The Impact of Artificial Intelligence on Unemployment among Educated People with Disabilities: An Empirical Analysis

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ABSTRACT
The impact of artificial intelligence (AI) on unemployment is a subject of debate among researchers and policymakers. This study investigates how AI affects unemployment among educated people with disabilities in 33 countries from 2004 to 2021. Several conclusions have been reached. First, both static and dynamic panel data estimators show that AI reduces aggregate unemployment and unemployment among educated men with disabilities. In contrast, there is no significant impact on the unemployment of educated women with disabilities. Second, the panel smooth transition regression model provides compelling evidence for the existence of two regimes and a nonlinear impact of AI on unemployment among educated women with disabilities. The impact is not significant when AI is low (first regime), but the situation changes when AI exceeds a given threshold level (second regime). Therefore, educated women with disabilities may have more opportunities to integrate into the job market due to the increased adoption of AI. Countries are recommended to foster an employment-friendly environment that promotes inclusion and equitable opportunity for educated people with disabilities by developing and encouraging the adoption of AI technologies.

KEYWORDS
artificial intelligence, disability, unemployment, dynamic panel data, threshold, nonlinear effects

INTRODUCTION
The relationship between artificial intelligence (AI) and unemployment among people with disabilities is a new, complex, and multidimensional topic (Mutascu, 2021; Nazareno and Schiff, 2021; Shiohira, 2021). There is no simple explanation for how AI affects unemployment among people with disabilities, but different perspectives depend on the fields, contexts, and participants involved (Schall et al., 2021; Paul and Hollederer, 2023). AI can positively or negatively affect the employment of people with disabilities, depending on how it is designed, developed, and used (Rodrigues, 2020). On the one hand, AI can offer innovative solutions to improve accessibility, autonomy, and social participation for people with disabilities, for example, through assistive technologies based on voice recognition, text-to-speech, optical character recognition, or word prediction (Schur et al., 2021). AI may also create new needs or new forms of disability, for example, by increasing the cognitive or emotional demands of work. On the other hand, AI may also contribute to the discrimination or exclusion of disabled people, mainly if it partially replaces human decision-making in areas such as recruitment, assessment, or promotion (Smith and Smith, 2021).

The literature examining the effects of AI on the employment of people with disabilities in both developed and developing countries is nascent but a growing field of research (Ravali et al., 2022; Yang et al., 2022; Baldo et al., 2023; Chakraborty et al., 2023). The impact of AI on employment is indeed multifaceted, with various dimensions that include job displacement and transformation, skill requirements and education, inclusive AI design, government policies and support, job market dynamics, entrepreneurship, and remote work. Mondolo (2022) indicated that automation and AI technologies could lead to the displacement of specific routine and repetitive tasks, potentially resulting in
job losses in some sectors. While specific jobs may be displaced, AI may also contribute to the transformation of job roles, creating new opportunities and requiring a shift in skill sets. Brown and Souto-Otero (2020) showed that the implementation of AI requires a concentrated effort to enhance and retrain the workforce in order to match the changing requirements of the labor market. In other words, educational institutions must adapt their curricula to incorporate AI-related skills and ensure graduates are well-equipped for the changing workforce. Braganza et al. (2021) argued that achieving inclusive design of AI systems requires the mitigation of biases to prevent discriminatory consequences in hiring, promotions, and other employment-related procedures. Inclusive design considers accessibility for individuals with disabilities, ensuring that AI technologies do not create barriers for them. In addition, Mutascu and Hegerty (2023) indicated that governments play a crucial role in establishing regulatory frameworks to address ethical concerns, data privacy, and fairness in AI applications. Governments may implement support programs, such as financial incentives for AI adoption, workforce training initiatives, and policies that promote responsible AI practices.

Guliyev (2023) highlighted that AI contributes to creating new job opportunities, particularly in areas such as AI development, data science, and AI-related services. Indeed, labor market dynamics change as employers seek candidates with a combination of technical AI skills and soft skills, fostering adaptability and creativity. Magdeline (2023) demonstrated that AI presents opportunities for entrepreneurship, allowing individuals to create innovative products and services leveraging AI technologies. Therefore, entrepreneurial ventures in AI contribute to economic growth, job creation, and the development of new markets. Aleem et al. (2023) showed that AI technologies enable the implementation of remote work solutions, providing flexibility and accessibility for employees. The implementation of AI in remote work enables firms to access a diverse range of talents from around the globe, thereby potentially enhancing workforce diversity.

AI technology has obviously gained widespread recognition in many industries, including education. Indeed, education has recently witnessed the emergence of AI, which brings a range of tools for students and teachers to enhance the quality and effectiveness of the educational experience (Alfaro et al., 2020; Krishnan, 2022; Sanusi et al., 2022; Adams et al., 2023; McGrath et al., 2023; Rice and Dunn, 2023). AI may be employed in education in several ways, including intelligent tutorial systems, automatic assessment systems, collaborative learning environments, and learning games (Edyburn, 2004, 2013). Moreover, it can aid in tackling other challenges, including efficiently fulfilling the diverse requirements of individuals (UNESCO, 2019). Tutorial systems are characterized by a deep understanding of the content and methodology of the educational process (Catlin and Blamires, 2019). These systems may provide solutions for individuals when encountering obstacles in the problem-solving process. They may also provide them with guidance during the learning process. These systems could particularly improve the learning experience of people with disabilities. By using automatic assessment systems, people with disabilities can review their learning activities and gain insight into their strengths and weaknesses through automatically corrected tests. In addition to identifying their skills and abilities, they also provide valuable information about those skills and abilities. In other words, collaborative learning environments provide the context and tools for enabling individuals to work together and interact collaboratively.

Integrating intelligent systems and software agents in educational settings also allow for the creation of personalized, interactive, and effective learning experiences. Facilitating collaboration by these systems improves student engagement and the successful attainment of educational objectives. Game-based learning makes it possible to carry out activities that would have been impossible using traditional resources because of the budget allocated, the time, infrastructure, and security (Sánchez et al., 2008). An example of this is an intelligent courseware that adjusts to the student’s learning pace. The problem lies in equipping instructors with the necessary skills to integrate these tools into their instructional practices. This involves adjusting the course format, upgrading teaching materials, and enriching instructional design. However, it is imperative to address ethical considerations, data privacy, and inclusivity when designing and implementing such systems in education (Sánchez et al., 2008).

In recent years, AI has gained extensive interest from scholars, considering its impact on the employment of people with disabilities (Guliyev, 2023). Although the effect of AI on unemployment has been studied before, its impact on the unemployment of people with disabilities remains unanswered. The primary purpose of this study is to fill this gap by exploring the impact of AI on the unemployment of educated people with disabilities by gender using linear and nonlinear estimation techniques in 33 countries during the period 2004-2021. By doing so, this paper contributes to the literature in different ways. First, this study is the first to conduct a nonlinear analysis to examine the influence of AI on unemployment among educated people with disabilities. Unlike previous studies that suggested a linear relationship between AI and unemployment, the present study shows that AI may have a nonlinear effect. Second, the study examines whether the effects of AI on the unemployment of educated people with disabilities depend on a given threshold level for AI. In other words, the empirical analysis examines if the adoption level of AI (low/high) is important when checking its impact on the unemployment of educated people with disabilities. Third, the research explores the effects of AI on the unemployment of educated people with disabilities by gender. Therefore, the unemployment of both educated men and educated women with disabilities is considered in the analysis. Finally, in contrast to most prior research studies, this paper provides a comprehensive empirical analysis using an extended dataset that includes the majority of technologically advanced countries worldwide. The rest of the paper is organized as follows. The following section describes the data and methodologies used in this study. The results are discussed in the Empirical Results and Discussion section. The Conclusion and Policy Implications section concludes the paper with policy implications and recommendations.
DATA AND METHODOLOGY

Data

This study uses panel data from 33 European countries from 2004 to 2021. The 33 countries under study include 10 Northern European countries (Denmark, Estonia, Finland, United Kingdom, Ireland, Iceland, Lithuania, Latvia, Norway, and Sweden), 7 Eastern European countries (Bulgaria, Czech Republic, Hungary, Moldova, Poland, Romania, and Slovakia), 9 Southern European countries (Albania, Spain, Greece, Croatia, Italy, Malta, Portugal, Serbia, and Slovenia), and 7 Western European countries (Austria, Belgium, Switzerland, Germany, France, Luxembourg, and the Netherlands). The dependent variable is the unemployment rate among educated people with disabilities (U) in thousands. AI is measured in this study by the annual number of patent applications per million people. In addition, six control variables are introduced into the analysis; economic growth measured by gross domestic product (GDP) per capita (GDP) in constant 2015 US$, government expenditure (GE) as a share of GDP, inflation (IF) measured by the annual growth rate of the consumer price index, and gross school enrollment for primary education (SEP), secondary education (SES), and tertiary education (SET). Data on AI and the unemployment rate are collected from Our World in Data and international labour organization statistics (ILOSTAT), respectively. All control variables are extracted from the World Development Indicators of the World Bank. The natural logarithm transformation is applied to all variables.

Methodology

In this study, we utilize a combination of the static and dynamic panel estimation techniques and the panel smooth threshold regression (PSTR) model to estimate the impact of AI on the unemployment of educated people with disabilities. The static panel estimation techniques considered in this study include cross-section pooled ordinary least squares (POLS), random effects (RE), fixed effects (FE), and panel-corrected standard error (PCSE) models. The dynamic panel estimation techniques include the Arellano-Bond generalized method of moments (GMM) estimator. Finally, the PSTR model proposed by González et al. (2005) is used. The procedures for estimating these models are further discussed in the subsequent sections.

GMM estimator

To examine the nexus between AI and the unemployment of educated people with disabilities (U), we formulate the following model:

\[ U_{it} = \alpha_i + \beta_1 A_{it} + \beta_2 GDP_{it} + \beta_3 GE_{it} + \beta_4 IF_{it} + \beta_5 ED_{it}^m + \theta_i + \lambda_t + \eta_{it} \]  

where \( U_{it} \) denotes the total unemployment of educated people with disabilities, the unemployment of educated men with disabilities, and the unemployment of educated women with disabilities, respectively. \( A_{it} \) designates the proxy of AI. GDP, GE, and IF rate. \( ED_{it}^m (m = 1, 2, 3) \) denotes SEP, SES, and SET, respectively. \( \theta_i \) indicates the country-specific effect, \( \lambda_t \) is the time-specific effect, and \( \eta_{it} \) is the error term. The indices \( i \) and \( t \) refer to countries (\( i = 1, 2, \ldots, N \)) and periods (\( t = 1, 2, \ldots, T \)).

Unlike previous studies that used cointegration and causality techniques, we implement the GMM estimator proposed by Arellano and Bond (1991) as a dynamic panel data estimation technique. This technique allows for addressing the issue of potential endogeneity in all explanatory variables used in the estimated models rather than just focusing on the variable of interest, as is the case with instrumental variables. The first differences of the endogenous explanatory variables are instrumented by their lagged values (two periods at least) in levels. Taking the first difference involves subtracting the previous value of a variable from its current value. This transformation is often used to make a time series stationary, simplifying the analysis and improving the reliability of statistical analysis. According to this hypothesis, the correlation between the individual effect and the endogenous explanatory variables in level is constant over time. The resulting system of equations is estimated using the GMM. The estimates performed correspond to the two-step estimation procedure. In the first step, the self-correlation structure of the perturbations is taken into account, and the error terms are assumed to be independent and homoscedastic over time and between individuals. The vector of residuals estimated in the first step is then used in the second step to estimate convergently the variance–covariance matrix of the perturbations. This procedure is preferred given its greater asymptotic efficiency compared to that of one-step estimation (Roodman, 2009a, b). To test the validity of instruments, we implement the Hansen (1982) test for over-identification of moment restrictions, as suggested by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). It allows testing the validity of the lagged values in level and difference as instruments (Kpodar, 2007). We also carried out the autocorrelation (AR) test of the errors, as proposed by Arellano and Bond (1991).

The PSTR model

To examine the relationship between AI and unemployment among educated people with disabilities, we perform the threshold-effect panel data model. This model is generally used to analyze nonlinear economic phenomena, where the behavior of economic series depends on different regimes. The threshold models incorporate a threshold variable that dictates the regime to which the data belong. The transition between one regime to another is assessed by a transition function. According to Hansen (1999), nonlinearity arises because the dependent variable is generated by distinct regimes. The choice between these regimes is determined by the value of a variable known as the transition variable. The transition between the two regimes is assumed to be abrupt.
The PSTR model proposed by González et al. (2005) is an extension of threshold modeling proposed by Teräsvirta (1994, 1998). It allows for a smoother transition between regimes. Instead of an abrupt shift, the transition function in PSTR is continuous, representing a gradual change. The PSTR model is particularly useful when the transition from one regime to another is not sudden but occurs gradually. In this context, the PSTR model is more appropriate for describing the change in economic behavior induced by quantitative regime variables. These could be variables that measure the intensity or level of certain factors, such as the degree of AI adoption. Therefore, the present study explores the relationship between AI and unemployment among educated people with disabilities using the threshold regression model. The choice between Hansen’s (1999) model and González et al.’s (2005) PSTR model depends on the nature of the transition between regimes—whether it is abrupt (Hansen) or gradual (PSTR). PSTR models are considered more appropriate when the transition is smoother, providing a continuous representation of the change in economic behavior induced by quantitative regime variables. A smooth transition threshold model proposed by González et al. (2005) is used.

To illustrate the relationship between AI and unemployment among people with disabilities, we assume the simple case of the PSTR model with two regimes and a single transition function:

\[ U_{t}^i = \alpha_i + \beta_i AI_{t,i} + \gamma_i Z_{t,i} × \Gamma(q_{i,t};\lambda,c) + \eta_{i,t}, \]  

where \( U_{t}^i \) (j = 0, 1, and 2) denotes the total unemployment of educated people with disabilities, the unemployment of educated men with disabilities, and the unemployment of educated women with disabilities, respectively. \( AI_{t,i} \) is AI and \( Z_{t,i} \) is a K-dimensional vector of the other control variables generally considered in the literature on unemployment. \( \alpha_i \) indicates the country-specific effect and \( \eta_{i,t} \) is the error term. \( i \) and \( t \) denote countries (\( i = 1, 2, \ldots, N \)) and time (\( t = 1, 2, \ldots, T \)), respectively. The transition function \( \Gamma \) is continuous and depends on the threshold variable \( q_{i,t} \) and on \( c = \{ c_1, c_2, c_3, \ldots, c_n \} \), which is a vector of threshold parameters, and the parameter \( \lambda \) determines the slope of the transition function. Like Granger and Teräsvirta (1993) and González et al. (2005), we consider the following logistic transition function:

\[ \Gamma(q_{i,t};\lambda,c) = \left( 1 + \exp\left( -\lambda \prod_{j=1}^{n}(q_{i,t} - c_j) \right) \right)^{-1}, \]  

\( \lambda > 0, c_1 < \ldots < c_n. \)

The PSTR model provides a parametric approach to account for the heterogeneity of individuals both in the instability over time of the coefficients of the AI—unemployment of disabled people—as well as a smooth change in these variables with respect to the threshold variable. For example, if the transition variable \( q_{i,t} \) is different from AI (\( AI_{t,i} \)), then the sensitivity of the AI for the ith country at time t is defined as follows:

\[ \delta_{i,t}^{\gamma} = \frac{\partial U_{t}^i}{\partial AI_{t,i}^{\gamma}} = \beta_0 + \beta_i \Gamma(q_{i,t};\lambda,c) \left\{ \begin{array}{ll} q_{i,t} \leq c: & \text{first regime} \vspace{1em} \\
q_{i,t} > c: & \text{second regime} \end{array} \right. \]  

where \( \delta_{i,t}^{\gamma} \) represents the elasticity of unemployment of disabled people with respect to AI over time and in the country. The model is subdivided into two regimes (first and second) according to the parameter \( c \). When the transition function is \( \Gamma(q_{i,t};\lambda,c) \rightarrow 0 \), the parameter \( \beta_0 \) is expressed as an AI coefficient only. On the other hand, the sum of the coefficients \( (\beta_0 + \beta_i) \) corresponds to the AI coefficient when the transition function is \( \Gamma(q_{i,t};\lambda,c) \rightarrow 1 \).

Regarding the number of transition equations, the test procedure is conducted as follows. We test:

\[ \begin{align*}
H_0: r &= r^* \\
H_1: r &= r^* + 1
\end{align*} \]  

If \( H_0 \) is not rejected, the procedure stops. Otherwise, we test:

\[ \begin{align*}
H_0: r &= r^* + 1 \\
H_1: r &= r^* + 2
\end{align*} \]  

The test procedure continues until \( H_p \) is accepted.

**EMPIRICAL RESULTS AND DISCUSSION**

**Static panel data model estimation results**

Using the static panel data models, we estimate our specification for a panel of 33 countries. The estimation results are presented in Table 1. The dependent variable \( U_{t,i}^{\gamma} \) represents the total unemployment, with \( U_{t,i}^{\gamma} \) being the unemployment of men with disabilities and \( U_{t,i}^{\gamma} \) being the unemployment of women with disabilities. To begin, one should select the appropriate estimation method. First, a cross-section POLS method is used to estimate model (1). Based on the results, we can conclude that the coefficients of all variables have the expected signs and are statistically significant at 1 and 5% levels (except for SEP, AI for unemployment of women, and GE). In the same way, the estimation results have the expected signs using the RE model. In fact, for the ordinary least squares (OLS) model, the R-squared ranges between 0.880 and 0.901, while for the RE model, it is between 0.802 and 0.845. The coefficients for these two models are close to one, indicating a good quality of adjustment and that both models are significant. Nevertheless, the Hausman test can be applied to determine whether the FE or RE model is appropriate. The results of the Hausman test confirm that the hypothesis of no correlation between the error term and the model’s explanatory variables is rejected (P value = 0.011; 0.029 and 0.031). Therefore, FE estimations are more consistent and efficient than RE estimations. Therefore, the unbiased FE model is preferred since it provides better estimates. In addition to individual effects, panel data models
Table 1: Estimation results of static panel data models.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
<th>Model 10</th>
<th>Model 11</th>
<th>Model 12</th>
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</thead>
<tbody>
<tr>
<td>AI</td>
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<td>-0.003***</td>
<td>-0.007</td>
<td>-0.015***</td>
<td>-0.005***</td>
<td>-0.008</td>
<td>0.019***</td>
<td>-0.006***</td>
<td>-0.009</td>
<td>-0.012***</td>
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</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.008)</td>
<td>(0.156)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.104)</td>
<td>(0.000)</td>
<td>(0.005)</td>
<td>(0.128)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>GDP</td>
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<td>-0.214***</td>
<td>-0.128***</td>
<td>-0.271***</td>
<td>-0.301***</td>
<td>-0.276**</td>
<td>-0.238***</td>
<td>-0.205***</td>
<td>-0.401***</td>
<td>-0.325***</td>
<td>-0.220**</td>
<td>-0.313**</td>
</tr>
<tr>
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<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.013)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.014)</td>
<td>(0.001)</td>
<td>(0.035)</td>
<td>(0.151)</td>
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<td>-0.015</td>
<td>-0.023</td>
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<td>-0.024</td>
<td>0.021</td>
<td>0.012</td>
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<td>(0.105)</td>
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<td>(0.247)</td>
<td>(0.101)</td>
<td>(0.141)</td>
<td>(0.208)</td>
<td>(0.551)</td>
<td>(0.281)</td>
<td>(0.274)</td>
<td>(0.175)</td>
<td>(0.621)</td>
<td>(0.335)</td>
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<tr>
<td>IF</td>
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<td>-0.017**</td>
<td>-0.012***</td>
<td>-0.011***</td>
<td>-0.018**</td>
<td>-0.009***</td>
<td>-0.014***</td>
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<td>-0.008**</td>
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<td>(0.005)</td>
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<td>(0.008)</td>
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<td>(0.029)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.030)</td>
<td>(0.031)</td>
<td>(0.045)</td>
<td>(0.000)</td>
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<td>0.013</td>
<td>0.017</td>
<td>0.020</td>
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<td>(0.301)</td>
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<td>(0.273)</td>
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<td>(0.185)</td>
<td>(0.118)</td>
<td>(0.186)</td>
<td>(0.195)</td>
<td>(0.521)</td>
<td>(0.314)</td>
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<tr>
<td>SET</td>
<td>-0.015**</td>
<td>-0.014**</td>
<td>-0.022***</td>
<td>-0.027***</td>
<td>-0.029**</td>
<td>-0.031***</td>
<td>-0.033**</td>
<td>-0.036***</td>
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<td>-0.030**</td>
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<tr>
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<td>(0.003)</td>
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<td>(0.006)</td>
<td>(0.023)</td>
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<td>(0.012)</td>
<td>(0.047)</td>
<td>(0.005)</td>
<td>(0.019)</td>
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<tr>
<td>SES</td>
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<td>-0.040**</td>
<td>-0.037***</td>
<td>-0.035***</td>
<td>-0.042**</td>
<td>-0.031***</td>
<td>-0.036**</td>
<td>-0.029**</td>
<td>-0.030***</td>
<td>-0.033**</td>
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<td>(0.001)</td>
<td>(0.000)</td>
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<td>(0.068)</td>
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<td>(0.000)</td>
<td>(0.008)</td>
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<td>(0.019)</td>
<td>(0.030)</td>
<td>(0.017)</td>
<td>(0.011)</td>
<td>(0.028)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Diagnostic tests

- $R^2$: 0.889, 0.880, 0.901, 0.845, 0.811, 0.802, 0.889, 0.825, 0.903, 0.847, 0.946, 0.919
- LM test: 345.574***, 366.081***, 371.068***
- Hausman test: 68.504***, 64.301**, 57.173***

Notes: Parentheses indicate the $P$ values. ***, **, and * represent the statistical significance at 1, 5, and 10%, respectively.
Abbreviations: AI, artificial intelligence; FE, fixed effects; GE, government expenditure; IF, inflation; PCSE, panel-corrected standard errors; POLS, pooled ordinary least squares; RE, random effects; SEP, school enrollment for primary education; SES, school enrollment for secondary education; SET, school enrollment for tertiary education.
also address the issue of correlations and heteroscedasticity. According to Table 1, the explanatory variables are correlated with the residuals squared, and there is evidence of heteroscedasticity (the \( F \)-statistic does not exceed 5%). Hence, it produces inconsistent estimators when the explanatory variables and error terms are correlated.

To address the heteroscedasticity problem, we use the PCSE estimator. In Table 1, the last three columns report the estimation results. The R-squared is close to 1 (between 0.825 and 0.903), which shows a good adjustment quality of the model. The coefficients of the explanatory variables have the expected signs and are statistically significant at the 1 and 5% levels, except AI for unemployed women with disabilities (model \( U_{i,t}^{0} \)), \( GE \), and primary school enrollment, which are insignificant or have unexpected signs. In addition, AI, economic growth, IF, secondary school enrollment, and tertiary school enrollment have negative impacts on the unemployment rate of people with disabilities (total and men). In contrast, the effect of AI on unemployed women with disabilities is insignificant. Regarding the control variables, the findings show that economic growth has the most significant impact on unemployment among people with disabilities, followed by tertiary school enrollment, secondary school enrollment, and IF. Indeed, for model \( U_{i,t}^{0} \), when economic growth, tertiary education, secondary education, and IF increase by 10%, total unemployment among people with disabilities decreases by 3.25, 0.33, 0.30, and 0.06%, respectively. In model \( U_{i,t}^{1} \), unemployment of men with disabilities decreases by 2.20, 0.35, 0.24, and 0.08%, respectively, while in model \( U_{i,t}^{2} \), the effect of AI on the unemployment of women with disabilities is negative but insignificant.

It is worth mentioning that static panel data models do not allow capturing the dynamic nature of the data, which is a fundamental issue in the empirical literature. Furthermore, these estimators can only deal with structural heterogeneity in the form of random or FE but require the model’s slope coefficients to be homogeneous between countries despite the significant differences.

**Dynamic panel data model estimation results**

In this section, we employ the GMM estimator to examine the hypothesis of linearity in Okun’s law and investigate the relationship between unemployment, AI, school enrollment, economic growth, IF, and \( GE \). Results of the difference GMM, system GMM (S-GMM) and least squares dummy variable (LSDV) are reported in Table 2.

The findings suggest several problems when using the two-step S-GMM estimator. First, the instruments used in our regressions are invalid because the Sargan test rejects the validity of the lagged variables in level and difference as instruments. Furthermore, we note a second-order autocorrelation of the errors in the difference equation autocorrelation (AR2) as the Arellano and Bond second-order autocorrelation test allows us to reject the hypothesis of no second-order autocorrelation.

To overcome this shortcoming, we employ the LSDV approach, which produces less biased estimates than the GMM technique. The results show that the lagged dependent variables \((U_{i,t-1}, U_{i,t}, U_{i,t-2})\) are positively and significantly correlated with the dependent variables \((U_{i,t}^{0}, U_{i,t}^{1}, U_{i,t}^{2})\). In other words, unemployment in the year \( t \) depends positively on unemployment in the year \( t-1 \). Okun’s law is validated for the aggregate and disaggregate unemployment specifications, given the negative and statistically significant coefficients of GDP in Table 2. The results show that a 10% increase in GDP leads to a 2.38% reduction in total unemployment. This result is statistically significant at the 1% level. When the economic growth increases by 10%, the unemployment of men with disabilities drops by 2.05%.

In addition, AI also shows a negative and statistically significant coefficient, suggesting that AI is negatively associated with aggregate and male unemployment rates for people with disabilities. Specifically, a 10% increase in AI decreases aggregate and male unemployment rates by 0.19 and 0.06%, respectively. In contrast, the effect of the AI variable on \( U_{i}^{2} \) is not statistically significant. This suggests that AI does reduce the unemployment rates of educated women with disabilities. Women may access these fields if reskilling and upskilling programs are provided. The female labor force also requires digital skills to understand and raise concerns about the implemented systems. Despite qualifications and job opportunities, women can still not access these jobs. Policymakers should, therefore, work to narrow and close these gaps. It is imperative for the government, institutions, organizations, and enterprises to provide substantial support for females, with a specific focus on science, technology, engineering, and mathematics (STEM) subjects. This assistance will play a crucial role in fostering the progress of women in AI technologies. According to our results, AI does not have any significant impact on the unemployment of educated women with disabilities. The results are consistent with those of Acemoglu and Restrepo (2018), Tambe et al. (2019), and Cerit et al. (2020) but contradict those of Webb (2020) and Lu et al. (2023).

As expected, the relationship between education and unemployment among educated people with disabilities is negative. A 10% increase in secondary school enrollment leads to a decrease of 0.33, 0.36, and 0.28% in \( U_{i}^{0}, U_{i}^{1}, \) and \( U_{i}^{2} \), respectively. Furthermore, a 10% increase in tertiary school enrollment leads to a decrease of 0.32, 0.29, and 0.30% in the \( U_{i}^{0}, U_{i}^{1}, \) and \( U_{i}^{2} \), respectively. IF significantly and negatively impacts aggregate (\( U_{i}^{0} \)) and disaggregate unemployment (\( U_{i}^{1} \) and \( U_{i}^{2} \)). Indeed, IF reduces \( U_{i}^{0}, U_{i}^{1}, \) and \( U_{i}^{2} \) by 0.09, 0.14, and 0.17%, respectively. Therefore, the results validate the Phillips curve hypothesis, which suggests an inverse relationship between IF and unemployment.

**Estimation of the PSTR model**

The final step of the empirical investigation consists of implementing the PSTR model. Before examining the effects of AI on the unemployment of educated people with disabilities (U) using AI as a threshold variable, we used the test the lagrange multiplier Fisher test (LMF) and the lagrange multiplier Wald test (LMW). This will allow us to determine the most suitable model for the study, either the linear panel
Table 2: Results from dynamic panel data estimation models.

<table>
<thead>
<tr>
<th>Variables</th>
<th>D-GMM</th>
<th></th>
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<th>S-GMM</th>
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<th>LSDV</th>
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</table>

Diagnostic tests

Sargan test: 0.022 (0.018) 0.013 (0.013) 0.019 (0.016) 0.011 (0.006) 0.012 (0.013) 0.006 (0.006) 0.010 (0.015) 0.017 (0.017)

Note: Parentheses indicate the P values. ***, *, and * represent the statistical significance at 1, 5, and 10%, respectively. Abbreviations: AI, artificial intelligence; D-GMM, difference GMM; GE, government expenditure; GMM, generalized method of moments; IF, inflation; LSDV, least squares dummy variable; SEP, school enrollment for primary education; SES, school enrollment for secondary education; SET, school enrollment for tertiary education; S-GMM, system GMM.
model or the nonlinear panel model (PSTR model) (see Table 3). Using AI as the threshold variable, the LMW and LMF linearity tests reject the null hypothesis of the linear model and confirm the suitability of the PSTR model with at least two regimes at a significance level of 1% for the \( U^2 \) model, while for the \( U^0 \) and \( U^1 \) models the null hypothesis of the linear model could not be rejected.

For the \( U^2 \) model, it is crucial to determine the number of regimes (PSTR model) to study the effect of AI on the unemployment of educated women with disabilities. The LMW and LMF tests are presented in Table 4. Under the null hypothesis, the preferred model is the PSTR model with two regimes, while under the alternative hypothesis, the preferred model is the PSTR model with at least three regimes. The LMW and LMF tests lead us to accept the null hypothesis and reject the alternative hypothesis of the existence of at least three regimes. The preferred model is, therefore, the PSTR model with two regimes.

We examine the nonlinear effects using AI as the threshold variable and report the findings in Table 5. As shown, the threshold level for AI is significant when considering the unemployment rate of educated women. The results particularly indicate that women whose AI adoption exceeds a certain threshold experienced a negative and significant impact on unemployment (when AI is greater than 5.217). On the contrary, AI does not significantly affect unemployment when AI is below this threshold. The results show that a 10% increase in AI decreases \( U^2 \) by 0.05% when exceeding the threshold level of 5.217. In addition, if countries exceed a certain AI threshold, the effect of this variable on the unemployment of educated women with disabilities would be negative and significant. Indeed, AI can effectively contribute to reducing unemployment among women with disabilities by helping them overcome the barriers and challenges they face in the labor market (Sandybayev, 2018; Pedreschi et al., 2019). In other words, AI can create jobs that are more accessible to people with disabilities. For example, it can be used to automate repetitive, physically demanding, or dangerous tasks, reducing reliance on physical strength. This widens the scope of potential jobs for women with disabilities. Furthermore, AI can provide personalized training tailored to the needs of women with disabilities (Kral et al., 2019; Packin, 2021). This can prepare them for jobs suited to their skills, thus removing barriers to learning. Indeed, AI technologies, such as screen readers, voice recognition software, and assistive communication systems, improve the accessibility of digital work environments, enabling women with disabilities to participate more effectively (Kovacova et al., 2019; Mutascu, 2021). In addition, AI tools can contribute to more inclusive recruitment by eliminating bias in the selection processes. They can analyze candidates’ skills and experience, reducing potential discrimination (Brunn and Duka, 2018; Kim, 2018). In other words, AI can facilitate remote working by enabling online communication, collaboration, and project management. This offers women with disabilities the flexibility to work from home, reducing mobility constraints. AI can also raise awareness of diversity and inclusion by providing educational content, promoting inclusive practices, and encouraging employers to diversify their workforce (Moss, 2020; Adeliyi et al., 2022). However, it is essential to mention that integrating AI into solving the unemployment problems of women with disabilities requires coordinated action from governments, enterprises, and society. Supportive policies, accessibility standards, and awareness-raising are as important as technology in creating an inclusive working environment.

Table 3: Linearity test results.

<table>
<thead>
<tr>
<th>Threshold variable</th>
<th>Wald tests (LMW)</th>
<th>Fisher tests (LMF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI</td>
<td>(0.437)</td>
<td>(0.504)</td>
</tr>
<tr>
<td>AI</td>
<td>(0.412)</td>
<td>(0.377)</td>
</tr>
<tr>
<td>AI</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Note: \( H_1 \): linear model; \( H_2 \): linear model; \( H_3 \): multiple regimes PSTR model. The values in parentheses are \( P \) values.

Table 4: Nonlinearity test results.

<table>
<thead>
<tr>
<th>Threshold variable</th>
<th>Wald tests (LMW)</th>
<th>Fisher tests (LMF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI</td>
<td>(0.145)</td>
<td>(0.206)</td>
</tr>
</tbody>
</table>

Note: \( H_1 \): 2 regimes of the PSTR model; \( H_2 \): at least three regimes of the PSTR model. The values in parentheses are \( P \) values.

Table 5: Results of PSTR estimation.

<table>
<thead>
<tr>
<th>Threshold</th>
<th>First regime ( \lambda_1 \leq 5.217 )</th>
<th>Second regime ( \lambda_1 &gt; 5.217 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI</td>
<td>-0.002 (0.251)</td>
<td>-0.005*** (0.000)</td>
</tr>
<tr>
<td>GDP</td>
<td>-0.401** (0.014)</td>
<td>-0.420*** (0.000)</td>
</tr>
<tr>
<td>GE</td>
<td>-0.011 (0.186)</td>
<td>-0.016** (0.026)</td>
</tr>
<tr>
<td>IF</td>
<td>0.011** (0.071)</td>
<td>-0.013** (0.055)</td>
</tr>
<tr>
<td>SEP</td>
<td>-0.019 (0.388)</td>
<td>-0.026** (0.037)</td>
</tr>
<tr>
<td>SES</td>
<td>-0.016** (0.032)</td>
<td>-0.018*** (0.005)</td>
</tr>
<tr>
<td>SET</td>
<td>-0.028* (0.082)</td>
<td>-0.033** (0.012)</td>
</tr>
</tbody>
</table>

Notes: Parentheses indicate the \( P \) values. ***, **, and * represent the statistical significance at 1, 5, and 10%, respectively. Abbreviations: AI, artificial intelligence; GE, government expenditure; IF, inflation; PSTR, panel smooth threshold regression; SEP, school enrollment for primary education; SES, school enrollment for secondary education; SET, school enrollment for tertiary education.
as GE and SET, are negative and insignificant in the first regime ($\lambda \leq 5.217$) and negative and significant in the second regime ($\lambda > 5.217$). On the other hand, IF has a significant and positive effect on $U^2$ in the first regime and a negative and significant effect in the second regime. In the case of the first regime, the results show that a 10% increase in GDP, SES, and SET decrease $U^2$ by 4.01, 0.16, and 0.28%, respectively, while a 10% increase in IF increases $U^2$ by 0.11%.

**Robustness check**

To test the robustness of the PSTR model results, we employ the GMM estimator to estimate a nonlinear version of the unemployment specification, which incorporates AI and its squared term.

The regression equation may take the following form:

$$U^2_{i,t} = \alpha_i + \lambda_1 U^2_{i,t-1} + \lambda_2 AI_{i,t} + \lambda_3 AI^2_{i,t} + \lambda_4 X_{i,t} + \epsilon_{i,t}, \quad (7)$$

where $\epsilon_{i,t}$ represents the error term, the other variables being defined previously. Equation (7) contains AI and AI squared, which allows us to consider the nonlinearity in the unemployment specification. This specification also makes it possible to determine the marginal effect of AI on unemployment among educated people with disabilities.

The estimation results reported in Table 6 reveal the existence of a monotonically decreasing impact of AI on aggregate unemployment among educated people with disabilities and unemployment among educated men with disabilities. In contrast, the relationship is an inverted U-shaped for women. Therefore, the estimated quadratic equation allows us to determine the threshold of AI, which makes it possible to minimize unemployment among educated women with disabilities.

From a mathematical point of view, this level of AI cancels the first derivative. Thus, the minimization condition allows us to obtain:

$$\frac{\partial U^2}{\partial AI} = 0 \Rightarrow 0.006 - 2 \times 0.005 AI = 0 \Rightarrow AI = 60\%.$$

The coefficient of AI is positive and significant at the 1% level (0.006). This means that a 10% increase in AI induces an increase in unemployment among educated women with disabilities of 0.06%. In addition, the coefficient of AI square is negative and significant at the 1% level (−0.005). These results show that an increase in AI by 10% beyond this threshold leads to a decrease in unemployment among educated women with disabilities by 0.05%. The analysis of the coefficient (−0.005) of the AI in relation to unemployment among educated women with disabilities reveals that it is negative and significant at the 1% level. This means that AI nonlinearly affects the unemployment of educated women with disabilities. The threshold of the positive effect of AI on unemployment among educated women with disabilities is 60%. Beyond this level, the effect of AI is negative.

In summary, Table 6 suggests that the nonlinear GMM model confirms the results obtained using the PSTR and GMM approaches. The results indicate that the relationship between AI and unemployment among educated people with disabilities follows a decreasing monotonic pattern for the full sample and men but an inverted U-shaped pattern for women.

**CONCLUSIONS AND POLICY IMPLICATIONS**

This study aims to identify the linear and nonlinear effects of AI on unemployment among educated people with disabilities in 33 countries during the period 2004–2021 using static, dynamic, and threshold panel data models. We estimate the effects of AI on aggregate unemployment and unemployment among educated men and women with disabilities. In addition to the interest variable (AI), the unemployment specification is augmented by many control variables, including school enrollment (primary, secondary, and tertiary), GE, IF, and economic growth.

The results may be summarized as follows. First, the static and dynamic GMM estimation techniques show that AI, economic growth, IF, primary school enrollment, and tertiary school enrollment have significant and negative impacts on the unemployment of educated people with disabilities.
and unemployment among educated men with disabilities. In contrast, AI does not significantly affect educated women unemployment. Second, robust evidence has been provided by the PSTR model regarding the nonlinear effects of AI on the unemployment of educated women with disabilities. In addition, AI has no significant effect on the unemployment rate of educated women with disabilities in the lower regime, i.e. low AI. However, the situation is different for the upper regime. This research suggests that while AI adoption may not have immediate significant impacts on educated women with disabilities, there is potential for positive outcomes in the long term as countries continue to embrace AI technologies.

Based on the empirical investigation, several policy implications can be drawn. (i) Increased accessibility: AI-based technologies, such as screen readers, speech recognition software, and adaptive user interfaces, improve the accessibility of computers and digital devices. This makes it easier for people with disabilities to participate in the digital workforce. (ii) Job adaptation: AI can be used to adapt jobs to the needs of people with disabilities. For example, robots can help people with physical disabilities perform physically difficult tasks. (iii) Training and Assistance: AI systems can provide personalized training and assistance to people with disabilities, adapting training programs and tools to their specific needs. (iv) Online labor market: AI-based online platforms offer new remote work opportunities, which can benefit people with disabilities by reducing mobility barriers. (v) Awareness and education: AI can also raise awareness of diversity and inclusion and educate employers about the benefits of hiring people with disabilities. (vi) Adapting the work environment: AI-based systems can help adapt the work environment to the needs of workers with disabilities by controlling lighting, temperature and assistive devices. However, it is essential to note that the impact of AI on the unemployment of women with disabilities will also depend on societal factors, government policies, and the willingness of employers to implement inclusive practices. AI is a powerful tool to promote inclusion, but it cannot solve the problems related to the unemployment of women with disabilities on its own. It must be integrated into a broader awareness framework, policies, and measures to create fair opportunities in the labor market.

Numerous avenues for further research can be explored based on this paper limitations. First, we examine whether AI affects unemployment among educated people with disabilities at the country level without disentangling the effects by sector. Indeed, AI adoption may differ from one sector to another. Therefore, conducting a sectoral analysis will be interesting. Second, we investigated the threshold level of AI when panel data sets are used, and this may be followed by a future study that applies time series threshold models to evaluate potential threshold levels for a specific country. Third, this paper investigates the effects of AI on unemployment among educated people with disabilities. However, a future study may examine whether there are threshold levels for other AI measures, such as data science, machine learning, and robots.

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