at an angle of 45 degrees. Thus, based on multiple linear regression with the independent variable year, *HDI*, their interaction, and the parameterization by the country, c, we conclude that there is a global (negative) relation between the development of the ratio of women students studying computing in a country and the change in HDI of the country.

Our analysis shows that the variable HDI has a p-value of 1.113%. In statistical terms this means that the probability that the data set (or a more extreme) could have randomly occurred when there were, in fact, no linear relation between the proportion of women students in computing education and the HDI of a country is 1.113% (i.e., one in 99). Further, that the variable year is also significant with a p-value of 1.18×10^{-133}, and that the interaction of year and HDI is significant with a p-value of 1.96×10^{-15}. The p-value for each country varies. The adjusted R^2 is 0.819 which tells us that 81.9% of the variation in the ration of women students in computing education can be explained by our model, i.e., the factors HDI, year, the interaction of year and HDI when taking into account the individual country. These are extraordinary numbers, as usually a p-value below 5% is the generally accepted criteria for *statistical significance*, and R^2 of above 60% indicates a good predictive power of the model.

The statistical model predicts that a change in the Human Development Index of $+0.1$ **HDI** (additional human development) will result in a negative change of -4.0 **pp** (diminished percentage points) in the percentage of women students in computing education. The detected (negative) relationship is furthermore statistically supported by its strongly significant p-values which strongly refutes the possibility that the proportion of women students admitted in computing education and HDI are not linearly correlated.

[3] As the p-values are very small, R is unable to compute the specific p-value.

The coefficient for the variable year is negative which suggest a negative trend over the years when other variables are held constant. The effects of the country variable are mixed, with some countries having positive coefficients and others having negative coefficients, indicating varying fixed levels of the proportion of women in computing studies across different countries. The year–HDI interaction term is slightly positive, suggesting that the negative impact of HDI on the proportion of women in computing diminishes over time.

Based on our analysis, we can further conclude that though the negative relation between HDI and the ratio of women students in computing education is *global*, there is a difference between countries. The difference between countries is the baseline offset (ϵ_c); i.e., the *baseline offset* for the percentage of women students in computing education is *country specific*. We can thus conclude that independently of whether some countries experience a high, middle, or low proportion of women students in computing education, the change (decline) in the proportion of women students in computing education is global; i.e., the women decline as a function of country development is independent of a given country. With a general intercept term, a, of 58.13% (at imaginary 0.000 HDI). The country-specific variation (ϵ_c) ranges from -13.4pp for Belgium to $+25.5$pp for Jordan. The country-specific intercept (a_c) is found by adding the global intercept (a) and the country-specific baseline offset (ϵ_c); i.e., $a_c = a + \epsilon_c$. Please see Table 3 for the main and country-specific baseline offsets.

Figure 2b is a visualization of the *linearity* of the correlation between the proportion of women students in computing education and HDI globally in a multiple linear regression model only factoring HDI parameterised by country. That is, the data for the proportion of women students in computing education

Country	Offset
Jordan	+25.5 (83.6)
Turkey	+14.7 (72.8)
Taiwan	+13.2 (71.3)
Bulgaria	+12.5 (70.6)
Romania	+11.7 (69.8)
Canada	+7.9 (66.0)
United States	+7.1 (65.2)
Estonia	+6.2 (64.3)
Russia	+4.9 (63.0)
South Africa	+4.5 (62.6)
New Zealand	+2.4 (60.5)
Finland	+0.4 (58.5)
Austria	+0.4 (58.5)
Malta	+0.2 (58.3)
Australia	0.0 (58.1)
Colombia	-1.7 (56.4)
Latvia	-1.7 (56.4)

Country	Offset
Spain	-1.9 (56.2)
Luxembourg	-2.1 (56.0)
Norway	-2.5 (55.6)
Slovakia	-3.3 (54.8)
Germany	-3.9 (54.2)
Italy	-4.0 (54.1)
Brazil	-4.2 (53.9)
United Kingdom	-4.2 (53.9)
Czechia	-4.3 (53.8)
Portugal	-4.4 (53.7)
Netherlands	-4.6 (53.5)
Denmark	-4.7 (53.4)
Ireland	-4.9 (53.2)
Lithuania	-5.5 (52.6)
Chile	-7.9 (50.2)
France	-10.4 (47.7)
Switzerland	-12.5 (45.6)
Belgium	-13.4 (44.7)

Fig. 3: Country-specific offsets (to general intercept $a = 58.1$).

has been adjusted such that the baseline for all countries is the same. This has been achieved by a transformation of the value of the proportion of women students in computing education for each data point for the country c according to the country-specific baseline offset (ϵ_c), see Table 3. By doing so, the data for each country is shifted up or down in Figure 2a, but the variation in the data for each country is not changed. Crucially, the *linearity* of the effect is obviously unaffected by shifting according to the country-specific offsets. This allows us to illustrate the global trend without the "noise" from the country-specific variation, ϵ_c (aka, noise terms).

In summary, we observe a **strongly linear effect**, as also testified by the strongly significant (low) p-value. Based on the data available and the statistical analysis of it, we can *confirm* the study hypothesis:

> **OBSERVATION 2 (National Perspective):** The gender equality paradox is a trend that exists and persists over time as a national trend across the world.

V. Discussion

Correlation does, of course, not imply *causation*. End of discussion.

VI. Threats to Validity

We now discuss the limitations of out study. First, we consider the extent to which our data quantifies what it is intended to measure (construct validity). Then, we investigate the extent to which our findings accurately represent the phenomena under study: the HDI–Gender correlation (internal validity). Hereafter, we ponder the extent to which our results generalize (external validity).

A. Construct Validity

Defining computing education? During data collection, we requested data from, e.g., ministries and universities, in regard to their computing educational programs. This meant that not only we, but also ministries and universities, were responsible for judging which studies to interpret as a computing educational study programme. This can obviously impact our results since some computing-related programs may have more women students than other programs. The comparison *between* countries may therefore not be optimal and can contribute to exaggeration in the country-specific variation. Importantly, however, the determination of which computing programs to include is *consistent for each country*, and the statistical model does indeed take *country-specific variation* into account. The temporal perspective should thus be unaffected by such "noise" in the data. Please note that this may thus account for some of the variation in country-specific offsets (cf. Table 3).

Is the data representative for the country? Some countries are only represented by data from few or even a single university, possibly from specific sub-region(s) within a given country. This poses a risk in that the data does not necessarily generalize to the entire country; particularly in the case of small data sets from large countries. We mitigate this threat by removing small data sets (e.g., North Macedonia where we only had data from 697 students). All data sets are based on, at least, 1,500 students and data from at least five years.

If a university has a low ratio of women students, there may be a risk that the administration or management would be reluctant to release the data to us. We mitigated this risk by guaranteeing all universities anonymity.

There may also be substantial HDI variation within a country (*northern* vs *southern* Italy is a classic example of this). The HDI data is, however, consistent for each country and, once again, the statistic regression model allows for *country-specific baseline offset* (similar to the previous threat).

Enrolled vs admitted students? The data from some countries (e.g., Spain and United States) consists of *enrolled students* in contrast to the rest of the data being *admitted students*. As a consequence, the results may show a slight delay in the proportion of women students, and the variation might not be as evident as for admitted students. We decided to keep the data, since it will display the same overall tendencies as for admitted students; in particular, the ratio of women students should not be substantially affected by this.

Measuring gender? In all likelihood, the data from each country is presumably based on biological sex at birth rather than self-identification gender. It would, of course, have been more interesting to work with gender rather than sex; however, we do not expect the findings to differ in any significant way, given the sheer size of the populations investigated. For the vast majoirty of the world population (97% on average), the two perspectives coincide [23].

B. Internal and External Validity

Country selection bias? Invariably, there will be some bias in the countries included in this study. Stage 1 was based towards countries with *public data*, which is most likely, in turn, biased towards countries with higher HDI. We attempted to mitigate this bias by adding data collection Stages 2 & 3, targeting also lower HDI countries. We decided that the sample was representative considering that all continents are represented and HDI varies substantially between 0.60–0.96.

Country exclusion? We excluded the two largest countries in the world (China and India) which collectively accounting for roughly a third of the world population. China was excluded because of a distorted gender ratio in the population [17] and India because the data gathered came from elitist IITs institutions, not representative of the country [20]. Since these are factors expected to non-trivially impact the gender ratio of computing students in both countries, we opted for excluding the countries from our data.

Beyond countries investigated? Since N=35 countries and all continents were represented in our data set and the results yielded a strong correlation, we speculate that the results hold for the rest of the world (subject to further investigation).

VII. Related Work

The ICT Gender Equality Paradox delineates a general discrepancy between countries that have achieved higher gender equality and the proportion of women in computing education [24]–[27]. The body of research on the subject can be divided into those who follow a national development over time, and those who compare global snapshots.

From the national perspective, for example, figures show that the percentage of women students in computing education dropped from 37% to 18% in the last three decades [28] in the United States. Similar declines have been detected in other wealthy countries such as Australia, New Zealand, and the Republic of Korea [29]–[33].

One explanation for the ICT gender-equality paradox is the so-called 'Affluent Nation' argument, which suggests that in more egalitarian societies, women's "innate preferences" emerge, leading them away from ICT careers [34]. However, [35] argue that gender disparities stem from math-related stereotypes, as seen in PISA data (2003 & 2012). They highlight the persistence of gender essentialism even as male primacy declines [36]. In wealthier nations, progressive values can reinforce the need to express 'gendered selves,' influencing career choices. Aligning with Inglehart's theory of post-materialistic values, as HDI increases, individuals prioritize self-realization in gendered ways [37].

A major critique of this argument is that it attributes gender disparity to women's choices while overlooking structural inequalities. It aligns with a neoliberal perspective that assumes gender equality is achieved, making disparities appear as personal preferences rather than systemic issues [38]. Such reasoning shifts focus away from organizational biases that sustain inequality.

A key blind spot in current research is *neosexism*—the belief that sexism no longer exists [39]. As overt discrimination has become socially unacceptable, sexism manifests in more covert forms [40]. Studies show that neosexism is prevalent in online discourse in developed countries [41] and remains constant even as other forms of sexism decline [42]. Subtle sexist biases are crucial in shaping perceptions of gender inequality [43]. Thus, our study does not endorse the 'Affluent Nation' argument but underscores the need to address the growing ICT gender paradox (especially whenever HDI rises).

A. Socio-Cultural Factors and the Gender Gap

One category of research has focused on identifying socio-cultural factors which lead to a gender gap in computing. For instance, women tend to be better represented (in science in general, rather than computing exclusively) as both students and faculty in countries where women are more likely to attend single-sex schools, such as predominantly Catholic countries [44] or Muslim countries. In Saudi Arabia, for instance, women comprised more than 40% of ICT students in 2019 [45]. Another country that presents interesting data is Malaysia, where computing is associated with office work and recognized as "suitable career path for women" [46].

In the United States and Western European countries, gender-based stereotypes and biases are found among the cultural barriers that mostly reduce women's willingness to choose computing education [47]. Among these, are parental influence and early social exposure to computers, as well as *stereotypes* about gender-related cognitive abilities [48], [49]. [35] similary present a cross-country analysis suggesting that essentialist gender norms regarding math aptitude can explain the link between development and segregation.

B. Economic Factors and the Gender Gap

Another body of research has presented evidence for economic factors influencing women in computing education. One study indicates that certain times of economic crisis impact the inclination of students to pursue a career in computing [50]. The authors report *job security* among the most important factors when choosing a career in computing. Research by [51] shows that the enrollment in Computer Science and Information Systems in the United States and Western Europe declined rapidly in relation to the 2000–01 "dot-com bubble." The burst of the dot-com bubble resulted in the failure and bankruptcy of many IT companies; hence, presumably lowering the perceived job security within the IT sector in its wake.

In the Science article from 1994, *Surprises Across the Cultural Divide*, Marcia Barinaga presents a speculation by Beatriz Ruivo (The National Board for Science and Technological Research in Portugal) that the *historical perspective* plays a significant role: Ruivo postulates that in countries where science and technology became firmly established during an era where women were not in the labor market, these disciplines became "a male domain" (deprived of women).

C. A Combination of Influences

Stoet & Geary used the PISA 2015 [52] assessment of 67 nations/regions to show that the gender equality paradox relating to computing education is driven by two processes: (1) broad contextual influences, such as relatively poor living conditions; *and* (2) more proximal factors, which include personal academic strengths and attitudes. The authors find a correlation between these two general factors and affirm that wider social factors may influence perceived individual strengths in what they call *expected long-term value of a chosen academic path*. In this sense, computing education can become more attractive in countries with lower economic opportunities.

[53] collected a wide range of global perspectives that show how women's underrepresentation in computing is largely influenced by both cultural and economic factors. One of the articles in the book, by [54], provides a descriptive mapping of gender inequality in careers and educational programs within computing, globally. They look at occupational data from 2017 and document gender differences in fifty countries. Their findings show that in a snapshot, socioeconomic modernization coincides with larger gender inequality in computing. Chow & Charles suggest that an explanation of these results can be found in the relationship between career aspirations and gender stereotypes in more developed societies.

While research has identified many of the dynamics that seem to be at play in explaining the gender gap in STEM, we have fewer comparative studies looking at a historical perspective, and even fewer studying *computing* in particular. The pipeline seems to be particularly leaky at the point of choice of tertiary education (college and university), and thus our analysis focuses on that point.

D. Experiences on how to recruit more women

There are a number of actions worth pursuing in computing eductaions in higher HDI countries to appeal to a broader body of students. First, it is crucial to address motivations that go beyond "safe career" path, but but focus on motivational factors such as passion, interest, enjoyment, and meaning [55], [56], [57]–[59]. Second, ability beliefs and self-efficacy have high impact on the choice of women to pursue an education in computing [60], [61], [62]. Academic self-concept is formed during a long journey throughout school experiences, feedback from others, and personal attributions to achievements [63]. Peer exchange and awareness among school teachers about gender imbalance can mitigate differences and increase women students' perceived capability to pursue further education in computing [64]. Third, it is imperative to avoid gender stereotypical communication [65] as well as overcome gender-specific attributions [61]. Efforts to increase women's participation in computing may benefit from building more inclusive cultures and providing students with early experiences that show them how success in this field can be distributed equally among girls and boys [26], [66].

VIII. Conclusion and Future Work

This study found evidence of a **strong negative correlation between the proportion of a country's HDI and its ratio of women studying computing** for N=35 countries from which data was available. The finding contributes two novel perspectives to existing research, namely that the ICT gender equality paradox persists and increases *over time*, and that this is a trend that also persists nationally around the world as HDI increases.

There is, of course, always the possibility that the relationship between HDI and the gender ratio in computing is *spurious*, without any relationship between the two variables. We deem this highly unlikely given the prior research and our present exploration of the gender equality paradox involving a large data set over the course of about three decades.

Our analysis revealed a large variation in the country-specific intercept, a_c (see Table 3) which supports the argument for socio-cultural, country-dependent explanatory factors. Given recent research, in particular, the impact of stereotypes [35], we believe best research efforts should focus on identifying socio-cultural factors on an *organizational* and *national* level which positively impact the increase of women students in ICT. Furthermore, given the prevalence of neosexism in developed countries [42], [43], we highlight a potential to uncover covert catalysts of gender segregation, for instance by considering knowledge and expertise from fields such as anthropology, psychology, and sociology.

The results underscore the importance of understanding the mechanisms behind gender disparities in computing education to inform policy and institutional interventions that promote equitable recruitment and retention. Without such research, efforts to address the gender gap risk being misdirected or ineffective. As digital technologies increasingly shape society, ensuring equal access and participation in computing education is not only a matter of fairness but also essential for fostering inclusive innovation and diverse technological development.

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