MASTERARBEIT | MASTER'S THESIS

Titel | Title

Gender Gap in Exposure to GenAI: Evidence from Austria

verfasst von | submitted by

Anastasiia Rubanik

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2026

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 913
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Applied Economics
Betreut von | Supervisor:	Assoz. Prof. Daniel Garcia PhD

Contents

Abstract

The goal of this thesis is to quantify the gender gap in the exposure to generative AIs in Austria. It uses the genAI exposure index for occupations (ILO 2025) combined with Labour Force Survey Data from Statistics Austria (Statistics Austria 2025). The main method is the twofold Oaxaca-Blinder Decomposition. The calculations were performed using the oaxaca package in R (Hlavac 2022). The influence of factors such as the age, the education, the migration background, the type of household and the type of work (full-time or part-time) on the gap was analyzed. It was confirmed that women have higher exposure to genAI than men in Austria: the average exposure to genAI for women is 17.5% higher than for men (0.27 for men and 0.32 for women). In addition, the effect on the genAI exposure of obtaining the university education for women was estimated to be weaker than for men. And, the level of education was found to be a strong predictor of the exposure and accounts for 72% of the gap. It was tentatively confirmed that (married) women with children in households without other people are expected to have higher exposure to genAI than men in the same circumstance, compared to other household types. Lastly, it was shown that the first-generation migrants are less exposed to genAI than people without the migration background or later generation migrants.

Abstract

Ziel dieser Arbeit ist die Quantifizierung der geschlechtsspezifischen Unterschiede in der Exposition gegenüber generativer künstlicher Intelligenz (genAI) in Österreich. Hierfür wird der genAI-Expositionsindex für Berufe (ILO 2025) mit Daten der Mikrozensus-Arbeitskräfteerhebung von Statistik Austria kombiniert (Statistik Austria 2025). Die Hauptmethode ist die zweifache Oaxaca-Blinder-Dekomposition. Die Berechnungen wurden mit dem R-Paket oaxaca (Hlavac 2022) durchgeführt. Der Einfluss von Faktoren wie Alter, Bildungsniveau, Migrationshintergrund, Haushaltstyp und Vollzeit- oder Teilzeitbeschäftigung auf die Unterschiede wurde analysiert. Es konnte bestätigt werden, dass Frauen in Österreich einer höheren genAI-Exposition ausgesetzt sind als Männer: die durchschnittliche Exposition von Frauen liegt 17.5% höher als die von Männern (0.27 bei Männern und 0.32 bei Frauen). Darüber hinaus wurde der Einfluss eines Hochschulabschlusses auf die genAI-Exposition bei Frauen als geringer festgestellt als bei Männern. Das Bildungsniveau erwies sich als starker Prädiktor für die Exposition und erklärt 72% der Unterschiede. Es wurde vorläufig bestätigt, dass (verheiratete) Frauen mit Kindern in Haushalten ohne weitere Personen voraussichtlich einer höheren genAI-Exposition ausgesetzt sind als Männer in derselben Situation, verglichen mit anderen Haushaltstypen. Schließlich zeigte sich, dass Migranten der ersten Generation weniger von genAI betroffen sind als Menschen ohne Migrationshintergrund oder Migranten späterer Generationen.

1 Introduction

All over the world, including in Austria, gender inequality in the workplace persists (Statistics Austria 2025; OECD 2024; PwC 2024). At the same time, artificial intelligence (AI) is increasingly used to perform more and more work tasks. This naturally results in a discussion of the impact of AI on the labour market (OECD 2023; IMF 2023). There are multiple scenarios of how generative AIs will affect the workplace in different occupations: some occupations will be complemented by AIs, while other occupations will be eliminated. Automation and AI reshape labour demand, displacing some workers while creating new complementary tasks and job opportunities (Acemoglu and Restrepo 2018; 2019). Generative AI increases risks of inequality, with evidence of disproportionate impacts on women and other vulnerable groups (LinkedIn 2024; Dencik et al. 2025). There is a real possibility that artificial intelligence will affect the gender gap in the labour market, possibly making it larger or changing it in some way. AI exposure indexes (TEAI, ILO genAI Index) help quantify which occupations are most at risk or likely to be augmented by AI technologies (Colombo et al. 2024; ILO 2025).

A review of the literature begins with the work of Keynes, who introduced the concept of "technological unemployment". This concept refers to a situation where technological progress and mechanisation reduce the demand for labour faster than new jobs can be created (Keynes 1930). Later, one of the first systematic analyses of the potential of computerisation to substitute human labour was conducted, using the input-output modeling to estimate the long-term impact of automation on the employment. This work laid an important foundation for subsequent research on automation and labour market transformation (Leontief and Duchin 1986). Around this time, the concept of the "glass ceiling" emerged in the research literature, becoming one of the key concepts regarding gender inequality in the labour market. It describes a situation where women formally have access to professional development, but in reality, face invisible barriers preventing them from reaching it. This concept showed that even with equal input into education and participation in the labour market, equal career outcomes are not guaranteed (Morrison, White, & Van Velsor 1987).

At the beginning of the 21st century, the debate about the introduction of new technologies and computerisation on the labour market continued. An important concept was introduced:

new technologies would not necessarily replace human labour, but would change work tasks. Thus, tasks were categorised as routine tasks, non-routine interactive tasks and non-routine analytical tasks. It has been argued that new technologies replace routine tasks but complement the non-routine analytical and the non-routine interactive tasks (Autor, Levy, and Murnane 2003). Later, Acemoglu and Autor developed these ideas and introduced a formal "task-based model" to understand the impact of automation on various occupational groups. The essence of this work was that automation does not replace workers directly, but displaces routine tasks and complements analytical and the creative ones. Hence, automation reduces the labour demand for workers performing routine tasks (Acemoglu and Autor 2011). Later, Frey and Osborne assessed the risk of job automation in the United States and concluded that approximately 47% of jobs were at high risk of computerisation. This highlighted the potential impact of automation on the employment, sparking a broader debate about the future of the labour market. This was one of the first studies to attempt to identify which occupations were at risk of being replaced by new technologies (Frey and Osborne 2013). In addition, Brynjolfsson and McAfee argued that the development of digital technologies is leading to a new phase of technological change, referred to it as the digital revolution. This phenomenon significantly increases labour productivity and transforms the structure of the employment and the labour markets (Brynjolfsson and McAfee 2014). In 2016, a comprehensive analysis of the gender pay gap and occupational segregation was presented. This study aimed to explain why the gender wage gap persists despite increased education, labour market participation among women, and formally equal rights. The authors pay particular attention to the institutional and structural factors that maintain persistent income differences between men and women. Among other things, this work emphasised that women with children often experience slower wage growth (Blau and Kahn 2017). Later, it has been shown that technologies can not only replace or complement tasks, but also create new ones (Acemoglu and Restrepo 2018). At the same time, empirical data has shown that the increased use of industrial robots leads to a reduction in employment and a decrease in wages in regions most susceptible to automation, due to the substitution of some work tasks by the machines. It was concluded that although new technologies can create new jobs, they do not always compensate for the losses caused by automation (Acemoglu and Restrepo 2020).

In recent years, the impact of digitalisation and the development of artificial intelligence on gender gap in the labour market has received increasing attention, combining these two topics. For example, research by LinkedIn shows that these technological changes have a disproportionate impact on women, increasing existing gender inequality in employment (LinkedIn 2024).

Despite Austria's high level of democratisation and human rights protection, a gap in income and career opportunities between men and women still exists. For example, in 2023, according to the Gender Pay Gap indicator, women in Austria earned on average 18.3% less than men in terms of average gross hourly earnings. This is higher than the EU average of 12% (Statistics Austria 2025; BMFWF 2025).

All this leads to the next research question which is the key issue in this thesis: to what extent are women and men in Austria exposed to generative AIs in the workplace, and what are the key factors affecting their exposure to genAI? Hence, the goal of this thesis is to quantify the gender gap in the exposure to generative AIs in Austria.

This is the first work that investigates the gender gap in exposure to genAI in the workplace in Austria.

During the research process, four hypotheses were put forward and tested, outlined below.

The Hypothesis 1 is that women have higher exposure to genAI than men in Austria. This is based on the evidence that gender inequalities in the labour market outcomes are present, despite the progress made in the recent decades (Böheim, Fink, and Zulehner 2019; Leitner 2023). In particular, in 2023 Austria observed 18.3% gender pay gap, one of the highest levels in the European Union (Statistics Austria 2025). This, combined with the fact that women are disproportionately concentrated in clerical, administrative and service occupations (Leitner 2023), which are expected to be particularly impacted by generative AI (ILO 2023; Cazzaniga et al. 2024), leads me to propose this hypothesis.

The Hypothesis 2 of this thesis is that the effect of obtaining the university education on the genAI exposure is stronger for women than for men. This is based on the evidence of possibility of discrimination of women with same qualifications as men in the labour market outcomes (Blau and Kahn 2017), particularly in highly skilled positions (Grund 2015). And, the fact that the proportion of women receiving higher education is higher than that of men in Austria (Statistics Austria 2025) provides preliminary support for this hypothesis.

The Hypothesis 3 is that (married) women with children in households without other people are expected to have higher exposure to genAI than men in the same circumstance, compared to other household types. In households without other people, childcare is less likely to be shared, increasing time constraints on parents. Mothers in such households face stronger incentives to choose flexible forms of employment (Berghammer 2014; Riederer and Berghammer 2020). This results in a higher proportion of women with children who work part-time and are predominantly employed in office, administrative, and service occupations compared to men in similar circumstances (Riederer and Berghammer 2020; Leitner 2023). These occupations are particularly susceptible to automation (Cazzaniga et al. 2024; ILO 2023; Bishnu et al. 2025), suggesting a higher exposure to genAI for women.

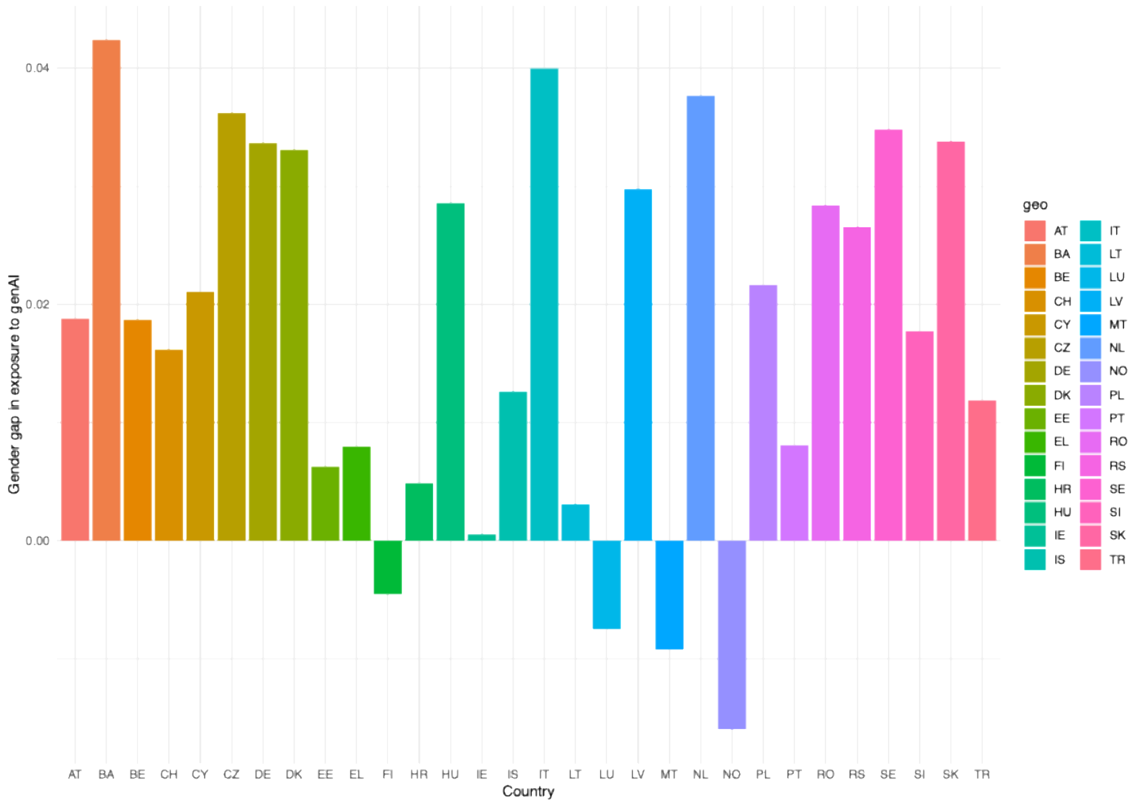
The fourth and last Hypothesis of this thesis is that first-generation migrants are less exposed to genAI than people without the migration background or later generation migrants. The evidence for Austria suggests that first-generation migrants are disproportionately represented at both low and highly educated workers, but underrepresented among the workers with intermediate-level of qualifications (Expert Council for Integration 2024; Leitner 2023; Ingwersen and Thomsen 2021). This with the evidence that middle-skilled occupations are more susceptible to automation (Acemoglu and Restrepo 2018; OECD 2023) suggests support for this hypothesis.

Before performing the main analysis, a preliminary analysis was carried out to determine whether a gender gap in exposure index exists. To begin with, I estimated the difference in mean cross-occupation exposure between men and women in Austria. The goal was to verify that the gap exists and to compute a baseline gender gap in the exposure index. The genAI exposure index estimated by the ILO (ILO 2025), and was aggregated by ISCO-08 3-digit occupations, and an average weighted by the proportion of genders in each occupation was estimated for men and women. The proportion of genders in each occupation was calculated based on the employment data for 2024 year from Eurostat (Eurostat 2024). The preliminary result is that on average, women in Austria are more exposed to genAI than men. The average exposure index for women is 0.32, and for men is 0.28.

Then, for a comparative analysis and assessment of the general situation in the entire Eurozone, the same analysis was carried out for all European Economic Area (EEA) countries and Switzerland in order to see the overall picture that would form the background for this study. It is important to note that although Switzerland is not part of the European Economic Area, it is integrated with this group of countries and is located on the same continent as other countries in this union, so it was also chosen as a subject of the analysis. This comparative analysis was conducted to see if the gender gap in exposure is present in the EEA countries to establish a baseline. To obtain the results I used the same method of weighted averages, described in the previous paragraph, but applied to several countries.

The Figure 1 shows the graphical presentation of the results, obtained in this analysis. More specifically, the figure shows the difference in mean exposure to genAI between women and men for each country. Positive values indicate that the average exposure index for women is higher than for men. Tabulated numerical results are attached in the Appendix 1 "Gender gap in exposure to genAI in EEA area and Switzerland".

Figure 1. Gender gap in exposure to genAI in EEA countries and Switzerland



The result shows that most EEA countries (including Austria) observe a gender gap in the exposure to genAI. Figure 1 shows that women have consistently higher exposure than men across the EEA and Switzerland, except for four out of the thirty countries: Norway (NO) – (-0.016), Luxembourg (LU) – (-0.007), Malta (MT) – (-0.009) and Finland (FI) – (-

0.005). The highest positive values, or to put it differently, the largest gaps in the exposure to genAI, are observed for Bosnia and Herzegovina (BA) – 0.042, Italy (IT) – 0.04, Netherlands (NL) – 0.038, and Czech Republic (CZ) – 0.036. The countries with positive near zero values are Ireland (IE) – 0.001, Croatia (HR) – 0.005, Estonia (EE) – 0.006.

The rest of this thesis examines the structure of the gender gap in the exposure to genAI in Austria and its features are characterised based on the combination of the LFS data and ILO's exposure index.

This thesis consists of an introduction, four main chapters, a conclusion, a list of references and ten appendixes.

2 Data Overview

In order to answer the research question posed in the introduction, the following main data sources were used: GenAI exposure index from the International Labour Organisation paper for 2025, Austrian Microcensus Labour Force Survey / Housing Survey for 2025 (SUF edition) by Statistics Austria and Employment data from EUROSTAT for 2024.

2.1 Main data sources description

2.1.1 GenAI exposure index from the International Labour Organisation (ILO) paper, 2025

It is a synthetic index of occupational exposure to genAI calculated by ILO. The index was originally released in 2023, and a new version was released in late May 2025 using an updated methodology.

The detailed calculation of the index is stated in the article and is as follows: first, the authors used "a representative sample from the 29.753 tasks in the Polish occupational classification system and a survey of 1.640 people employed in each 1-digit ISCO-08 groups." In addition, "52.558 data points were collected regarding perceived potential of automation for 2.861 tasks." As a next step, "this input was compared with a survey and several rounds of Delphi-style discussions among a smaller group of international experts. Based on that procedure, a repository of knowledge about task automation was created that goes beyond national specificities." The authors used it "to develop an AI assistant able to predict scores for tasks in the description of ISCO-08" (ILO 2025).

In other words, genAI exposure index is a mean of per occupation tasks’ exposure to genAI. First, an exposure index is estimated for each task. Then, per task indices are aggregated for ISCO-08 occupations to produce a mean exposure index for each occupation.

It is worth noting that the index targets genAI specifically (and not just AI) due to its availability and reported potential for task augmentation in the workplace. To define this term in more detail, various definitions of generative AI are presented in the Appendix 2. To sum up these definitions, genAI is a subset of AI that is capable of generating new ideas and content, and thus capable of performing tasks previously performed by humans (for instance, writing programming codes, teaching material as a teacher, or even painting as an artist). Hence, this particular subset of AI was chosen as the subject of this study because of the potential for replacement of the workforce by this type of AI.

2.1.2 Austrian Microcensus Labour Force Survey / Housing Survey for 2025 Quarter 1 (SUF edition) by Statistics Austria

“With about 20000 households surveyed per quarter, the Microcensus is the largest regularly conducted sample survey in Austria. It is an important data source for national and international labour market indicators and regularly provides information on housing and families” (Statistics Austria 2025). Further in the analysis I refer to this dataset as LFS data for convenience.

Data from this survey is not publicly available, therefore access to it was requested in the beginning of the research process. However, descriptions of variables are published and available in the open access, and so this study reproduces the descriptions.

At the time of this research, only the data for the first quarter of 2025 were available, which is the most recent data for this study. In particular, the quarterly data was requested and not the yearly data to avoid the sampling bias and preserve variability. Since the goal was to determine gap in the exposure to genAI in Austria as accurately as possible, it was decided to combine the ILO’s genAI exposure index with this LFS data for Austria. This particular survey was chosen as the data source because it provides the most detailed description of the labour force in Austria.

2.1.3 Employment data from EUROSTAT for 2024

This source provides aggregate employment data for the EU based on the European Union Labour Force Survey data. Eurostat data were used to conduct a preliminary analysis before accessing LFS data from Statistics Austria. In addition, this source was used for the cross-country comparative analysis presented in the introduction in order to get a benchmark. It is not for the year 2025, since during the research (October 2025 – April 2026) the data for the year 2025 was not available. Although this data is for the year 2024, it was assumed that the year-on-year change should be negligible.

2.2 Data limitations

Before moving on to the data preparation process, it should be mentioned that using the ILO index leads to several limitations in the analysis. First of all, ILO's genAI exposure index is available at the occupational level and not at the individual level. Hence, it is not possible to compare men and women in the same occupation directly. And second, ILO's index is not available for military occupations due to the specifics of these particular occupations and the index methodology. Therefore, these occupations are excluded from the scope of this analysis.

3 Method

The methodology used in this thesis consists of the six main stages, briefly presented below and described in detail later in this chapter.

First, the initial data preparation was performed. Parameters suitable for testing the hypotheses were selected, and variable transformations were performed where necessary. In addition, ISCO-08 codes were aggregated to enable further analysis. Next, weighted averages of the exposure index for the EEA and Switzerland countries were estimated using the employment data from Eurostat. This stage provided an overview of the situation across the EU and a preliminary estimate of the gender gap in Austria, allowing for comparative analysis. Furthermore, it allowed further verification of the calculation results obtained using the LFS data from Statistics Austria. The genAI exposure index from the ILO paper was assigned to individuals from LFS data. This was done to conduct the main analysis of the study, which is described below. After that, the twofold Oaxaca-Blinder decomposition was performed. Within this method, the OLS regression specification was used. The reference coefficients for the twofold Oaxaca-Blinder decomposition were obtained by performing the OLS regression on the pooled sample and included the group indicator variable (female). As a next step, analysis of the results of the decomposition and underlying regressions was performed and the results were described.

In addition, robustness checks were performed. Standard errors for the Oaxaca-Blinder decomposition estimates were obtained using the bootstrap method. Estimates obtained by combining the ILO index and Eurostat data to calculate the gender gap in the exposure to genAI in Austria were compared with the results from the analysis conducted using the ILO index and Statistics Austria LFS data. Moreover, two separate models with different education groupings were estimated to validate the selection of variables.

3.1 Data preparation

The data preparation process started with removing unemployed persons from the LFS data and aggregation of the ILO index by ISCO-08 3-digit codes to make it compatible with the LFS data. Then, categorical variables were expanded into dummy variables, removing dummies that represent the baseline categories for each categorical variable to avoid multicollinearity.

Variables selected for this thesis are summarised in the Table 1 below. The selection of the variables was conducted in stages to identify key variables that have an effect on the exposure and are in line with the research question and postulated hypotheses. It is worth noting that the full description and the complete list of variables from this dataset is publicly available in German from the Statistics Austria website. The description in the Table 1 is based on the Austrian Labour Force Survey codebook published by Statistics Austria (Statistics Austria 2025), but reformulated, shortened and translated into English.

Table 1. Description of the selected variables for the analysis (based on Statistics Austria 2025)

Variable	Description	Type of variable
xdberug08	A collection of responses to the question "What is your occupation?" coded according to the 4-digit ISCO-08 codes (occupational categories).	Nominal categorical
bsex	A variable for gender, can be male or female.	Binary
xbalt5	Age categories, which are divided into 5-year groups.	Ordinal categorical

Variable	Description	Type of variable
kartab11	The highest level of education obtained.	Nominal categorical
xeinw	Division of municipalities into classes based on population size.	Ordinal categorical
xhhtyp4	A variable for the private households. Type IV provide a more detailed breakdown of households: by (married) couples, with or without children, and with or without another person in the household; single-parent households, with or without another person; households with two or more families, etc.	Nominal categorical
dseitz	Experience in months at the last place of work (tenure).	Discrete
xmigr_gen	This variable divides respondents into groups: those with no migration background, first-generation migrants, and second-generation migrants. Those with a migration background had both parents born abroad, first-generation migrants were themselves born abroad, and second-generation migrants were born in Austria.	Nominal categorical
danzn	Enterprise size categories by the reported number of employees.	Ordinal categorical
xdstd	Part-time/Full-time (hourly allocation). This variable groups usual weekly working hours into part-time (up to and including 35 hours) and full-time (more than 35 hours).	Binary

Since the ILO's index assigns indices to occupations, it is not possible to use occupations directly, because they are perfectly correlated with the exposure index. And, columns "ÖNACE-Gruppen" (aggregate of answers to the question "In which sector do you work?") were not selected for the study, as sectors are closely related to occupations.

It is important to note that the variables in the data were modified in order to test the hypotheses and enable the application of the Oaxaca-Blinder decomposition.

The ILO's exposure index was joined with the LFS data on ISCO-08 codes. First, the mean of the exposure index for each 3-digit ISCO-08 code was calculated. Then, the inner join of the exposure index and LFS data on the ISCO-08 codes was performed. The inner join was used here to filter out occupations that were missing from either dataset.

Gender (variable "bsex") was converted to a variable that represents females, named "female". The value of the female variable was set to 1 where "bsex" was equal to 2 (Female) and set to 0 otherwise.

A new variable “is_large_city” was created. This variable was set to 1 where “xeinew” variable in the source data corresponded to the municipality population of more than 100000, and to 0 otherwise.

A new variable “experience” was created by dividing the variable “dseitz” by 12, to convert months of experience at the last place of work to years.

A new variable “is_first_gen_migr” was created. This variable was set to 1 where “xmigr_gen” was equal to 1, and to 0 otherwise. This was done to create a variable representing first-generation migrants (i.e., people who were themselves born abroad and immigrated to Austria). This variable is important for testing the Hypothesis 4 (that first-generation migrants are less exposed to genAI).

A categorical variable “enterprise size” was created from the “danzn” variable to represent the enterprise size. The values of “danzn” that represent enterprise size below 10 were aggregated in the dummy “enterprise.size.employees.less_than_10”. The values of “danzn” from 10 to 13 were converted to binary variables: “enterprise.size.employees.10_to_19”, “enterprise.size.employees.20_to_49”, “enterprise.size.employees.50_to_249”, “enterprise.size.employees.250_or_more”. Last, a binary variable was created to represent “danzn” values equal to 15: “enterprise.size.employees.unknown_10_or_more”. These variables were selected for the analysis, along with the variable indicating the population size of the place of residence, to partially replace occupations, which cannot be included in the regression due to their presence in the ILO index. These indicators are not directly related to occupations, but indirectly reflect their characteristics.

A new variable “child_single_family_household” was created to represent the narrowed household type. This variable was set to 1 where the household type IV variable (“xhhtyp4”) was equal to 3 ((married) couples with children without any other person), and 0 otherwise. The Statistics Austria’s survey questionnaire makes no distinction between married couples and registered partnerships. This was done to check the Hypothesis 3 (it was hypothesized that women in (married) couples with children in households without other people are expected to have higher exposure to genAI than men in the same circumstances, compared to other household types).

A new variable “full_time” was created. The “full_time” variable was set to 1 where “xdsdt” variable was equal to 2, and to 0 otherwise. Values of “xdstd” equal to 2 correspond to normal working hours from 36 hours, and values of “xdstd” equal to 1 correspond to normal working hours up to and including 35 hours.

The highest level of education of an individual in the source data is represented as a level variable “kartab11”. The original variable has 19 levels and corresponds to the Austrian classification of education. The “kartab11” variable was converted to the ISCED 2011 classification to allow for reproducibility, improve result stability, and reduce estimation uncertainties. It was done based on the “Umschlüsselung nationaler Bildungsformen zu ISCED 2011 im Rahmen der Mikrozensus-Arbeitskräfteerhebung (ab 2014)” document (Statistics Austria 2014). The exact mapping is presented in the Appendix 3.

3.2 Estimation of the weighted average of the exposure index using the employment data from Eurostat

As a preliminary research step, the cross-occupation weighted gender gap in the exposure index was computed for Austria (and in addition for the comparative purposes – for the EEA countries and Switzerland). The goal was to compute a baseline gender gap in the exposure index. This was computed using a weighted average of the exposure index across occupations, weighted by the proportion of women in each occupation.

As a result, three weighted averages of the exposure index were computed in this part of the analysis: the average exposure index for women, weighted by proportion of women in each occupation, the average exposure index for men, weighted by proportion of men in each occupation and the average exposure index, weighted by the number of employed persons in each occupation.

3.3 Twofold Oaxaca-Blinder decomposition

The main method of this thesis, used to answer the research question, is the twofold Oaxaca-Blinder decomposition. There are two types of the Oaxaca-Blinder decomposition: twofold and threefold. I chose the twofold decomposition instead of the threefold decomposition because the unexplained component of the twofold decomposition captures the discrimination effects in one estimate (Rahimi and Nazari 2021), while in the threefold decomposition the discrimination effect is split into two estimates. And, similar studies that focus on the different treatment of males and females also use the twofold decomposition.

The Oaxaca-Blinder decomposition method was originally introduced in the 1973 paper by Robert Oaxaca, in which he investigated the wage gap between men and women in the labour market (Oaxaca 1973). Nowadays, it is widely used to study differences (gaps) between two groups. For example, this method is often used to analyse wage differences by gender, ethnicity, economic region, etc. More precisely, the use of this method can be seen in studies about the gender pay gap (Leythienne and Ronkowski 2018; Hedija 2023), the wage gap between immigrants and natives (Ingwersen and Thomsen 2021), and health inequalities between the urban and rural residents (Rahimi and Nazari 2021).

This method estimates the decomposition of the effects into two parts: explained and unexplained. The explained part captures the effect of the differences in the observable characteristics. The unexplained part contains unobserved effects, and as was assumed, includes discrimination. In other words, this is the proportion of differences that cannot be explained by the observed characteristics. The unexplained part captures difference in treatment and also captures possible discrimination and modeling errors.

The Equation 1 shows the detailed formula used for the twofold Oaxaca-Blinder decomposition analysis:

Equation 1. Oaxaca-Blinder Decomposition Specification

$$\Delta Y = E(log(Y_A)) - E(log(Y_B)) = \underbrace{(E(X_A)' - E(X_B)')\tilde{\beta}_R}_{Explained} + \underbrace{\{\overbrace{E(X_A)'(\tilde{\beta}_A - \tilde{\beta}_R)}^{UnexplainedA} + \overbrace{E(X_B)'(\tilde{\beta}_R - \tilde{\beta}_B)}^{UnexplainedB}\}}_{Unexplained}$$

$$log(Y_g) = X_g'\beta_g + \epsilon_g, \quad E(\epsilon_g) = 0 \quad g \in (A, B)$$

Where: "Y_g" is the outcome variable, i.e. the exposure index; "$\tilde{\beta}_R$" is the vector of the adjusted pooled regression estimates; E(X) are the vectors of means of the explanatory variables; "$\tilde{\beta}_A$" is the vector of the adjusted regression estimates for men; "$\tilde{\beta}_B$" is the vector of the adjusted regression estimates for women; subscripts represent the groups: A is men, B is women, and R is reference group (pooled).

The logarithm of the exposure was chosen as the outcome variable instead of the absolute value since the goal was to compare the effects and because the absolute value of the index is not meaningful by itself. At the same time, the OLS regression was chosen because it provides consistent, efficient, and unbiased estimates under the assumptions of this thesis. And, it ensures comparability with existing studies.

The regression estimates were adjusted according to the procedure proposed by Gardeazabal and Ugidos (Hlavac 2022; Gardeazabal and Ugidos 2004) to ensure the invariability of the decomposition estimates to the choice of the omitted baseline category. The procedure is implemented in the oaxaca package (Hlavac 2022) used in this thesis. The use of this procedure allowed for the estimation of the effect of the omitted education category.

The coefficient estimates were obtained via three separate regressions. The first regression was based on the samples for group A – males. Second regression was based on the samples for group B – females. The third regression estimated using the pooled samples from the both groups (A and B) and included the female variable. The first two are the parts of the standard Oaxaca-Blinder decomposition procedure. The third regression provides reference coefficients used in the twofold Oaxaca-Blinder decomposition.

There is a choice when selecting the reference coefficients. The oaxaca package for R calculates 6 options for the reference coefficients. This thesis uses the estimates obtained via the pooled regression that included the group variable “female”. This method of deriving reference coefficients was first proposed by Neumark (Neumark 1988). Using the pooled regression allowed me to avoid systematic bias by not choosing the non-discriminated group manually, and instead using coefficients estimated from the population as the reference. And, including the group variable in the pooled regression ensured that the decomposition estimates were not distorted due to the omitted variable (Jann 2008).

The empirical analysis was conducted using the R statistical software. In particular, the oaxaca package created by Marek Hlavac (Hlavac 2022) was used to perform the Oaxaca-Blinder decomposition and the generation of the decomposition plots.

Since the outcome variable is the logarithm of the exposure, it should be noted that the Equation 2 is used in interpreting the results and converting the estimated coefficients into percentages:

Equation 2. Formula for converting the estimated regression coefficients to percentages

$$\Delta\% = 100 * (e^{x} - 1)$$

3.4 Bootstrap standard error estimation procedure

The standard errors for the estimates obtained via the Oaxaca-Blinder decomposition were estimated using the bootstrap method. This method was used instead of the analytical formula since it provides robust estimates and asymptotically converges to analytical result, while the analytical formula requires separate derivation and is outside of the scope of this thesis.

More accurately, the bootstrapped standard errors are calculated based on the user-specified number (R) of sampling replicates. The process of calculating standard errors that the oaxaca package employs in this analysis is as follows according to the article by the creator of this package: "R resamples are randomly sampled with replacement from the relevant set of observations. Decomposition estimates are calculated for each of the R resamples. The bootstrapped standard error is the standard deviation of the R decomposition estimates" (Hlavac 2022). In addition, it is relevant to mention that using more than 1000 replicates (R=1000) is not particularly useful for the purposes of this thesis, since it provides minimal improvements.

4 Results

This chapter presents the results obtained during the research process and provides an interpretation for them. First, a summary of the overall findings is provided. A graphical analysis of the sample is presented for the context and the subsequent analysis of the results. Then, the key parameters for the hypotheses are discussed. Next, additional results for the variables with most significant effects on the gap are presented.

4.1 Results summary

First, as was mentioned before in the text, the preliminary analysis, consisting of the estimation of the weighted average of the exposure index using the employment data from Eurostat showed that on average, women in Austria are more exposed to genAI than men and the average exposure index for women is 0.32, and for men is 0.28.

After that the Oaxaca-Blinder decomposition was carried out. Particularly, the twofold Oaxaca-Blinder decomposition was performed that used pooled regression estimates from the regression that included the group indicator variable "female" as reference coefficients.

Regression summaries are presented in Appendixes 4, 5 and 6. Means and estimated effects from the individual regressions are attached in the Appendix 7. The twofold Oaxaca-Blinder decomposition estimates are presented in the Appendix 8.

After performing the Oaxaca-Blinder decomposition, I found that the average exposure to genAI for women is 17.5% higher than for men in Austria. The difference of mean exposure indices, and decomposition estimates divided into explained and unexplained parts and arranged as an equation are presented in the Equation 3:

Equation 3. Gender gap in exposure to genAI in Austria

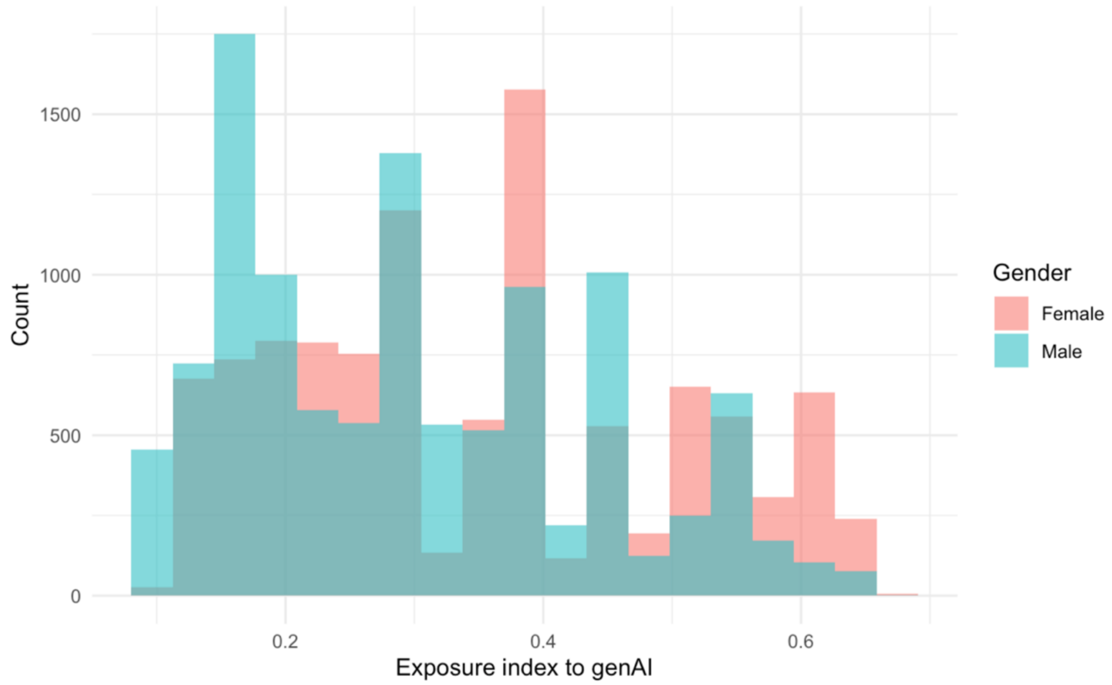
$$\underbrace{(-1.3124) - (-1.1508)}_{\Delta Y} = \underbrace{\overset{(0.00368)}{(-0.0085)}}_{Explained\ (5.3\%)} + \underbrace{\overset{(0)}{0}}_{Unexplained\ A\ (0\%)} + \underbrace{\overset{(0.00638)}{(-0.1531)}}_{Unexplained\ B\ (94.7\%)}$$

The explained part, shown in the Equation 3, accounts for 5.3% of the gap, and the unexplained part accounts for 94.7%. A is men, B is women. The standard errors, which were estimated using the bootstrap method, are stated above the decomposition estimates in the brackets. The unexplained estimate is statistically significant at 0.1% confidence level and the explained estimate is statistically significant at 5% confidence level. The unexplained coefficient for the group A (men) is 0. This occurs because I included the female variable in the pooled regression. This indicates that men are the non-discriminated group in this research context. It is important to mention for the future results interpretation that the gap is negative and is -0.1616. This means that the average exposure index for women is higher than for men. Hence, the Hypothesis 1 that women in Austria are more exposed to genAI that men was confirmed.

It is worth noting that such large unexplained part is expected, since the difference in the means is small and not significant for the majority of the parameters (this is demonstrated further in the analysis of the results).

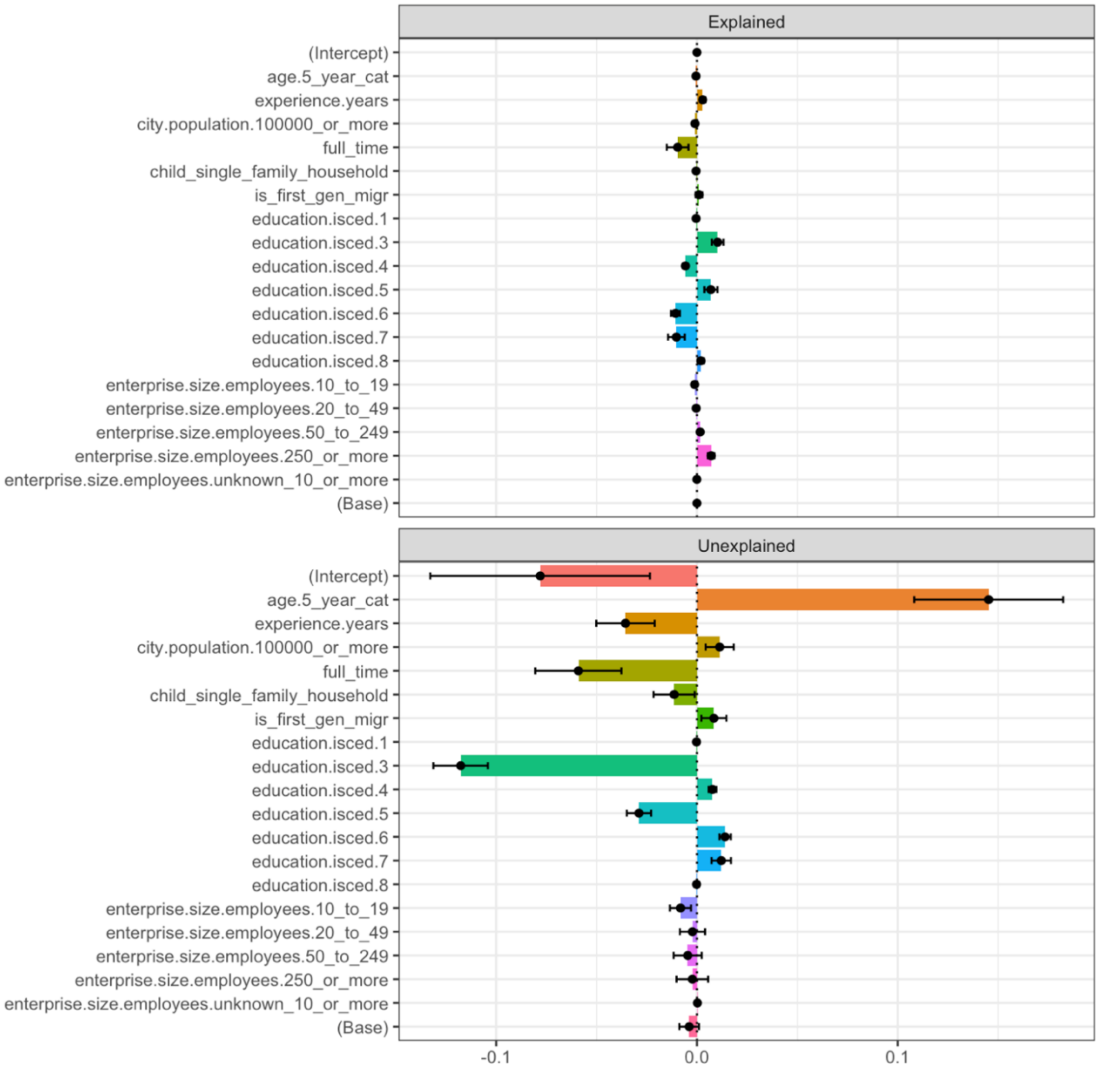
Figure 2 shows the exposure index distribution in the sample by gender.

Figure 2. Exposure index distribution in the sample by gender



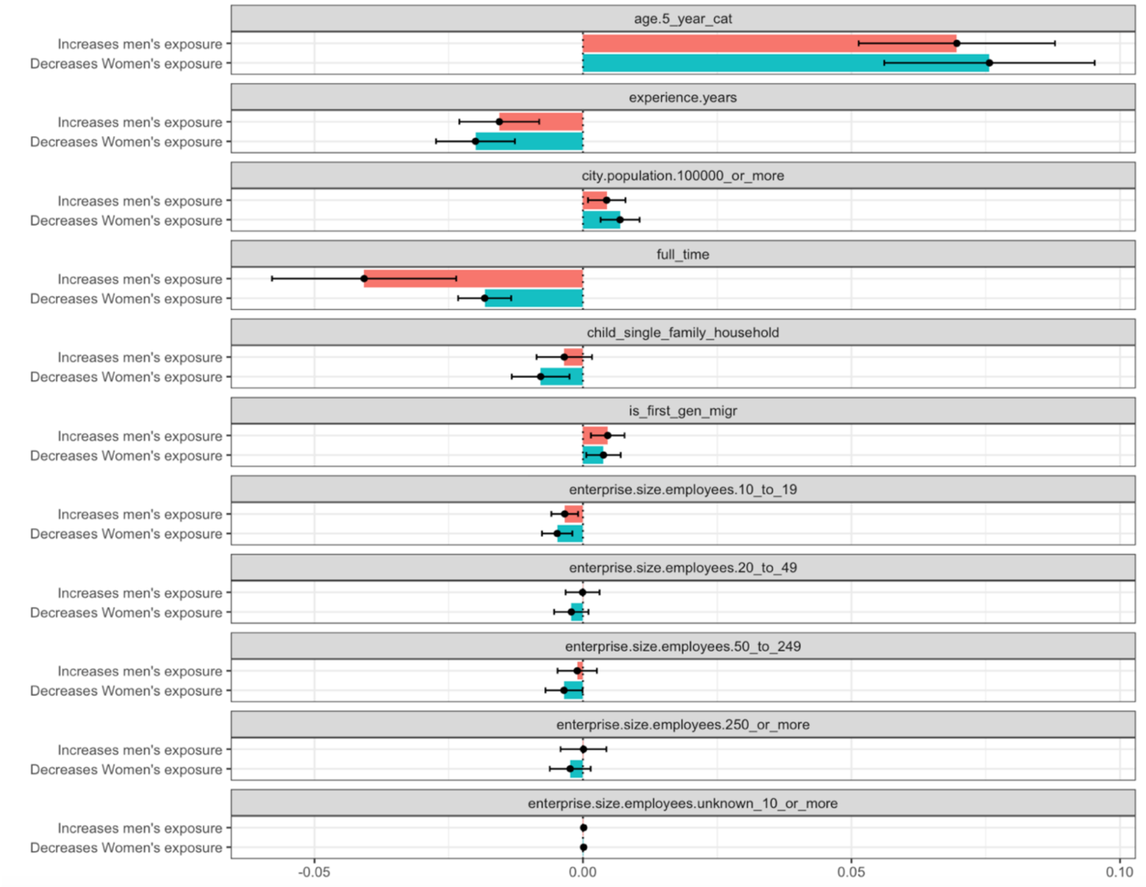
The y-axis of the histogram in the Figure 2 is the count of observations in each bin, the x-axis is the exposure to genAI index, and the histogram has 19 bins (0.03 per bin). This distribution graph shows that there are more men than women with low and close-to-medium index values, while there are more women than men with higher index values (from approximately 0.46 to the end of the axis), as well as at the medium values.

Figure 3. Decomposition estimates divided into explained and unexplained part



The Figure 3 shows the variable-by-variable decomposition estimates. The colored bars represent explained and unexplained parts of the decomposition, and the smaller black lines represent the 95% confidence intervals. Positive values of the decomposition decrease the gap (since the gap is negative). The unexplained effect is greater than the explained one. A more detailed analysis of the results is presented further in this chapter.

Figure 4. Unexplained decomposition estimates for men and women for all variables except education



The Figure 4 shows which variables, except for the intercept and education, affect the exposure to genAI for men and women and to what extent. First, the age reduces the gap. Furthermore, the age for women is decreasing the exposure, while for men it increases the exposure. In addition, the magnitude of the effect of age on the exposure index is larger for women than for men. Similarly, the experience, the full-time, and the household type variables affect women more than men, and increase the gap. It is also important to note that the first-generation migrants see their exposure index decrease compared to other migration backgrounds. For men being a first-generation migrant increases the exposure to genAI, but for women it decreases the exposure.

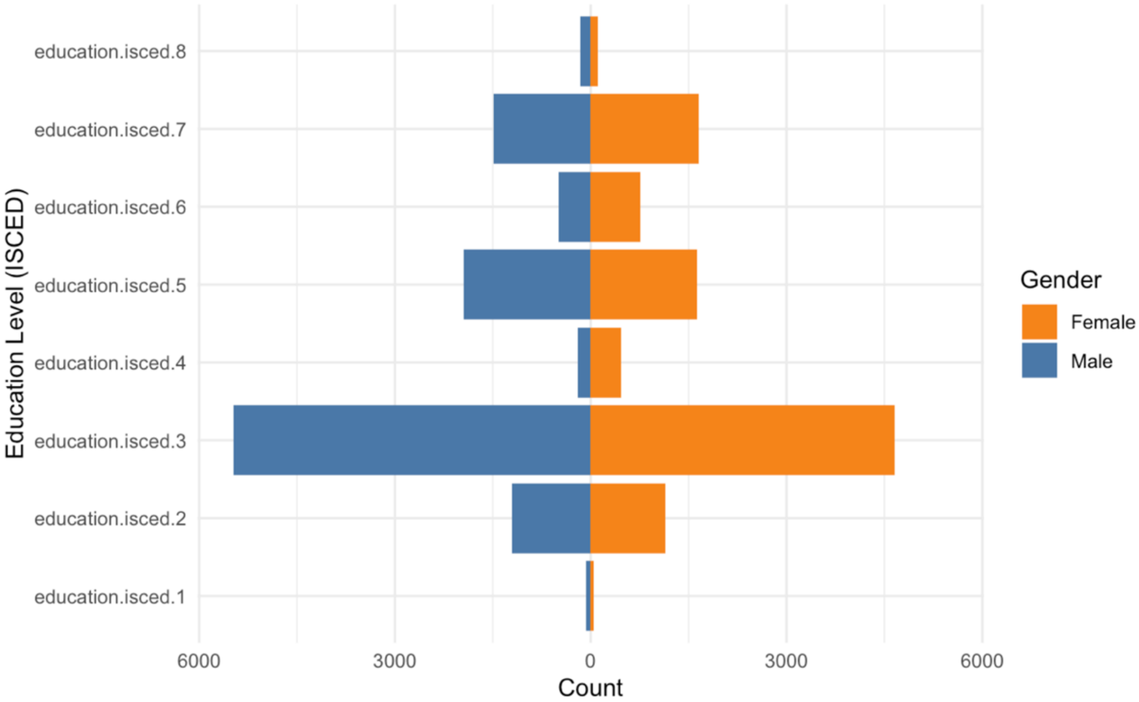
Figure 5. Unexplained decomposition estimates for men and women for ISCED education classification

In the case of education, the Figure 5 shows that, in contrast to the Figure 4, the effect of education is unidirectional. More specifically, if a certain level of education increases male exposure to genAI, it also increases it for women, and vice versa. It is important to note that all per-group unexplained estimates are statistically significant for all values (at 0.1% level). "(Base)" corresponds to the ISCED 2 education which is the baseline category of education in this thesis. The coefficients for the "(Base)" were obtained using the adjustment method described in the Chapter 3.

4.2 Effect of education

In this chapter, I analyse the estimates for education variables and evaluate the Hypothesis 2. The analysis of the initial classification of education is supplied in the Appendix 9.

Figure 6. Education Pyramid by gender

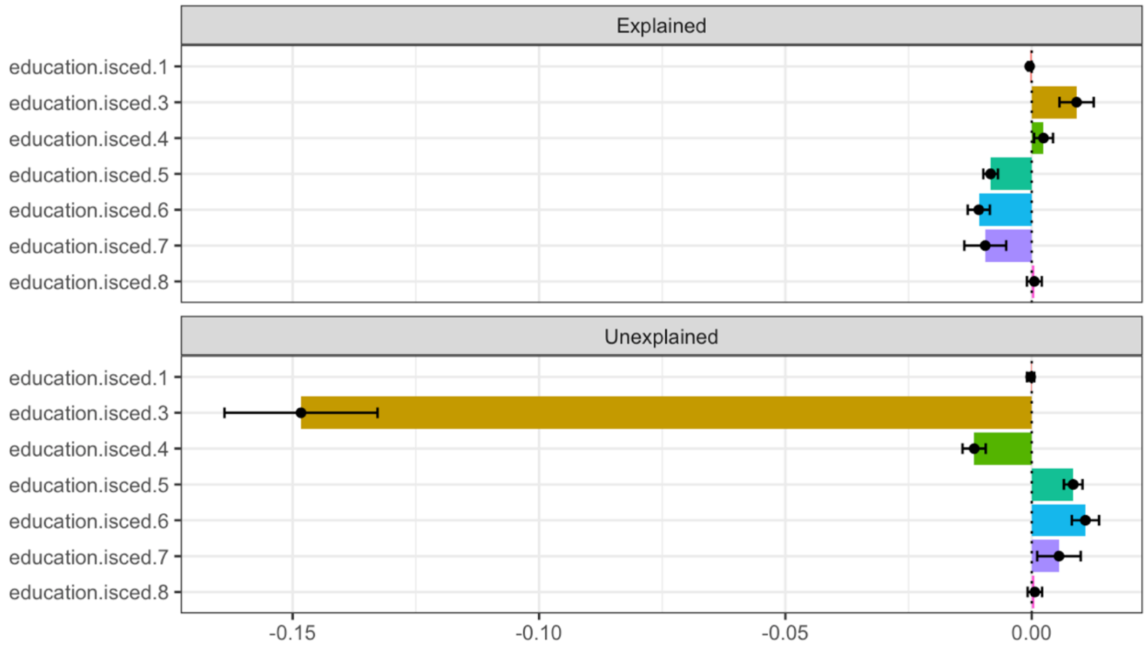


From the Figure 6 I can conclude that the most common level of education is the ISCED 3. Approximately equal numbers of men and women reached the ISCED 2 education type. The ISCED 4 education is achieved by far more women than men. It is interesting to note that starting from the ISCED 4 level of education and until the ISCED 8 level, there is a predominance of women over men.

Education is a strong predictor of the exposure. All education regression estimates for all three regressions are statistically significant at 1% level (Appendixes 4, 5 and 6).

Then, I analyse the decomposition estimates for the education. The Figure 7 shows the graphical presentation of decomposition estimates for education variables.

Figure 7. Oaxaca-Blinder decomposition results for education (ISCED levels classification)



Overall, education variables account for the 72% of the gap. The strongest effect is due to the ISCED 3 education level. The unexplained estimate for the ISCED 3 education is -0.1177. The explained and unexplained estimates for ISCED 3-7 levels are all significant at 0.1%. For the ISCED 1, the explained estimate is significant at 5% and the unexplained estimate is not significant. Similarly, for the ISCED 8, the explained estimate is significant at 1% and the unexplained estimate is not significant. For the ISCED 2, the unexplained estimate is significant at 10%.

It is interesting to note that if the education variables are considering separately, a clear conclusion about whether the gap increases or decreases can be drawn visually only for levels 3, 4, and 7, while for other levels, the prevailing effect must be assessed. It can be observed that the explained effect for levels 5 and 6, which are highly statistically significant, is approximately equal to their unexplained effect. Therefore, in this case, it is necessary to compare the specific estimates in order to determine which effect prevails and whether a given level decreases or increases the gender gap in the exposure to genAI.

Next, to evaluate the Hypothesis 2, I consider the university levels of education (ISCED 6-8). The Table 2 summarises the means, the estimated effects from individual regressions, and the decomposition estimates for all eight ISCED levels.

Table 2. Education results summary

	Mean men	Mean women	Difference of means	β_{men} %	β_{women} %	β_{pooled} %	Explained	Unexplained men	Unexplained women
ISCED 1	0.006	0.004	0.002	-14.364	-22.988	-16.542	0	-0.001	0.001
ISCED 3	0.497	0.445	0.052	10.988	34.256	21.98	0.01	-0.168	0.05
ISCED 4	0.017	0.045	-0.028	34.332	20.142	22.946	-0.006	-0.003	0.01
ISCED 5	0.176	0.155	0.021	30.351	45.455	38.567	0.007	-0.054	0.025
ISCED 6	0.044	0.073	-0.029	59.736	34.715	44.334	-0.011	-0.006	0.02
ISCED 7	0.135	0.159	-0.023	61.529	48.947	55.657	-0.01	-0.028	0.04
ISCED 8	0.014	0.01	0.004	62.607	45.707	58.731	0.002	-0.003	0.003

The returns to university education for women are lower than for men and the reference group at the same level of education. In other words, women see weaker effect on the exposure index of obtaining the university level education than men.

The unexplained estimates for the ISCED 6 and the ISCED 7 decrease the gap, while the unexplained estimate for the ISCED 8 slightly increases the gap.

However, as there are more women with Bachelor and Master degrees (ISCED 6 and 7) than men, and because the pooled regression estimates are positive, the effect from the explained estimates somewhat compensates the effect of the unexplained estimates. The net effect of the ISCED 6 level of education decomposition estimate is the decrease of the gap by 0.003, and the net effect of the ISCED 7 is the decrease of the gap by 0.002. The ISCED 8 decomposition estimates decrease the gap by 0.002.

In summary, the university levels of education decrease the gap in the exposure to genAI. Hence, the Hypothesis 2 is rejected.

4.3 Effect of household type

The variable "child_single_family_household" was created to represent the narrowed household type. This variable was set to TRUE where the household type IV variable ("xhhtyp4") was equal to 3 ("(married) couples with children with no other person"), and FALSE otherwise.

In this subchapter, I evaluate the Hyphothesis 3 that states that (married) women in couples with children in households without other people are expected to have higher exposure to genAI than men in the same circumstance, compared to other household types.

Table 3. Households' distribution in the sample

Specification	Number of people from the sample
Women who in the household type «households of a (married) couple with a child and no other household members»	4494
Men who in the household type «households of a (married) couple with a child and no other household members»	5104
Women who in the other type of household	5974
Men who in in the other type of household	5917

Table 3 shows that 46% of men and 43% of women in the sample belong to the "(married) couples with children without other persons" household type.

The regression estimate for men corresponds to the decrease in the exposure index by 2% compared to the baseline group and it is significant at 5% level. The regression estimate for the pooled regression corresponds to the decrease in the exposure index by 1.2% and it is significant at 5% level. The regression estimate for women is not significant at 5% level.

The explained decomposition estimate is -0.0004 and it is marginally significant at 5% level ($p = 0.056$). The unexplained decomposition estimate is -0.011 and it is significant at 5% level. The unexplained decomposition estimate for men is -0.003 and it is not significant at 5% level. The unexplained decomposition estimate for women is -0.008 and it is significant at 1% level.

To conclude, the Hypothesis 3 was tentatively confirmed, as the explained estimate and the unexplained decomposition estimate for women increase the gap in the exposure to genAI. However, the effect on the gap is small and the effect of all decomposition estimates accounts for only 7% of the gap.

4.4 Effect of migration background

The migration variable ("xmigr_gen") was converted to the binary variable ("is_first_gen_migr") such that it is TRUE for the first-generation migrants and FALSE otherwise.

In this subchapter, I evaluate the Hyphothesis 3 that states that first-generation migrants are less exposed to genAI than people without the migration background or later generation migrants.

Table 4. Migration background distribution in the sample

Specification	Number of people from the sample
Women who are the first-generation migrants	2202
Men who are the first-generation migrants	2248
Women who are NOT the first-generation migrants	8266
Men who are NOT the first-generation migrants	8773

20.7% of individuals in the sample are first-generation migrants. In terms of the gender, the Table 4 shows that 20% of men and 21% of women in the sample are first-generation migrants.

First-generation migrants, regardless of the gender, are expected to have the exposure index 15% lower than the baseline group. This effect is significant at 0.1% ($p < 0.001$). This confirms the Hypothesis 4.

The explained decomposition estimate is not significant at 5% level. The unexplained decomposition estimate is 0.0084 and it is significant at 1% level. It decreases the gap. The unexplained decomposition estimate for women is 0.00382 and it is significant at 5% level. For men, the unexplained decomposition estimate is 0.00461 and it is significant at 1% level.

To sum up, the Hypothesis 4 was confirmed. First-generation migrants are less exposed to genAI than people without the migration background or later generation migrants, with women seeing a 3.5% stronger effect on the exposure index than men.

4.5 Other key variables

In this chapter I consider the variables which are not directly related to hypotheses of this thesis, but account for the significant portion of the gap. Graphs and distribution tables for these variables are attached in the Appendix 10.

First, I examine the variable which is responsible for the age. It represents the individual's age and it is not the absolute age in years, but the ordered 5-year age category. For instance, age = 1 represents 15-19-year-olds, age = 2 represents 20-24-year-olds, etc.

The main conclusion is that the age is a strong predictor of the exposure. Overall, the age accounts for 28% of the absolute effects on the gap.

In addition, there is no significant difference in the age between men and women. However, the unexplained estimate for age is 0.1453 and it is significant at 0.1% and decreases the gap. It is the strongest offsetting effect and accounts for 72% of all unexplained offsetting estimates.

For women, the age decreases the exposure by 2.04% and for men it increases the exposure by 0.32% for a 5-year increase in age. The reference group sees the decrease in the exposure index by 0.8%. At the same time, the regression estimate for age for men is not significant ($p = 0.11$), but for women and the reference group it is significant at 0.1%. Also, an average man is expected to see the exposure index increase by 2% due to the effect of age, while an average woman is expected to see the exposure index decrease by 12% due to the effect of age.

Next, I consider the variable that accounts for the working type (full-time/part-time). The "full_time" variable is a binary variable, and is TRUE when reported working hours are greater than or equal to 36 hours.

This variable has a strong effect on the exposure and accounts for 11% of absolute effects. Besides, there is a significant difference in proportions of full-time workers between men and women. 86% of men report working full-time (≥36 hours/week), while only 46% of women report the same.

The explained decomposition estimate is -0.0096 and it is significant at 0.1%. At the same time, the unexplained decomposition estimate is -0.059 and it is significant at 0.1%. Overall, it increases the gap and accounts for 17% of all reinforcing effects.

For men, working full-time compared to working part-time results in the decrease in the exposure by 7%. This effect is significant at 0.1%. While for women, working full-time compared to working part-time results in the increase in the exposure index by 1.5%. However, this effect is not significant (p = 0.10). For the reference group, the effect of working full-time compared to working part time is the decrease in the exposure by 2.4%. This effect is significant at 0.1%.

As a next step, I consider the variable “experience.years” that represents the years of experience at the last work place. It was created from the variable representing the number of months of experience at the last work place, divided by twelve.

To begin with, experience at the last workplace in years, or tenure, is the 5th largest contributor to the gap. Furthermore, it accounts for 6.3% of the absolute effects on the gap. And, it increases the gap.

The explained decomposition estimate is 0.0028 and it is significant at 0.1%. Men, on average, have 11.6 years of tenure, while women have the average tenure of 9.9 years. At the same time, the estimated effect of an additional year of tenure for men is 0.029% increase in the exposure, while for women it is an increase of 0.37%.

An average woman is expected to see her exposure index increase by 3.7% due to years of tenure, while an average man is expected to see a 0.34% increase in the exposure due to the years of tenure.

The unexplained decomposition estimate is -0.0356 and it is significant at 0.1%. This accounts for 10% of all reinforcing effects.

Lastly, as was mentioned in the Data Preparation chapter, variables responsible for the enterprise size and municipality size are proxies for the occupation. The variable “city.population.100000_or_more” is a binary variable, and can be TRUE or FALSE. It is FALSE when the population of the city is lower than 100000 people. The categorical variable “enterprise size” was created from the “danzn” variable to represent enterprise size.

The “city.population.100000_or_more” variable accounts for 2% of absolute effects and decreases the gap. At the same time enterprise size variables account for 7.5% of absolute effects. Enterprise sizes “10-19”, “20-49”, “50-249”, “> 250” increases the gap, while the enterprise size “unknown, more than 10” decreases the gap.

4.6 Main findings

This subchapter summarises main findings of this thesis. First, the hypotheses posed in the introduction of the study are tested, and additional insight is outlined. Following this, additional conclusions that were obtained as a result of the study are formulated. Finally, general conclusions are discussed.

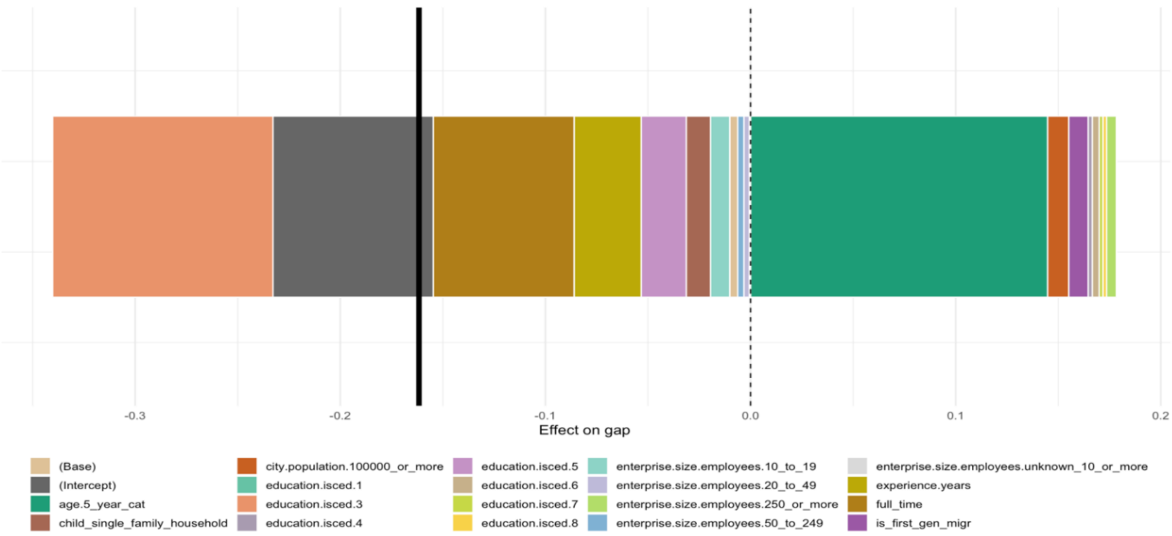
The Hypothesis 1 states that women have higher exposure to genAI than men in Austria. This hypothesis was confirmed. Precisely, in Austria the average exposure to genAI for women is 17.5% higher than for men (0.27 for men and 0.32 for women). In addition, it was also confirmed by the weighted averages analysis (the results were 0.28 for men and 0.32 for women).

The Hypothesis 2 states that the effect on the genAI exposure index of obtaining the university education for women is stronger than for men. This hypothesis was rejected since the effect on the genAI exposure index of obtaining university degrees for women is weaker than for men. Additionally, the level of education is a strong predictor of the exposure and accounts for 72% of the gap.

The Hypothesis 3 states that (married) women with children in households without other people are expected to have higher exposure to genAI than men in the same circumstance, compared to other household types. It was tentatively confirmed, as the explained estimate and the unexplained decomposition estimate for women increase the gap in the exposure to genAI. However, the effect on the gap is small and the effect of decomposition estimates accounts for only 7% of the gap.

The Hypothesis 4 states that first-generation migrants are less exposed to genAI than people without the migration background or later generation migrants. This hypothesis was confirmed. First-generation migrants are less exposed to genAI than people without the migration background or later generation migrants, with women seeing a 3.5% stronger effect on the exposure index than men.

Figure 8. Summary of effects on the gap



The Figure 8 summarises all the effects on the gap from the variables discussed in detail earlier in the chapter. The "(Base)" is the baseline level of education (ISCED 2). The thick line represents the value of the gap, and the dashed line represents 0. Effects that increase the gap are to the left of zero, while those that increase it are to the right. More precisely, the age and the fact of being the first-generation migrants decrease the gap in the exposure to genAI (since the gap is negative). On the other hand, the experience, the full-time and the household type variables increase the gap.

To summarise, I used the twofold Oaxaca-Blinder decomposition to investigate the effects of individual-specific variables, the education, and the enterprise size on the exposure to genAI. Approximately 94.7% of the difference in the exposure to genAI is due to unexplained effects. The most significant contributors to the unexplained portion of the difference are the age, the experience, the normal working hours, and the education. Interestingly, the effects of age are strong, but decrease the gap, while other variables increase it. And, the effect of the third level of the ISCED 2011 education is very strong and almost equal in magnitude to the effect of age, but has the opposite sign.

5 Robustness checks

The robustness of the results was verified using several methods. Standard errors were calculated for the decomposition estimates using the bootstrap method. The estimated standard errors were used to calculate the confidence levels for the results, and evaluated in the previous chapter.

Furthermore, the exposure gap estimated with the Oaxaca-Blinder decomposition was compared to the exposure gap estimated using the Eurostat data. The index for men estimated with the twofold Oaxaca-Blinder decomposition is 0.28, and with the weighted average is 0.27, and for women is 0.32 in both cases. Hence, it is possible to make the conclusion that the results are consistent.

Moreover, two separate models with different education groupings were estimated to validate the selection of variables.

Finally, F-tests for all three regressions showed high statistical significance, confirming the validity of the selected model for the purposes of this thesis.

6 Conclusion

In summary, this study has provided an extensive empirical investigation of the exposure to genAI in Austria, based on the genAI exposure index calculated by the ILO, and the LFS data from Statistics Austria. This combination of the sources made it possible to identify the factors that influence the gender gap in the exposure to genAI in Austria, as well as to calculate the gap itself, which exists as of the first quarter of 2025.

In the introduction, an analysis of the research literature was conducted, on the basis of which the following was identified: the existence of discrimination against women in Austria and the gender gap in several aspects, including the gender wage gap. It was also concluded that genAI is increasing its impact on the labour market. Based on these findings, the research question of this thesis was formulated, in particular: to what extent are women and men in Austria exposed to generative AIs in the workplace, and what are the key factors affecting their exposure to genAI? Furthermore, the goal of this thesis was defined as quantifying the gender gap in the exposure to genAIs at the workplace. The main contribution of this work is that it is the first study combining the ILO index and LFS data for Austria to provide a detailed analysis of the gender gap in exposure to genAI. As a preliminary study to test the hypothesis of the existence of a gender gap, Eurostat data were analysed for the EEA countries plus Switzerland, combined with the ILO's genAI index. Based on these results, it was concluded that in the overwhelming majority of countries, including Austria, women are presumably a discriminated group on this basis. To conclude, four main hypotheses were formulated in order to be tested further in the analysis.

The chapter Data Overview provided a detailed description of the three main data sources used for this study. As a last step of the data overview, limitations for the following study arising from the source data were described.

Next, the methods used in the study were formulated. The weighted average method used for the preliminary analysis was described. Furthermore, the variables selected for the analysis from LFS data and their transformations were described. As a next step, the main method, the twofold Oaxaca-Blinder decomposition, was discussed. The selected specification and formulas were presented, and the method itself and its features were described. At the end, the bootstrap method for the estimation of standard errors was described.

In the Results chapter, I tested the hypotheses posed in the introduction. As a result, two hypotheses were confirmed, one was tentatively confirmed, and one was rejected. This chapter also examined variables that were not directly related to the hypotheses but had a significant impact on the gap. Based on the chapter's conclusions, I drew conclusions related to the hypotheses. Furthermore, a figure was presented decomposing the gap into its components and summarising the results presented before.

To conclude, the conducted research touched upon an important social issue of the inequality of women in the workplace, and provides a basis for subsequent analyses and, ultimately, appropriate social policy for Austria.

7 References

1. Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, Vol. 4B, edited by Orley Ashenfelter and David Card, 1043–1171.
2. Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108 (6): 1488–1542.
3. Acemoglu, Daron, and Pascual Restrepo. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives* 33 (2): 3–30.
4. Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from U.S. Labor Markets." *Journal of Political Economy* 128 (6): 2188–2244.
5. Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–1333.
6. Berghammer, Caroline. 2014. "The Return of the Male Breadwinner Model? Educational Effects on Parents' Work Arrangements in Austria, 1980–2009." *Work, Employment and Society* 28 (4): 611–632.
7. Bishnu, Monisankar, Subhrasil Chingri, Debasis Mondal, and Klaus Prettner. 2025. "Automation, Gender, and Inequality: Which Tradeoffs Do Policymakers Face?" *Department of Economics Working Paper Series* No. 395. Vienna: WU Vienna University of Economics and Business.
8. Blau, Francine D., and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature* 55 (3): 789–865.
9. Böheim, René, Marian Fink, and Christine Zulehner. 2019. "About Time: The Narrowing Gender Wage Gap in Austria." *Empirica* 48 (4): 803–843.
10. Brynjolfsson, Erik, and Andrew McAfee. 2014. "The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies." New York: *W. W. Norton & Company*.
11. Bundesministerium für Frauen, Wissenschaft und Forschung. 2025. "Einkommen und der Gender Pay Gap." https://www.bmfwf.gv.at/frauen-und-gleichstellung/gleichstellung-am-arbeitsmarkt/einkommen-und-der-gender-pay-gap.html.

12. Cazzaniga, Mauro, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J. Panton, Carlo Pizzinelli, Emma Rockall, and Marina Mendes Tavares. 2024. "Gen-AI: Artificial Intelligence and the Future of Work." IMF Staff Discussion Note No. 2024/001. Washington, DC: *International Monetary Fund.*
13. Colombo, Emilio, et al. 2025. "Towards the Terminator Economy: Assessing Job Exposure to AI through Large Language Models." *Proceedings of the Thirty-Fourth International Joint Conference on Artificial Intelligence (IJCAI 2025).* Available at: https://www.ijcai.org/proceedings/2025/1066.pdf.
14. Dencik, Lina, Jessica Brand, Philippa Metcalfe, and Cate Hopkins. 2025. "AI Inequalities at Work." Cardiff*: Data Justice Lab*. Available at: https://datajusticelab.org/publication/ai-inequalities-at-work/.
15. Eurostat. 2024. "Labour Force Survey Microdata." Available at: https://ec.europa.eu/eurostat/web/microdata/public-microdata/labour-force-survey
16. Expert Council for Integration. 2024. "Integration Report 2024." Vienna: *Federal Chancellery of Austria*.
17. Feuerriegel, Stefan, Jochen Hartmann, Christian Janiesch, et al. 2024. "Generative AI." *Business & Information Systems Engineering* 66 (2): 111–126.
18. Frey, Carl Benedikt, and Michael A. Osborne. 2013. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Oxford Martin School Working Paper*.
19. Gmyrek, Paweł, Janine Berg, and David Bescond. 2023. "Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality." ILO Working Paper 96. Geneva: *International Labour Organization.* Available at: https://www.ilo.org/publications/generative-ai-and-jobs-global-analysis-potential-effects-job-quantity-and.
20. Grund, Christian. 2015. "Gender Pay Gaps among Highly Educated Professionals: Compensation Components Do Matter." *Labour Economics* 34: 118–126.
21. Hedija, Veronika. 2023. "Gender Pay Gap in the Czech Republic: Focused on Management." *Economic Research-Ekonomska Istraživanja* 36(3). Available at: https://doi.org/10.1080/1331677X.2023.2263510.
22. Hlavac, Marek. 2022. "oaxaca: Blinder-Oaxaca Decomposition in R." *Journal of Statistical Software* 104 (1): 1–38.
23. Hlavac, Marek. 2022. "oaxaca: Blinder–Oaxaca Decomposition in R. R Package Version 0.1.5." Available at: https://CRAN.R-project.org/package=oaxaca.

24. Ingwersen, Kai, and Stephan L. Thomsen. 2021. "The Immigrant–Native Wage Gap in Germany Revisited." *Journal of Economic Inequality* 19: 825–854.
25. International Labour Organization. 2025. "Generative AI and Jobs: A Refined Global Index of Occupational Exposure." Geneva: *International Labour Organization*.
26. International Monetary Fund. 2023. "Artificial Intelligence and the Global Labor Market." Washington, DC: *International Monetary Fund*.
27. Jann, Ben. 2008. "The Blinder–Oaxaca Decomposition for Linear Regression Models." *Stata Journal* 8 (4): 453–479.
28. Keynes, John Maynard. 1930. "Economic Possibilities for Our Grandchildren." In Essays in Persuasion. London: *Macmillan*.
29. Leitner, Andrea. 2023. "Gender Segregation in Education, Training and the Labour Market in Austria." Vienna: *Institute for Advanced Studies (IHS)*.
30. Leontief, Wassily, and Faye Duchin. 1986. "The Future Impact of Automation on Workers". New York: *Oxford University Press*.
31. Leythienne, Denis, and Piotr Ronkowski. 2018. "A Decomposition of the Unadjusted Gender Pay Gap Using Structure of Earnings Survey Data." Eurostat Statistical Working Paper. Luxembourg: *Publications Office of the European Union*.
32. LinkedIn Economic Graph Team. 2024. "Generative AI and Gender: Implications for the Future of Work." Available at: https://economicgraph.linkedin.com/content/dam/me/economicgraph/en-us/PDF/generative-ai-and-global-gender-work-classification.pdf.
33. McKinsey. 2024. "What Is Generative AI?" Available at: https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-generative-ai.
34. Microsoft. 2024. "What Is Generative AI?" Available at: https://www.microsoft.com/en-us/microsoft-copilot/for-individuals/do-more-with-ai/general-ai/.
35. Morrison, Ann M., and Mary Ann Von Glinow. 1987. "Breaking the Glass Ceiling: Can Women Reach the Top of America's Largest Corporations?" Reading, MA: *Addison-Wesley*.
36. Oaxaca, Ronald. 1973. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review* 14(3): 693–709.

37. OECD. 2023. “OECD Employment Outlook 2023: Artificial Intelligence, Job Quality and Inclusiveness.” Paris: *OECD Publishing*. Available at: https://www.oecd.org/en/publications/oecd-employment-outlook-2023_08785bba-en/full-report/artificial-intelligence-job-quality-and-inclusiveness_a713d0ad.html.
38. OECD. 2024. “OECD Economic Surveys: Austria 2024.” Paris: *OECD Publishing*. Available at: https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/07/oecd-economic-surveys-austria-2024_ed983e1c/60ea1561-en.pdf.
39. PwC Austria. 2024. “Women in Work Index: Österreich weiterhin nur auf Platz 26 von 33 analysierten OECD-Ländern.” Available at: https://www.pwc.at/de/presse/2024/women-in-work-index.html.
40. Rahimi, Ebrahim, and Seyed Saeed Hashemi Nazari. 2021. “A Detailed Explanation and Graphical Representation of the Blinder-Oaxaca Decomposition Method with Its Application in Health Inequalities.” *Emerging Themes in Epidemiology* 18 (1): 12.
41. Riederer, Bernhard, and Caroline Berghammer. 2020. “The Part-Time Revolution: Changes in the Parenthood Effect on Women's Employment in Austria across the Birth Cohorts from 1940 to 1979.” *European Sociological Review* 36 (2): 284–302.
42. Statistics Austria. 2014. “Umschlüsselung nationaler Bildungsformen zu ISCED 2011 im Rahmen der Mikrozensus-Arbeitskräfteerhebung (ab 2014).” Vienna: *Statistics Austria*.
43. Statistics Austria. 2025. “Microcensus Labour Force Survey / Housing Survey 2025 (SUF Edition).” Available at: https://data.aussda.at/dataset.xhtml?persistentId=doi:10.11587/M9UQ9K.
44. Statistics Austria. 2025. “Gender Pay Gap Was 18.3% in 2023.” Available at: https://www.statistik.at/fileadmin/announcement/2025/03/20250305GenderStatistik2025EN.pdf.
45. Statistics Austria. 2025. “Mikrozensus ab 2021: Codebook for the Austrian Labour Force Survey.” Vienna: *Statistics Austria*.
46. Stryker, Cole, and Paola Scapicchio. 2022. “What Is Generative AI?” IBM Think. Available at: https://www.ibm.com/think/topics/generative-ai.

APPENDIXES

Appendix 1. Gender gap in exposure to genAI in EEA area and Switzerland

Country	Average score	Average score women	Average score men	Gap
AT	0.333	0.331	0.312	0.019
BA	0.313	0.348	0.306	0.042
BE	0.352	0.336	0.317	0.019
CH	0.346	0.322	0.306	0.016
CY	0.359	0.357	0.336	0.021
CZ	0.307	0.328	0.292	0.036
DE	0.336	0.322	0.288	0.034
DK	0.341	0.335	0.302	0.033
EE	0.364	0.339	0.332	0.006
EL	0.326	0.323	0.315	0.008
FI	0.329	0.327	0.331	-0.005
HR	0.360	0.361	0.356	0.005
HU	0.320	0.324	0.295	0.029
IE	0.356	0.335	0.335	0.001
IS	0.334	0.323	0.310	0.013
IT	0.316	0.327	0.287	0.040
LT	0.342	0.320	0.317	0.003
LU	0.437	0.408	0.416	-0.007
LV	0.344	0.345	0.315	0,030
MT	0.361	0.355	0.364	-0.009
NL	0.349	0.324	0.287	0.038
NO	0.353	0.360	0.376	-0.016
PL	0.332	0.328	0.306	0.022
PT	0.332	0.320	0.312	0.008
RO	0.292	0.331	0.303	0.028
RS	0.316	0.340	0.313	0.027
SE	0.349	0.342	0.307	0.035
SI	0.332	0.328	0.310	0.018
SK	0.364	0.375	0.341	0.034
TR	0.269	0.310	0.298	0.012

Appendix 2. Definitions of genAI

Definition	Source
"Generative AI, sometimes called gen AI, is artificial intelligence (AI) that can create original content such as text, images, video, audio or software code in response to a user's prompt or request."	Stryker and Scapicchio 2022
"Generative AI is a type of artificial intelligence that creates new content by learning patterns from data and predicting the next element in a sequence. In this article, we'll discuss how generative AI differs from other types of AI and how Copilot generates AI images, text, and more."	Microsoft 2024
"Generative artificial intelligence (AI) describes algorithms (such as ChatGPT) that can be used to create new content, including audio, code, images, text, simulations, and videos."	Mckinsey 2024
"The term generative AI refers to computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data. The widespread diffusion of this technology with examples such as Dall-E 2, GPT-4, and Copilot is currently revolutionizing the way we work and communicate with each other. Generative AI systems can not only be used for artistic purposes to create new text mimicking writers or new images mimicking illustrators, but they can and will assist humans as intelligent question-answering systems."	Feuerriegel, S., Hartmann, J., Janiesch, C. et al 2024

Appendix 3. ISCED Mapping (based on "Umschlüsselung nationaler Bildungsformen zu ISCED 2011 im Rahmen der Mikrozensus-Arbeitskräfteerhebung (ab 2014)" by Statistics Austria)

Kartab11 Value	Label in German (original)	English translation of the Label	ISCED 2011 Level
1	kein Pflichtschulabschluss	No compulsory school leaving certificate	1
2	Pflichtschulabschluss	Compulsory school leaving certificate	2
3	Lehre (Lehrabschlussprüfung)	Apprenticeship (final apprenticeship examination)	3
4	Fach- oder Handelsschule: < 2 Jahre	Vocational or commercial school: < 2 years	2
5	Fach- oder Handelsschule: 2 Jahre und länger	Vocational or commercial school: 2 years or longer	3
6	Diplomkrankenpflege	Diploma in Nursing	4
7	BHS, 3. Klasse abgeschlossen	BHS, 3rd grade completed	3
8	AHS-Matura (z.B. Gymnasium)	AHS Matura (e.g., Gymnasium)	3
9	BHS-Matura (z.B. HAK, HTL, BAKIP)	BHS-Matura (e.g. HAK, HTL, BAKIP)	5
10	Lehre mit Matura (Berufsreifeprüfung)	Apprenticeship with high school diploma (vocational diploma)	4
11	Bakkalaureat/Bachelor	Bachelor's degree	6
12	Master-, Magister- oder Diplomstudium	Master's, Magister or Diploma degree	7

Kartab11 Value	Label in German (original)	English translation of the Label	ISCED 2011 Level
13	Doktorat im Erstabschluss	Doctorate in the first degree program	7
14	Doktorat nach akademischem Erstabschluss	Doctorate after initial academic degree	8
15	Postgradualer Universitätslehrgang (z.B. MBA, MAS, MSc)	Postgraduate university course (e.g. MBA, MAS, MSc)	7
16	Akademie (z.B. Pädak, SozAK, Med.-Tech. Akademie, MilAK)	Academy (e.g. Pädak, SozAK, Med.-Tech. Academy, MilAK)	5
17	Kolleg, Abiturientenlehrgang an einer BHS	College, high school graduate course at a vocational high school	5
18	Hochschul-/Universitätslehrgang (akademisch geprüfter <Berufsbezeichnung>)	University course (academically certified <professional title>)	4
19	Meister- oder Werkmeisterprüfung	Master craftsman or foreman examination	5

Appendix 4. Regression estimates for pooled regression (including variable "female")

```
Call:
NULL

Residuals:
     Min       1Q   Median       3Q      Max
-1.19616 -0.35555 -0.00474  0.36214  1.21859

Coefficients:
                                      Estimate Std. Error t value Pr(>|t|)
(Intercept)                         -1.5337665  0.0154749 -99.113  < 2e-16 ***
age.5_year_cat                      -0.0081323  0.0014709  -5.529 3.26e-08 ***
experience.years                     0.0016414  0.0003469   4.731 2.24e-06 ***
city.population.100000_or_more       0.0889390  0.0074025  12.015  < 2e-16 ***
full_time                           -0.0244625  0.0071921  -3.401 0.000672 ***
child_single_family_household       -0.0129881  0.0061952  -2.096 0.036051 *
is_first_gen_migr                   -0.1610467  0.0078723 -20.457  < 2e-16 ***
education.isced.1                   -0.1808231  0.0422932  -4.275 1.92e-05 ***
education.isced.3                    0.1986834  0.0101890  19.500  < 2e-16 ***
education.isced.4                    0.2065777  0.0194929  10.598  < 2e-16 ***
education.isced.5                    0.3261849  0.0118419  27.545  < 2e-16 ***
education.isced.6                    0.3669626  0.0154471  23.756  < 2e-16 ***
education.isced.7                    0.4424853  0.0122010  36.266  < 2e-16 ***
education.isced.8                    0.4620423  0.0289090  15.983  < 2e-16 ***
```

```
enterprise.size.employees.10_to_19            0.0269207  0.0102707   2.621 0.008771 **
enterprise.size.employees.20_to_49            0.0354428  0.0095022   3.730 0.000192 ***
enterprise.size.employees.50_to_249           0.0706892  0.0089917   7.862 3.97e-15 ***
enterprise.size.employees.250_or_more         0.0945409  0.0087524  10.802  < 2e-16 ***
enterprise.size.employees.unknown_10_or_more -0.1196861  0.0527900  -2.267 0.023387 *
femaleTRUE                                    0.1531220  0.0066577  22.999  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4383 on 21469 degrees of freedom
Multiple R-squared:  0.1485,    Adjusted R-squared:  0.1478
F-statistic: 197.1 on 19 and 21469 DF,  p-value: < 2.2e-16
```

Appendix 5. Regression estimates for men

```
Call:
NULL

Residuals:
     Min       1Q   Median       3Q      Max
-1.25676 -0.33214 -0.01833  0.34778  1.16685

Coefficients:
                                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                                  -1.5021145  0.0210150 -71.478  < 2e-16 ***
age.5_year_cat                                0.0032242  0.0020330   1.586  0.11278
experience.years                              0.0002986  0.0004669   0.639  0.52252
city.population.100000_or_more                0.1077761  0.0103601  10.403  < 2e-16 ***
full_time                                    -0.0717454  0.0123617  -5.804 6.66e-09 ***
child_single_family_household                -0.0204974  0.0085143  -2.407  0.01608 *
is_first_gen_migr                            -0.1384534  0.0110772 -12.499  < 2e-16 ***
education.isced.1                            -0.1550617  0.0534748  -2.900  0.00374 **
education.isced.3                             0.1042539  0.0141911   7.346 2.18e-13 ***
education.isced.4                             0.2951427  0.0340043   8.680  < 2e-16 ***
education.isced.5                             0.2650576  0.0164244  16.138  < 2e-16 ***
education.isced.6                             0.4683510  0.0235107  19.921  < 2e-16 ***
education.isced.7                             0.4795115  0.0173970  27.563  < 2e-16 ***
education.isced.8                             0.4861679  0.0374556  12.980  < 2e-16 ***
enterprise.size.employees.10_to_19           -0.0045210  0.0153487  -0.295  0.76834
enterprise.size.employees.20_to_49            0.0349802  0.0135563   2.580  0.00988 **
enterprise.size.employees.50_to_249           0.0657399  0.0125287   5.247 1.57e-07 ***
enterprise.size.employees.250_or_more         0.0948829  0.0118421   8.012 1.24e-15 ***
enterprise.size.employees.unknown_10_or_more -0.0818785  0.0711013  -1.152  0.24952
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4346 on 11002 degrees of freedom
Multiple R-squared:  0.1633,	Adjusted R-squared:  0.162
F-statistic: 119.3 on 18 and 11002 DF,  p-value: < 2.2e-16
```

Appendix 6. Regression estimates for women

```
Call:
NULL

Residuals:
    Min      1Q  Median      3Q     Max
-1.2405 -0.3327  0.0213  0.3553  1.1537

Coefficients:
                                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                                  -1.3891341  0.0204554 -67.910  < 2e-16 ***
age.5_year_cat                               -0.0206008  0.0020920  -9.848  < 2e-16 ***
experience.years                              0.0036703  0.0005053   7.263 4.05e-13 ***
city.population.100000_or_more                0.0609050  0.0103381   5.891 3.95e-09 ***
full_time                                     0.0145687  0.0088889   1.639 0.101248
child_single_family_household                 0.0053796  0.0089630   0.600 0.548385
is_first_gen_migr                            -0.1792197  0.0108853 -16.464  < 2e-16 ***
education.isced.1                            -0.2612120  0.0669807  -3.900 9.69e-05 ***
education.isced.3                             0.2945754  0.0143069  20.590  < 2e-16 ***
education.isced.4                             0.1835063  0.0238301   7.701 1.48e-14 ***
education.isced.5                             0.3746937  0.0167652  22.350  < 2e-16 ***
education.isced.6                             0.2979884  0.0202764  14.696  < 2e-16 ***
education.isced.7                             0.3984218  0.0167803  23.743  < 2e-16 ***
education.isced.8                             0.3764283  0.0443112   8.495  < 2e-16 ***
enterprise.size.employees.10_to_19            0.0585643  0.0134705   4.348 1.39e-05 ***
enterprise.size.employees.20_to_49            0.0480656  0.0129877   3.701 0.000216 ***
enterprise.size.employees.50_to_249           0.0889598  0.0126080   7.056 1.82e-12 ***
enterprise.size.employees.250_or_more         0.1061862  0.0127657   8.318  < 2e-16 ***
enterprise.size.employees.unknown_10_or_more -0.1592851  0.0764218  -2.084 0.037158 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4292 on 10449 degrees of freedom
Multiple R-squared:  0.1333,	Adjusted R-squared:  0.1318
F-statistic: 89.28 on 18 and 10449 DF,  p-value: < 2.2e-16
```

Appendix 7. Means and estimated effects from individual regressions

Variable	Mean men	Mean women	Difference of means	β_{men} %	β_{women} %	β_{pooled} %
(Intercept)	1	1	0	-77.734	-75.071	-78.428
age.5_year_cat	6.13	6.071	0.059	0.323	-2.039	-0.81
experience.years	11.604	9.866	1.738	0.03	0.368	0.164
city.population.100000_or_more	0.235	0.246	-0.011	11.38	6.28	9.301
full_time	0.862	0.469	0.393	-6.923	1.468	-2.417
child_single_family_household	0.463	0.429	0.034	-2.029	0.539	-1.29
is_first_gen_migr	0.204	0.21	-0.006	-12.93	-16.408	-14.875
enterprise.size.employees.10_to_19	0.108	0.152	-0.044	-0.451	6.031	2.729
enterprise.size.employees.20_to_49	0.161	0.172	-0.011	3.56	4.924	3.608
enterprise.size.employees.50_to_249	0.216	0.193	0.023	6.795	9.304	7.325
enterprise.size.employees.250_or_more	0.279	0.204	0.075	9.953	11.203	9.915
enterprise.size.employees.unknown_10_or_more	0.003	0.003	0	-7.862	-14.725	-11.28
education.isced.1	0.006	0.004	0.002	-14.364	-22.988	-16.542
education.isced.3	0.497	0.445	0.052	10.988	34.256	21.98
education.isced.4	0.017	0.045	-0.028	34.332	20.142	22.946
education.isced.5	0.176	0.155	0.021	30.351	45.455	38.567
education.isced.6	0.044	0.073	-0.029	59.736	34.715	44.334
education.isced.7	0.135	0.159	-0.023	61.529	48.947	55.657
education.isced.8	0.014	0.01	0.004	62.607	45.707	58.731

Appendix 8. Twofold Oaxaca-Blinder decomposition estimates

Variable	Explained	Explained s.e.	CI explained	Unexplained men	Unexplained s.e. men	CI unexplained men	Unexplained women	Unexplained s.e. women	CI unexplained women
(Intercept)	0	0	-0.000 - 0.000	0.275	0.017	0.232 - 0.317	-0.353	0.018	-0.399 - -0.307
age.5_year_cat	0	0	-0.001 - 0.000	0.07	0.009	0.046 - 0.094	0.076	0.01	0.050 - 0.101
experience.years	0.003	0.001	0.001 - 0.005	-0.016	0.004	-0.025 - -0.006	-0.02	0.004	-0.030 - -0.010
city.population.100000_or_more	-0.001	0.001	-0.002 - 0.000	0.004	0.002	0.000 - 0.009	0.007	0.002	0.002 - 0.011
full_time	-0.01	0.003	-0.017 - -0.003	-0.041	0.009	-0.064 - -0.018	-0.018	0.003	-0.025 - -0.011
child_single_family_household	0	0	-0.001 - 0.000	-0.003	0.003	-0.011 - 0.004	-0.008	0.003	-0.016 - -0.000
is_first_gen_migr	0.001	0.001	-0.001 - 0.003	0.005	0.002	0.000 - 0.009	0.004	0.002	-0.001 - 0.008
enterprise.size.employees.10_to_19	-0.001	0	-0.002 - 0.000	-0.003	0.001	-0.007 - -0.000	-0.005	0.001	-0.009 - -0.001
enterprise.size.employees.20_to_49	0	0	-0.001 - 0.000	0	0.002	-0.004 - 0.004	-0.002	0.002	-0.006 - 0.002
enterprise.size.employees.50_to_249	0.002	0	0.000 - 0.003	-0.001	0.002	-0.006 - 0.004	-0.004	0.002	-0.008 - 0.001
enterprise.size.employees.250_or_more	0.007	0.001	0.005 - 0.009	0	0.002	-0.006 - 0.006	-0.002	0.002	-0.007 - 0.003
enterprise.size.employees.unknown_10_or_more	0	0	-0.000 - 0.000	0	0	-0.000 - 0.001	0	0	-0.000 - 0.001
education.isced.1	0	0	-0.001 - 0.000	-0.001	0	-0.002 - -0.001	0.001	0	0.001 - 0.002
education.isced.3	0.01	0.002	0.006 - 0.014	-0.168	0.006	-0.183 - -0.152	0.05	0.006	0.035 - 0.064
education.isced.4	-0.006	0.001	-0.007 - -0.004	-0.003	0	-0.004 - -0.002	0.01	0.001	0.008 - 0.012
education.isced.5	0.007	0.002	0.003 - 0.011	-0.054	0.003	-0.060 - -0.047	0.025	0.002	0.019 - 0.030

Variable	Explained	Explained s.e.	CI explained	Unexplained men	Unexplained s.e. men	CI unexplained men	Unexplained women	Unexplained s.e. women	CI unexplained women
education.isced.6	-0.011	0.001	-0.014 - -0.008	-0.006	0.001	-0.008 - -0.004	0.02	0.001	0.017 - 0.023
education.isced.7	-0.01	0.002	-0.016 - -0.005	-0.028	0.002	-0.033 - -0.023	0.04	0.002	0.035 - 0.045
education.isced.8	0.002	0.001	0.000 - 0.004	-0.003	0	-0.004 - -0.002	0.003	0	0.002 - 0.004

Appendix 9. Analysis of unexplained decomposition estimates with initial education classification.

In this Appendix I analyse the decomposition estimates of the twofold Oaxaca-Blinder decomposition with ungrouped education levels, keeping all other specifications the same. The baseline education in this case is the secondary school leaving certificate.

The results of the decomposition are presented in the Table 8. And the unexplained estimates are shown in the Figure 9.

Figure 9. Unexplained decomposition estimates for men and women for initial education classification

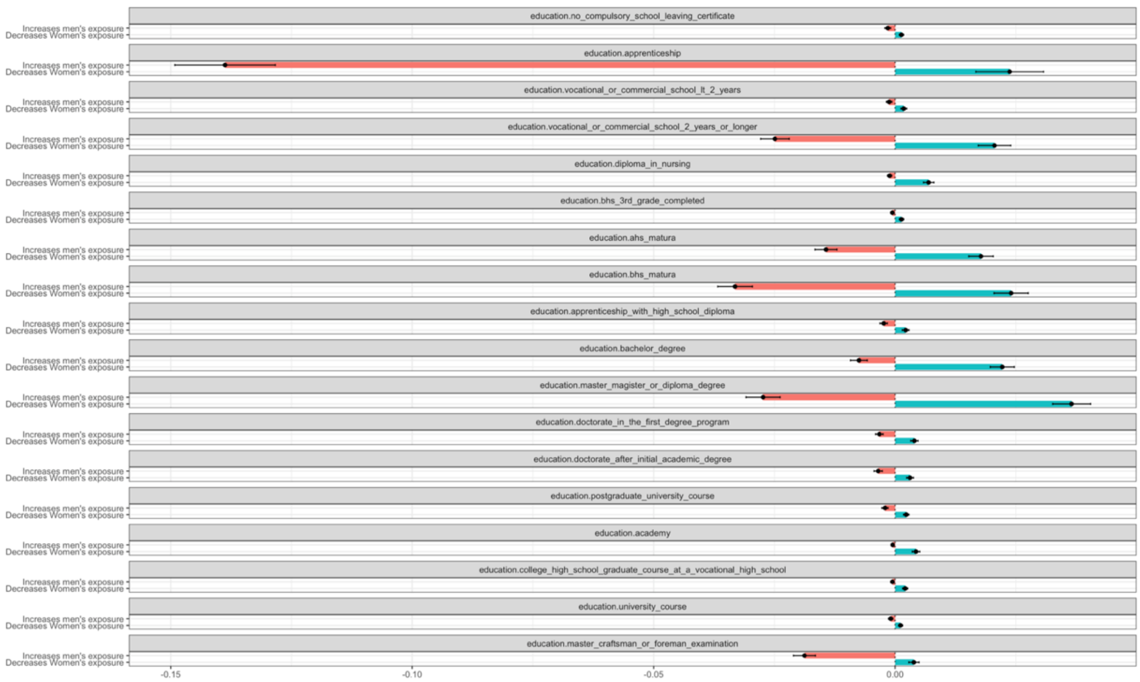
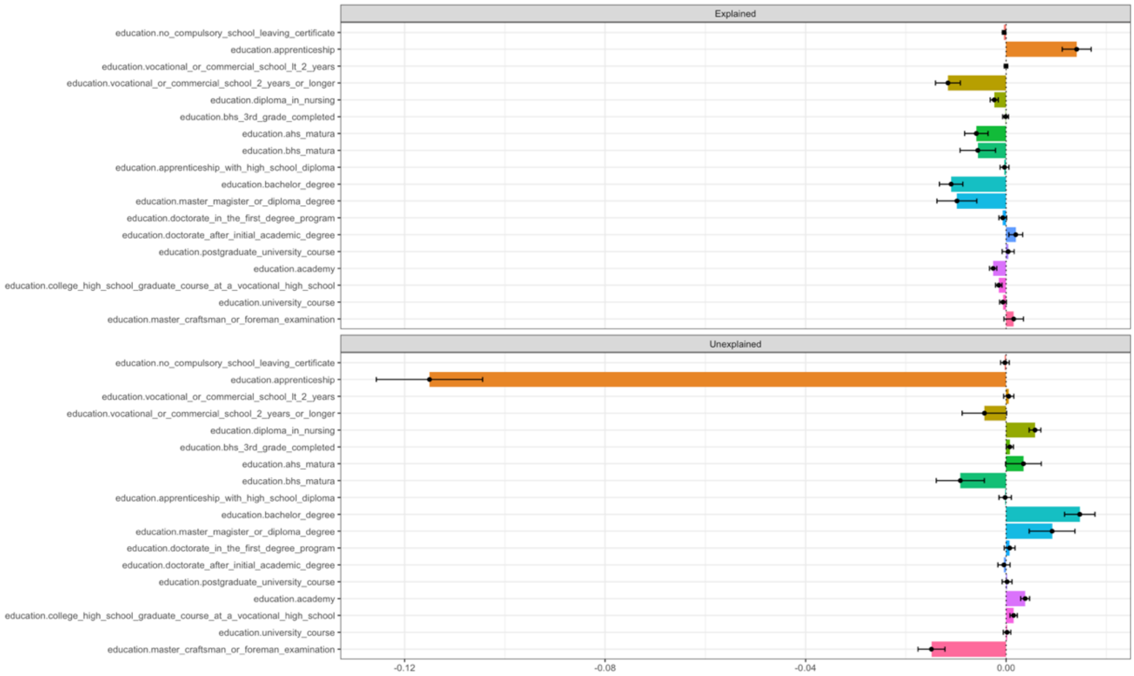


Figure 10. Decomposition estimates divided into explained and unexplained part with the initial classification of education



First, men with lower levels of education are favored in terms of effect on the exposure, which confirms the findings above.

It is worth noting that while the detailed classification may provide more detail compared to the ISCED-grouped education, the confidence intervals are much larger. This is due to the lower number of samples per education type. And, the detailed classification is specific to Austria, limiting the transferability of the results.

More precisely, the effect on the genAI exposure index of obtaining bachelor degree for women is weaker than for men, but there are more women with bachelor and master degrees than men. Overall, level of education is a strong predictor of the exposure.

Appendix 10. Distributions of variables not related to hypotheses

Figure 11. Age distribution in the sample by gender

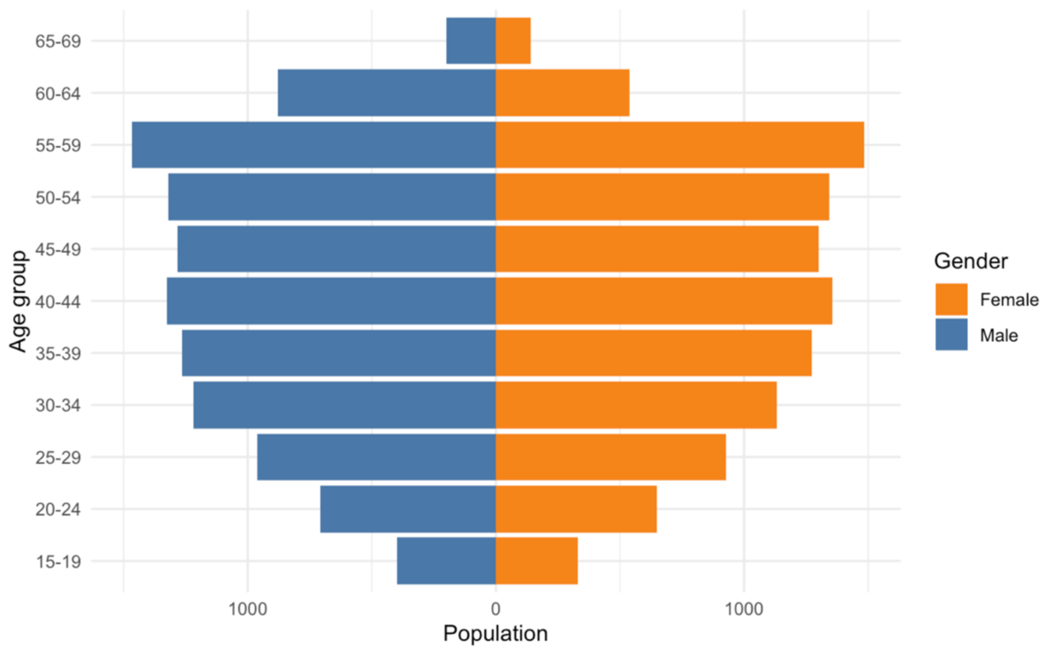


Figure 12. Distribution of experience at last work place for men and women

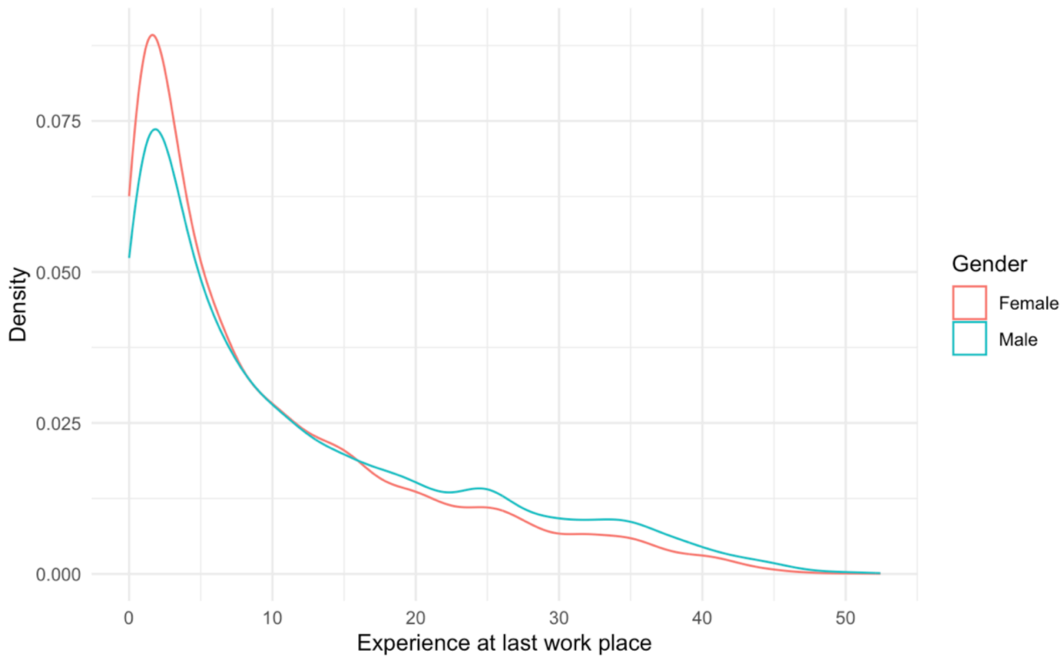


Figure 13. Enterprise size Pyramid by gender

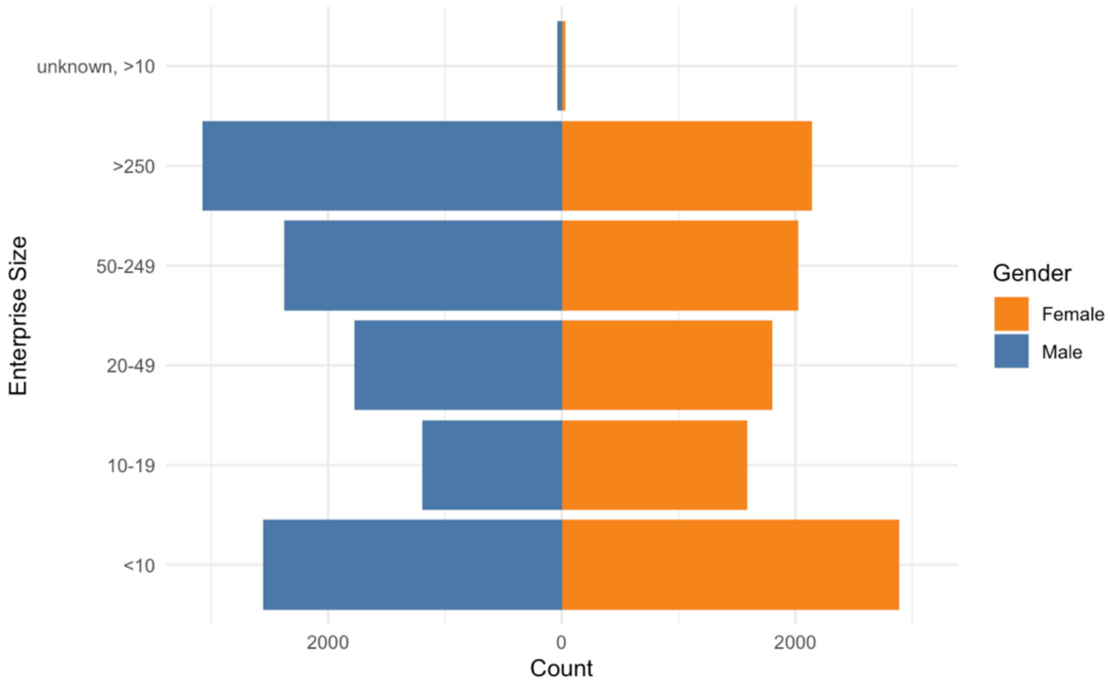


Table 5. Type of working distribution in the sample

Specification	Number of people from the sample
Women who work full-time	4909
Men who work full-time	9498
Women who work part-time	5559
Men who work part-time	1523

Table 6. City population distribution

Specification	Number of people from the sample
Women who live in the cities with the population larger than 100000 persons	2579
Men who live in the cities with the population larger than 100000 persons	2589
Women who live in the cities with the population smaller than 100000 persons	7889
Men who live in the cities with the population smaller than 100000 persons	8432