What contributes to gender parity in science? A Bayesian Network analysis

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We retrieve data from Dimensions, the World Bank Open Data (WBOA) and the UNESCO Institute for Statistics (UIS) to construct a country level longitudinal dataset including the yearly number of researchers by gender. Our aim is to predict when each country will reach gender parity and which factors may influence the increase of the proportion of women in science. Here we present some preliminary findings using the ARIMA and Exponential Smoothing forecasting models, and a first attempt to look into influencing factors using Bayesian Networks.

1. Introduction

The presence of women in science has increased in the last few decades, however, there is a widespread agreement that the experiences of men and women in the scientific workplace differ markedly (i.e. Macaluso, 2016). Overall, parity has not been achieved (Larivière et al., 2013), and about two thirds of scientists worldwide are men (United Nations Educational, Scientific and Cultural Organization, 2021). The "leaky pipeline" phenomenon describes the situation by which there tends to be more parity at the undergraduate level and the initial academic positions, but then the gender gap amplifies as we move up the career ladder (Corona-Sobrino et al., 2020). Secondly, we know there are differences between disciplines and countries (i.e. De Nicola & D'Agostino, 2021; Thelwall & Mas-Bleda, 2020). Disparities in the number of men and women participating in science are usually greater in fields such as STEM, economics or philosophy (i.e. Aramayona et al., 2022; Charlesworth & Banaji, 2019), while parity is somewhat largely achieved in humanities and some social sciences (i.e. Demaine, 2021). These field differences also vary by country. For instance, Indian women are encouraged to work at "computer" scientific jobs rather than do more technical tasks, since it is considered to be safer (Gupta, 2020), while countries with higher economic indicators have some of the largest gender gaps in STEMM disciplines (Science, Technology, Engineering, Math, and Medicine) (Charles & Bradley, 2009). Paradoxically, the democratization of higher education in some countries is not correlated with a higher "degendering" of fields (Stoet & Geary, 2018).

Policymakers are aware of this situation and try to raise awareness on the fact that there is still much work to be done. At the European level, the European Commission produces every 3 years the She Figures report (e.g., European Commission, 2021), which monitors gender equality in research and innovation across Europe. National legislators are also moving towards reaching gender parity. For instance, in Spain, the Congress recently passed the bill reforming Law 14/2011, of 1 June, on Science, Technology and Innovation (*BOE-A-2011-9617 Ley 14/2011, de 1 de Junio, de La Ciencia, La Tecnología y La Innovación.*, 2011), which includes legal security for gender equality in the science system. Also, the Spanish National Research Council publishes an annual report on the situation of women and science within the institution (Consejo Superior de Investigaciones Científicas, n.d.).

2. Background and purpose

The gender question has been looked at from numerous perspectives using a wide range of methodological approaches (González-Salmón et al., 2024). However, there is a lack of large-scale research done on estimations of when the situation will change and what leads to having more parity in some countries. Moreover, we lack a comprehensive analysis offering a global overview on gender in science, rather than just looking at case studies. One remarkable exception can be found in Holman et al. (2018). In their research, they use PubMed and arXiv to identify STEMM fields that will not reach parity without intervention. Using linear mixed models, they conclude that the gender gap is likely to persist for generations in some fields. Another exception is found in the work by Thelwall & Mas-Bleda (2020), in which they analyse Scopus data from 31 countries trying to show geo-cultural patterns and differences between countries and disciplines.

The present paper is part of a larger study in which we build from these studies with the aim of predicting parity in science worldwide and by country and identify national factors influencing the increase or decrease of gender parity. Here we present our preliminary trials at predicting gender parity and identifying influencing factors. We test the Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing models to predict gender parity given a 30-year time series of publication data. These models were deemed appropriate for forecast publication growth related to COVID-19 (Nane et al., 2023). To identify influencing factors, we test Bayesian Network models. Bayesian Networks models have been successfully applied to study, for instance, gender bias in peer review (Squazzoni et al., 2021) or predict author contributions statements in academia (Robinson-García et al, 2020). Here we show two illustrative cases of the performance of our methods. We look into Africa data and test the two forecasting methods aforementioned. Bayesian Network modelling is applied for the United Kingdom, by combining bibliometric data with external governmental sources.

3. Data and methods

In this research we work with Dimensions, World Bank Open Data (WBOA) and the UNESCO Institute for Statistics (UIS) data. All three are open sources that serve our purposes. All analyses are run in R (version 4.3.2).

3.1 Dimensions data and gender identification

We extracted 8.860.456 researcher profiles from the Dimensions database who had published at least five publications during the 1990-2021 period, limiting the research to authors that are somewhat established. Gender was assigned to authors based on bibliographic data using the WikiGenDex algorithm (González-Salmón & Robinson-García, 2024), which draws upon Wikidata and the World Gender Name Dictionary data. This algorithm takes country of origin and language into account. Furthermore, it considers national particularities on gender inference based on names and/or surnames. Compared to other gender assignment algorithms, it favours precision over recall, being less exhaustive than others (around 80% of recall, González-Salmón & Robinson-Garcia, 2024, Table1).

But still any finding using gender assignment algorithms is not free from biases and limitations. First, these algorithms consider gender as a binary variable (either a name is usually related to women or men in each country), thus hindering the fact that gender is not binary and other gender realities exist, such as nonbinary researchers. Moreover, given the state-of-the-art of the gender identification methods, it is not possible to obtain an appropriate estimation of gender of researchers of considerable regions and countries, such as some Asian countries and Saharan countries.

Figure 1 shows the percentage of researchers whose gender identification yielded either Woman/Man (that is, it was not "Unknown") given each country and Figure 1 explains this distribution by continents. As it is observable, gender identification reflects a more reliable image of the situation in Europe (with only 6.01% of names whose gender is unknown) than in Asia (with 44.5% of names whose gender is unknown).

Figure 1. Percentage of researchers whose gender identification was successful.

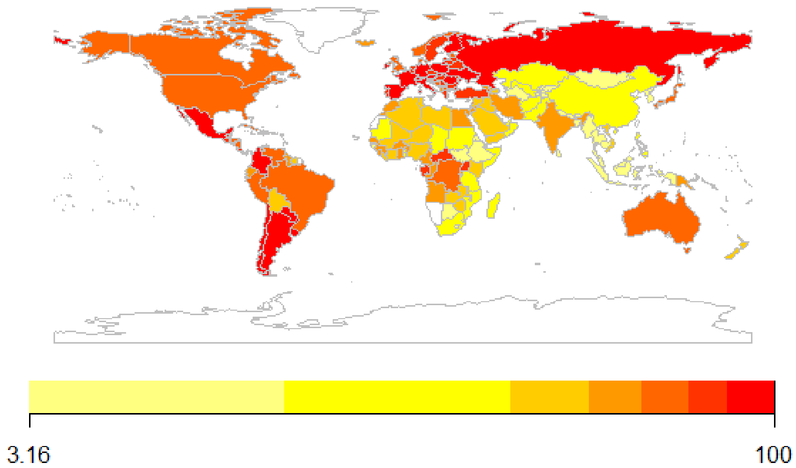


Table 1. Gender identification by continents

Continent	**Woman**	**Man**	**Unknown**
Africa	23.62%	48.18%	28.2%
America	34.5%	53.7%	11.81%
Asia	16.2%	39.29%	44.5%
Europe	37.56%	56.43%	6.01%
Oceania	37.29%	50.38%	12.33%

3.2 External data

In order to identify factors influencing gender parity levels, we enrich Dimensions data with data from the World Bank Open Data (WBOD) and UNESCO Institute for Statistics (UIS). WBOD is a database belonging to the World Bank that provides open access statistics on different elements related to development for all countries (available at: https://data.worldbank.org/). The most complete statistics go from 1990 until 2021 (except for Researchers in R&D which accounts until 2016). The UIS database is the United Nations database on country-level statistics on education, science, and culture (available on: https://uis.unesco.org/). The statistic we are using covers from 1996 until 2021.

We have downloaded data from WBOD and UIS related to education, gender, and general wealth of each country. Latest data on these indicators is mostly from 2021, which correlates with the Dimensions data. We have downloaded the following indicators from WBOD and UIS, as shown in Table 2. The data is not complete for all years nor countries.

Table 2. Yearly indicators from WBOD (1990-2021) and UIS (1996-2021)

Acronym	**Definition**	**Source**
R_expenditure	Research and development expenditure (% of GDP)	WBOD
R_million	Researchers in R&D (per million people)	WBOD
ArtHum	Female share of graduates in Arts and Humanities programmes (%, tertiary)	WBOD
BusAdLaw	Female share of graduates in Business, Administration and Law programmes, tertiary (%)	WBOD
AgriFore	Female share of graduates in Agriculture, Forestry, Fisheries and Veterinary programmes (%, tertiary)	WBOD
STEM	Female share of graduates from Science, Technology, Engineering and Mathematics (STEM) programmes, tertiary (%)	WBOD
Education	Female share of graduates in education (%, tertiary)	WBOD
Engineering	Female share of graduates in engineering, manufacturing and construction (%, tertiary)	WBOD
HealWelf	Female share of graduates in health and welfare (%, tertiary)	WBOD
InfoCom	Female share of graduates in Information and Communication Technologies programmes, tertiary (%)	WBOD
NatuMaths	Female share of graduates in Natural Sciences, Mathematics and Statistics programmes (%, tertiary)	WBOD
Other	Female share of graduates in other fields than Science, Technology, Engineering and Mathematics programmes,	WBOD

	tertiary (%)	
Services	Female share of graduates in services (%, tertiary)	WBOD
SociJourInfo	Female share of graduates in Social Sciences, Journalism and Information programmes (%, tertiary)	WBOD
Unknown	Female share of graduates in unknown or unspecified fields (%, tertiary)	WBOD
Domestic	Proportion of time spent on unpaid domestic and care work, female (% of 24 hour day)	WBOD
Leave	Length of paid maternity leave (calendar days)	WBOD
Out_school_f	Adolescents out of school, female (% of female lower secondary school age)	WBOD
Bachelor_f	Educational attainment, at least Bachelor's or equivalent, population 25+, female (%) (cumulative)	WBOD
Master_f	Educational attainment, at least Master's or equivalent, population 25+, female (%) (cumulative)	WBOD
Doctoral_f	Educational attainment, Doctoral or equivalent, population 25+, female (%) (cumulative)	WBOD
F_manager	Firms with female top manager (% of firms)	WBOD
Labor_force	Labor force participation rate, female (% of female population ages 15+) (modeled ILO estimate)	WBOD
School_enroll	School enrollment, primary (gross), gender parity index (GPI)	WBOD
Teachers_f	Trained teachers in upper secondary education, female (% of female teachers)	WBOD
Researchers_F	Researchers (HC) - % Female	UIS

A problem we have encountered with both WBOD and UIS data is the lack of data for some years and countries. We have obtained those 27 indicators from 226 countries/regions, belonging to five regions (East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America and Other). Data availability varies per country. For instance, we find robust coverage of yearly statistics in European countries, while coverage on South Asia is less complete. Reasons for this missing data range from lack of statistical capacity from some countries to the fact that some countries did not exist during the whole period we are covering (World Bank, 2024).

3.2 Methodological design

The first part of the research consists of an analysis of Dimensions data which focuses on the proportion of women researchers alone, by applying two of the most used time forecasting tools: Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing methods (Hyndman & Athanasopoulos, 2018). With these methods, we predict the number of researchers by gender by making use of the corresponding historical data only. ARIMA models account for both past data, as well as model error at previous time steps. The parameters, as well as the choice of the number of previous time steps accounted for are typically estimated using a maximum likelihood approach. Exponential smoothing methods account for past data by giving them exponentially decaying weights, with less recent data contributing less to the forecast than more recent data. Both models are implemented in R in the *forecast* package (Hyndman, 2024).

Since we are interested in forecasting the time to gender parity, we investigate the predictive performance of those models. That is, we split the time available interval into a training (by using 80% of the data) and a testing (which uses 20% of the data) set. The models are fitted on the training data only and their predicted performance on the test data is obtained. The predictive performance is investigated with respect to Mean Absolute Deviation (MAD), which is the average of the absolute errors of the forecasts with respect to the actual data. In this paper we investigate the predictive performance of the models using data on Africa. We have divided data on men and women researchers and applied both ARIMA and Exponential Smoothing to it. That represents 59,777 men and 21,350 women, ranging from 19 women in 1990 to 3,366 women in 2021, and from 153 men in 1990 to 8,409 men in 2021. Women represented 11.05% of researchers in Africa in 1990, 10.17% in 2000, 22.48% in 2010 and 28.59% in 2021.

Second, we test the use of Bayesian Networks (BNs). BNs are graphical models which capture dependencies between multiple variables. The dependencies are first-hand modelled through arcs from nodes (which represent random variables) and the structure of the BNs can be learned completely from data. They are popular methods which are employed in numerous applications (Scutari & Denis, 2021). Many algorithms are available to learn the BN structure, and we have used Hill-Climbing, a score-based Bayesian learning algorithm, included in the R Package *bnlearn* (Scutari, 2024). This innovative predictive method accounts for more information along the number of scientists by gender. The information includes, for example, female enrolment in different levels of education, weeks of paid maternity leave, etc. Bayesian Networks enable the identification of dependencies between such variables, and to model predictions of the number of women researchers considering these dependencies. Thus, we use BNs to explore the potential influence among variables.

Along with dependencies between certain variables relating to the number of women researchers, time dependencies could also be accounted for. With this respect, the Dynamic version of the Bayesian Networks could be employed, which also takes time into account in dependence modelling. Even though Dynamic Bayesian Networks will not be explicitly analysed in this paper, we emphasise their importance, and defer their analysis in a later manuscript. In this paper we explore the potential uses of Bayesian Networks using data on the United Kingdom, as it is one of the countries with more available data. Still information for some years and statistics was missing (only three years had information for all years, the rest of variables had at least one year's data missing), and we have interpolated the missing data (719 out of 1152 possible data was available, thus we have interpolated 37%). Data used goes from 1990 until 2021, and we have not used all indicators but eleven of them for the trial, thus we have 352 observations to construct the BNs.

4. Preliminary results

4.1 Predicting parity: ARIMA and Exponential Smoothing

Our analysis starts with using ARIMA and Exponential smoothing methods to forecast the number of women scientists. Figure 2 shows both models of data on researchers in African countries by gender. The data have been split into a training and test set. For the test set, both the forecast (in blue) and the actual data (in red) is presented. Along with point forecasts, 80% (light grey) and 95% (dark grey) confidence intervals capture the uncertainty inherited by the estimates. As it can be visually inspected, exponential smoothing yields more realistic predictions. The forecasts are closer to the actual data, and the uncertainty is considerably lower. Table 3 shows the MAD test, for comparison between sets. The MAD test shows how exponential smoothing performs better in the training data, but ARIMA has better accuracy for the testing data.

Figure 2. ARIMA applied to Dimensions data on African researchers identified as men (top left) and women (top right), and Exponential Smoothing applied to African researchers identified as men (bottom left) and women (bottom right).

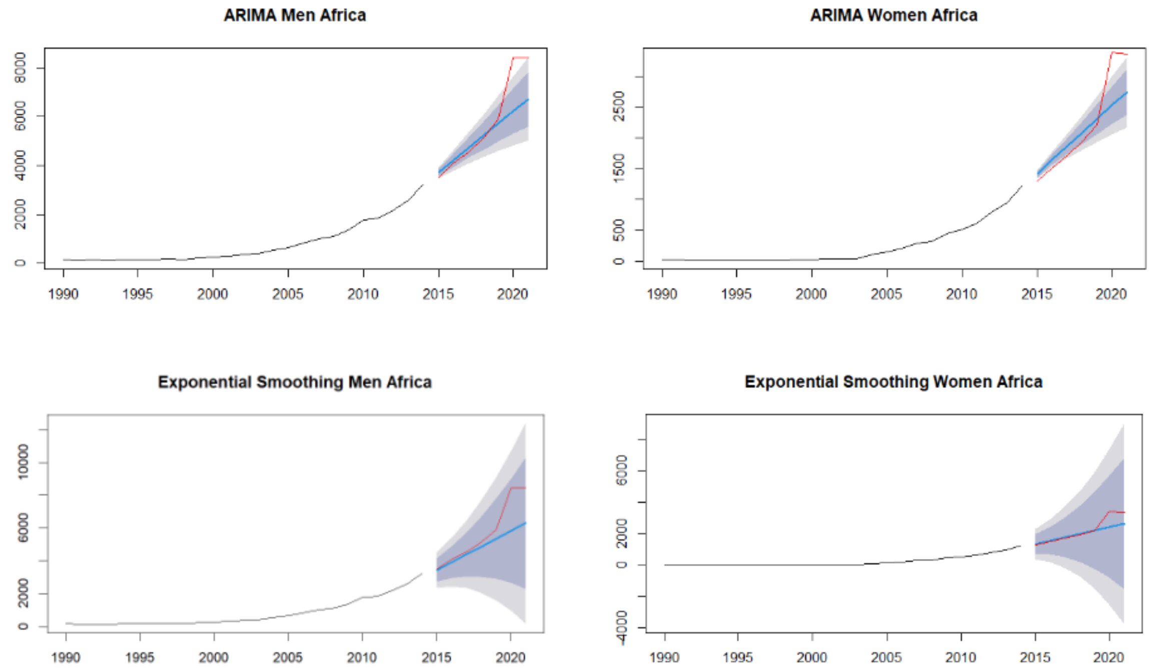


Table 3. MAD test for Africa data divided by gender

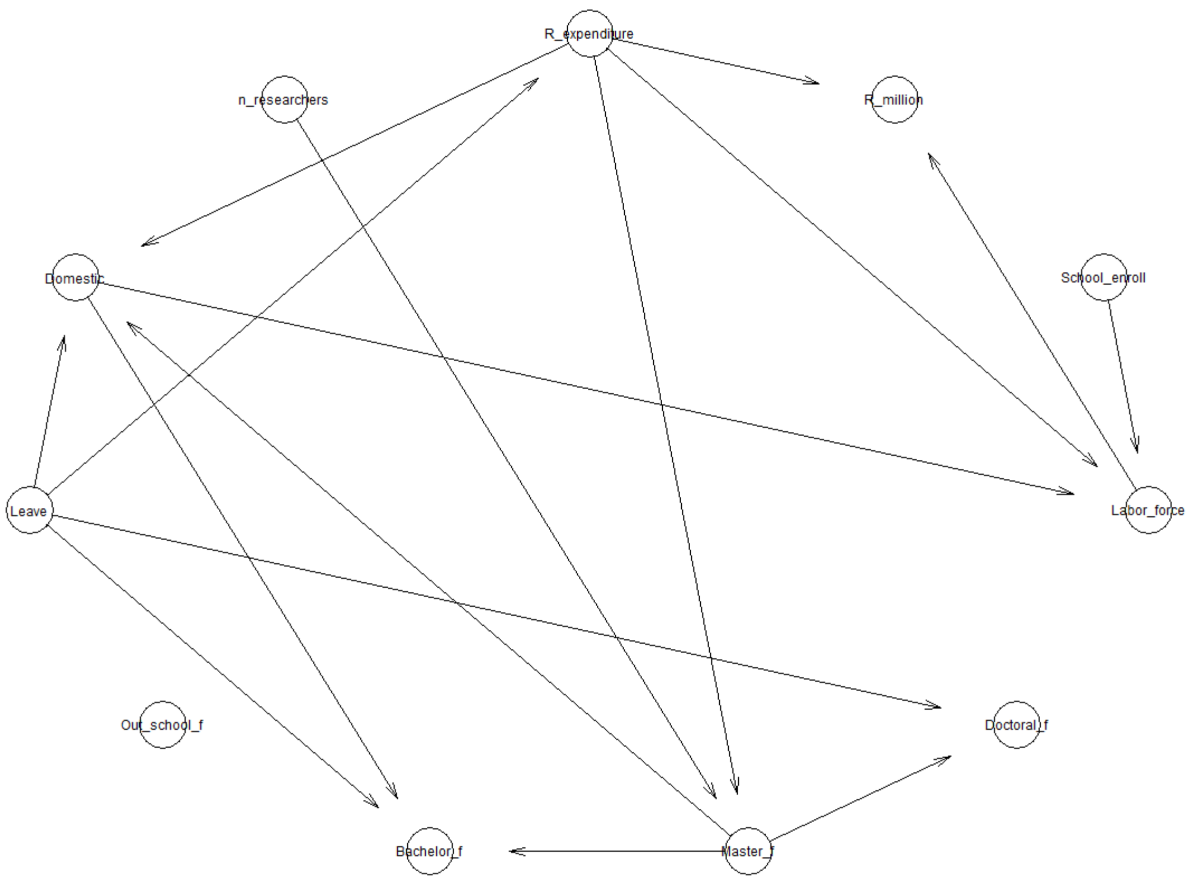
Model	MAD train Men	MAD test Men	MAD train Women	MAD test Women
Exponential Smoothing	0.121	846.740	0.258	266.673
ARIMA	73.270	659.757	20.041	300.743

However, using the ARIMA or the exponential smoothing model does not allow us to explore the relationship between the number of men and women researchers and other variables, such as the number of graduates in a specific field or R&D investment. It is assumed that additional information can explain and therefore support in better predicting the number of women scientists. Thus, we focus next on applying (Dynamic) Bayesian Networks.

4.2 Affecting factors: Bayesian Networks

Figure 3 shows a Bayesian Network applied to some of the aforementioned indicators for the United Kingdom (we have not included all to ensure readability[1]). We have included three indicators on the basic stats on academia on the United Kingdom (Share of women's researchers, R&D expenditure, number of researchers per million of habitants), three indicators related to women's labor force conditions (Proportion of time spent on unpaid domestic and care work, length of paid maternity leave and female labor force participation), and five indicators related to education (School enrolment, Adolescents out of school and female attainment of Bacherlor's, Master's and Doctorates). This range of indicators allows us to get a deeper understanding of the inner relationships between education, science and society in general.

Figure 3. Bayesian Network using UK data



This first approach to Bayesian Networks in the United Kingdom shows some insights. Each node represents a variable, and the directed edges represent dependencies in which the directionality is represented by the arrow. Directionality implies that the distribution of the child

[1] For this example, we have not selected those indicators related to graduates in certain disciplines, and we have focused on giving a general picture.

node (the node pointed at) is expressed conditionally by the distribution of the parent node (the node from which the arrow originates).

In this case, the variable of interest is n_researchers, which is a lonely node. Moreover, as we can see, the variable R_expenditure (Research and development expenditure) influences four other variables, as the directionality of the arrow shows. These variables are R_million (Researchers in R&D), Domestic (Proportion of time spent on unpaid domestic and care work, female), Master_f (Educational attainment, at least Master's or equivalent, population 25+, female) and Labor_force (Labor force participation rate, female). These variables, in turn, affect others. According to this interpretation, the only variable that does not affect nor is it affected by others is Out_school_f (Adolescents out of school, female). In other words, the variable 'Out_school_f' does not seem to be influenced nor to influence any other included variables.

5. Discussion & Conclusions

In this study, we show preliminary findings of a study which soughts to illuminate the complex dynamics of gender parity in science. Our findings suggest that while predictive models like ARIMA and Exponential Smoothing offer valuable insights into the trajectory of gender parity in scientific roles, they must be complemented by deeper explorations of the underlying factors influencing these trends. Specifically, the ARIMA model provides a robust framework for understanding temporal trends and forecasting future scenarios based on historical data. Meanwhile, Exponential Smoothing has proven particularly effective in capturing more immediate, short-term fluctuations in gender parity, thereby offering a nuanced view of potential short-lived deviations from longer-term trends.

Our first tests with Bayesian Network modelling still need further testing, as we can gather from the United Kingdom case in which our variable of interest appears to be a lonely node. However, the combination of bibliometric data with national statistics derived from WBOD and UIS will greatly inform our analyses. As reported beforehand, missing data is an important limitation when considering a global analysis on factors influencing gender parity levels. To solve this, we are applying Spline Interpolation methods to estimate the missing data. Spline Interpolation is a process of establishing unknown values given known ones. Here we are applying Cubic Spline Interpolation, which "uses third-order polynomials for interpolation between data points" (Cuevas et al., 2024, p. 163). We expect to report a more comprehensive dataset once we have identified the maximum data we can reasonably interpolate for each country.

The next steps will be determining how much WBOD and UIS data we can interpolate for results to still be robust. Then, we will be able to know how many countries we will analyse and apply the Bayesian Networks to. We are also considering if the use of Dynamic Bayesian Networks is possible. Dynamic Bayesian Networks, which have the advantage of being designed for time-series data, take into account the direction of time (Murphy, 2002).

Open science practices

Dimensions data, World Bank Open Data and UNESCO Institute for Statistics are open data, thus the replicability of the research is plausible. Data is being handled using R and RStudio, which are open source and freely available software. We have used the following R packages: bnlearn, forecast, ggplot2, dplyr and imputeTS. Furthermore, the gender identification algorithm used is openly available (https://github.com/egonzalezsalmon/WikidataGender).

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Author contributions
Elvira González-Salmón: Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project Administration

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Gabriela F. Nane: Writing – Review & Editing, Methodology, Visualization

Nicolás Robinson-Garcia: Conceptualization, methodology, resources, data curation, Writing – Review & Editing, Supervision, Project Administration

Competing interests
Authors of this research have no competing interests.

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