International Journal of Strategic Management and Economic Studies (IJSMES)
ISSN: 2791-299X

Technologically intensive SMEs and AI: determinants of the growing demand for specialized training profiles

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Abstract: This paper analyzes the determinants of the demand by technologically intensive SMEs for profiles trained in artificial intelligence (AI). The study is based on the Theory of Skill-Biased Technological Change (SBTC), which posits that AI increases the demand for highly skilled workers while making routine skills obsolete. The sample includes 238 SMEs, selected for their integration of AI and diversity in terms of size and sectors. These companies, although local, are innovation-oriented and internationally open, allowing for the assessment of AI's effects beyond major economic hubs. The adopted methodology is based on an econometric model using Ridge Regression. The results show that companies where AI complements human skills actively seek specialized profiles. The automation of routine tasks and the transformation of business models also contribute to this increased demand. Conversely, government support does not have a significant impact. Moreover, larger companies and those focused on exports exhibit a stronger need for qualified profiles.

Keywords: demand for AI profiles, technologically intensive SMEs, technological innovation, labor market polarization, competitiveness.

JEL Classification: J23, O33, M15, L25.

Digital Object Identifier (DOI): https://doi.org/10.5281/zenodo.14034447

Published in: Volume 3 Issue 3

1. Introduction

Artificial intelligence has emerged as a key driver of transformation for companies worldwide, significantly influencing organizational processes, business models, and, more notably, human resource needs. In an era of increased competitiveness, technologically intensive SMEs face challenges requiring increasingly specialized profiles to harness the opportunities offered by AI. This reality highlights a major strategic issue: how do these companies define and adjust their demand for AI-trained talent based on their internal characteristics and market positioning? This study aims to explore the key factors influencing the demand of SMEs for AI-trained profiles. It is grounded in the Theory of Skill-Biased Technological Change (SBTC), which states that technological advancements disproportionately benefit highly skilled workers, thereby exacerbating labor market polarization. This theory contextualizes the transformation of skill requirements within a framework where technological innovation continuously redefines tasks and professional responsibilities.

To understand this dynamic, the study is structured around several areas. First, it examines how the integration of AI transforms internal company processes, creating increased demand for advanced technical skills. Second, it analyzes the impact of automating routine tasks, which tends to reduce the relevance of general skills, thereby increasing the necessity of recruiting skilled workers capable of developing, managing, and optimizing AI-based solutions. Third, the study explores how the transformation of business models through AI drives companies to seek talent capable of supporting complex organizational innovations. Furthermore, this research considers specific characteristics of companies, such as their size, innovation capacity, and international orientation. The study highlights that large companies generally have more resources to invest in acquiring qualified talent, while export-oriented SMEs often face greater pressure to adopt technological skills to remain competitive in international markets. The analysis also addresses the effectiveness of current public policies supporting companies, revealing the shortcomings of subsidy mechanisms that have not yet achieved the expected impact on AI skill adoption. Thus, this paper aims to shed new light on the technological skill needs of SMEs in the Moroccan context while emphasizing the strategic implications for policymakers and decision-makers.

2. Literature review

Alekseeva et al. (2021) reveal a substantial increase in the demand for artificial intelligence skills and a significant wage premium in the U.S. labor market between 2010 and 2019. This underscores the growing pressure to attract specialized talent across various sectors, highlighting the strategic importance of AI skills. Rani, Pesole, and Gonzalez Vazquez (2024) delve deeper into this topic by analyzing algorithmic management practices in sectors such as logistics and healthcare. They note a sharp rise in demand for specialized AI skills, emphasizing the importance of adequate training to ensure worker adaptability and competitiveness, which necessitates significant investments in skill development programs. Manyika et al. (2017) also examine labor market transformations due to automation, projecting a notable increase in jobs within information technologies. Their research stresses the need for companies to prepare for this transition by training professionals who can work alongside AI systems, positioning workforce reskilling as a crucial element to meet skill demands in a rapidly changing technological landscape.

This idea is partly supported by Felton, Raj, and Seamans (2018), who emphasize the importance of essential skills in the era of AI. Their study identifies the abilities most susceptible to automation, suggesting that training specialized profiles could reduce the risk of being replaced by machines. Liu, Chen, and Lyu (2024) specifically explore the integration of AI into the labor market and its impact on skill demand in non-IT fields, such as statistics. Their study reveals a 31-fold increase in demand for specialized statistical skills in AI between 2010 and 2022, highlighting the enormous need for talent in machine learning and data analysis. They advocate for greater collaboration among governments, academic institutions, and companies to develop interdisciplinary skills. Moniz, Candeias, and Boavida (2022) describe the challenges facing the Portuguese automotive sector due to AI-driven automation. They emphasize that companies must invest in training to attract and retain highly skilled profiles to avoid technological stagnation and maintain productivity.

Brekelmans and Petropoulos (2020) find that the rise of AI and machine learning technologies is redefining the skills needed in the workforce, emphasizing highly qualified jobs that require non-routine communication and problem-solving abilities. This phenomenon leads to labor market polarization, with a decrease in mid-skilled jobs and an increase in demand for specialized profiles, particularly in AI-intensive sectors. Pettersen (2019) complements this perspective by highlighting that, despite AI advances, certain critical tasks still require human-machine collaboration, especially in areas like quality control and automated systems management. The demand for workers capable of effectively collaborating with machines remains high. Du (2024) broadens the discussion by explaining that AI adoption has ambivalent effects on employment: it threatens some positions through automation but also creates new opportunities for specialized AI roles, such as machine learning engineering and data science. Du (2024) underscores the importance of continuous training to help workers adapt to technological shifts. Duch-Brown et al. (2022) reinforce the notion of strong demand for AI skills by analyzing online labor markets, where projects requiring AI expertise are increasingly common and highly paid. However, they observe an imbalance caused by a limited supply of qualified professionals.

Ključnikov, Popkova, and Sergi (2023) add that the global labor market is transforming with the rise of smart technologies, creating a demand for specialized skills. According to them, companies now heavily depend on competent human resources to adapt to the demands of Industry 4.0, where continuous training and AI upskilling are crucial to maintaining competitiveness. Raj and Seamans (2018) stress the urgency of collecting accurate company-level data on AI usage. They explain that this approach is essential for anticipating skill requirements in the context of automation, especially given the changes induced by AI integration across various sectors. Meanwhile, Bertello et al. (2021) emphasize the rapid pace of digital technological evolution, accentuated by challenges like the pandemic. They argue that this context heightens the need for skilled AI talent, as companies experience significant efficiency gains from optimal technological integration, making AI training essential for sustaining organizational agility.

Szczepański (2019) adds that AI is transforming the labor market by increasing the demand for highly skilled workers, which in turn raises their wages while limiting opportunities for less skilled workers. This phenomenon exacerbates income inequality and underscores the importance of acquiring advanced digital skills. Echoing this perspective, Su, Togay, and Côté (2020) emphasize the need for a highly skilled workforce for AI development, highlighting the growing demand for roles such as data scientists and AI developers. These authors stress the importance of continuous training, as skills rapidly evolve in sectors adopting AI to optimize processes. Ahmed, Wahed, and Thompson (2023) note that the industry increasingly influences AI research, creating a significant gap between the skills taught and those required by companies. They call for educational reforms and targeted training initiatives to meet this heightened demand. Finally, Wilson, Daugherty, and Morini-Bianzino (2017) identify new AI-related job categories, such as 'Trainers' and 'Explainers,' which require specific skills to support and ensure the proper functioning of AI systems, illustrating the need for increased specialization in this area.

3. Methodology

3.1 Hypotheses and econometric model

The Theory of Skill-Biased Technological Change (SBTC) suggests that technological advancements disproportionately impact the labor market structure by increasing the demand for highly skilled workers while reducing the relevance of less specialized and routine skills. This theory highlights how technological innovations favor workers with advanced skills, thereby leading to labor market polarization. Autor (2003) explains that technological progress leads to labor market polarization, characterized by a rise in jobs requiring advanced technical and analytical skills, as well as growth in low-skilled jobs, while intermediate, often routine jobs decline. This dynamic contributes to widening wage inequality and increasing professional segregation between highly skilled and less specialized workers.

Card (2001) explores how technological changes alter skill demand in the labor market. He demonstrates that emerging technologies increase the demand for analytical, cognitive, and technical skills while decreasing the need for routine and manual skills. According to Card, this shift requires continuous adaptation through education and professional training to meet new labor market demands. Thus, this theory posits that technological advancements create a heightened demand for highly skilled workers while diminishing the relevance of less specialized skills. Here's how this theory applies to the need for companies to recruit AI-trained profiles:

- **Technology and Complementarity with Advanced Skills:** AI and automation innovations increase the productivity of skilled employees who master these technologies. Companies therefore seek talent with specific AI skills to remain competitive, as these employees can fully leverage new technologies.
- **Substitution of Routine Tasks:** AI replaces many repetitive or routine tasks, reducing the demand for less skilled workers. Conversely, demand increases for workers who can develop, manage, and improve these systems, justifying the need for AI-trained profiles.
- **Transformation of Business Models:** AI integration alters internal business processes, requiring new skills for innovation, complex problem-solving, and data management. AI training becomes essential as it provides companies with the human resources needed to adapt to these changes.
- **Labor Market Polarization Effect:** According to SBTC theory, technologies like AI drive labor market polarization, with high demand for highly qualified profiles. Companies prioritize specialized talent capable of mastering AI, anticipating greater value creation and long-term competitiveness.
- **Increasing Returns to Advanced Skills:** Mastery of AI tools not only enhances individual productivity but also introduces new methods of work and innovation. Companies that hire these profiles strengthen their capacity to adapt and develop innovative products and services.

Through these elements derived from the Skill-Biased Technological Change Theory, the following research hypotheses can be constructed:

- ***H1: The complementarity between AI technology and advanced skills in companies has a positive effect on the demand for AI-specialized profiles.***
- ***H2: The replacement of routine tasks by AI has a positive effect on the demand for AI-specialized profiles.***

- ***H3: The transformation of business models through AI integration has a positive impact on the demand for qualified profiles.***
- ***H4: The labor market polarization induced by AI positively influences the search for specialized profiles.***
- ***H5: The increasing returns to advanced skills in the use of AI boost the demand for highly qualified workers.***
- ***Once the research hypotheses are determined, the econometric model is constructed to test them.***

$$SPRD = \beta0 + \beta1.SKCM + \beta2.RTRP + \beta3.BSTR + \beta4.JMPZ + \beta5.IRSK + \beta6.FRMS + \beta7.GOVS + \beta8.EXIN + \varepsilon$$

The main variables of the study include several key dimensions related to the impact of artificial intelligence on the labor market and the demand for specialized skills. SPRD (Specialized Profiles Demand) represents the increased demand for AI-specialized profiles and advanced skills. SKCM (Skill Complementarity) measures the complementarity between AI technology and human skills, an essential factor for the seamless integration of AI within organizations. RTRP (Routine Tasks Replacement) captures the effect of AI-driven automation on the replacement of routine tasks, which has implications for employment and the nature of work. BSTR (Business Transformation) illustrates how AI integration transforms business models, altering organizational structures and skill requirements. JMPZ (Job Market Polarization) focuses on labor market polarization, which favors specialized profiles while reducing demand for intermediate skills. Finally, IRSK (Increasing Returns to Skills) examines the effect of increasing returns to advanced skills, a consequence of technological transformations that favor expertise. These variables are derived from 5 items for each main dimension. Principal Component Analysis (PCA) is applied to the scores to generate a representative variable, ensuring simplified measurements. This method captures the dimensions while accounting for the specific characteristics of firms and their economic environment

For the control variables, FRMS (Firm Size) represents the size of the company, measured by the number of employees, which can influence the capacity to adopt advanced technologies like AI. GOVS (Government Support) is a binary variable indicating whether the company receives public support or government subsidies, a factor that can play a crucial role in the adoption of new technologies and skill development. EXIN (Export Intensity) measures export intensity, expressed as the percentage of revenue generated from exports. This control variable can influence the company's strategy regarding skills and innovation, especially in response to international market pressures.

3.2 Data

The study is based on a sample of 238 SMEs selected for their high technological intensity and growing integration of AI. These companies, of varying sizes, reflect the diversity of innovative sectors. The selected companies are characterized by their adoption of innovative business models that integrate AI to enhance internal processes and improve efficiency. By implementing AI-based solutions, these SMEs transform their operations and reorganize their human resource management, which justifies an increased demand for specialized profiles. Additionally, these companies, although local, demonstrate international openness. The choice of this sample aims to analyze how AI integration influences the demand for advanced skills and transforms the job market. The sample also covers multiple regions, allowing for the exploration of AI effects beyond major economic hubs and reflecting a balanced geographical distribution to capture regional dynamics.

3.3 Choice of empirical method

Collinearity occurs when some explanatory variables in a model are highly correlated with each other, making it difficult to accurately estimate their individual effects. High collinearity can distort the coefficients, decrease their significance, and reduce the overall reliability of the econometric model. The Variance Inflation Factor (VIF) helps assess this phenomenon by identifying variables with problematic interdependence. High VIF values indicate pronounced collinearity, sometimes requiring adjustments, such as excluding certain variables or using data transformation methods.

Table 1: Variance Inflation Factors / OLS

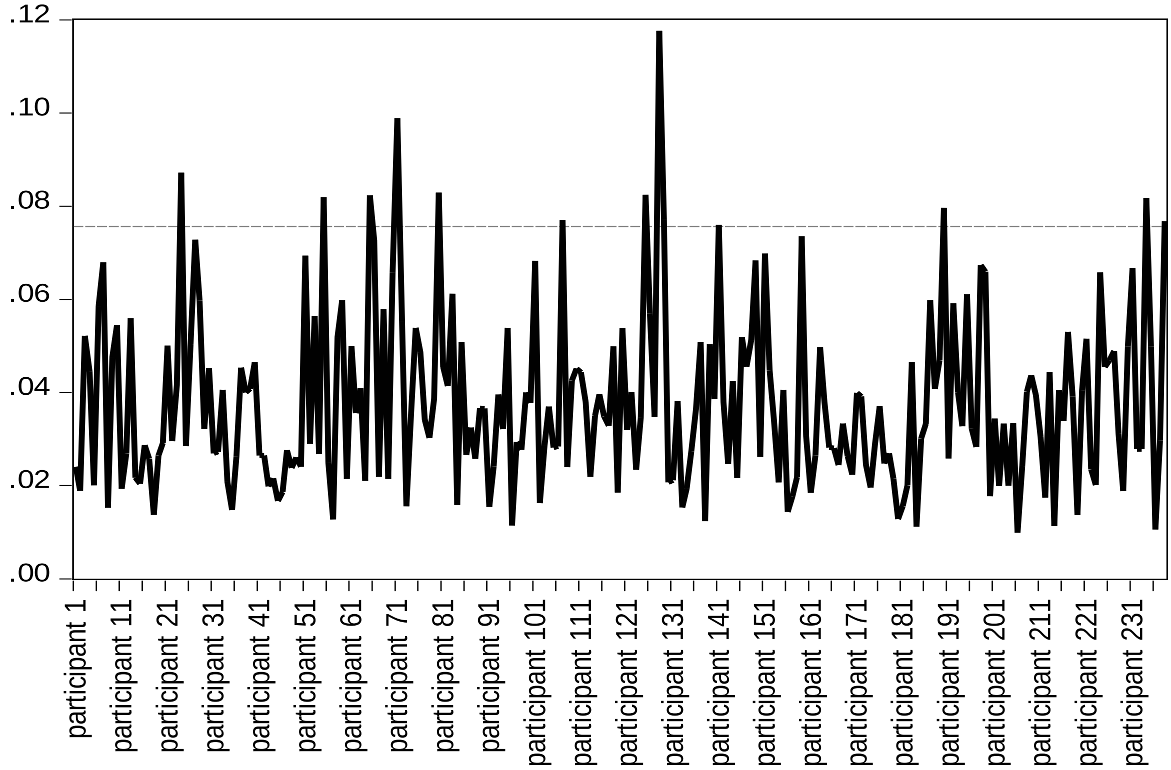
Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.017929	51.86815	NA
SKCM	0.065399	59.35747	14.60177
RTRP	0.067273	130.3067	24.69996
BSTR	0.018816	17.97180	4.464889
JMPZ	0.019255	17.80911	4.040598
IRSK	0.015199	24.90649	9.629942
FRMS	0.069190	60.69437	16.54518
GOVS	0.068751	64.44209	17.39499
EXIN	0.070643	166.0464	37.32227

Source: authors

Table 1 presents the results of both centered and uncentered VIFs for the various variables in the model. Variables such as Routine Tasks Replacement (RTRP) and Export Intensity (EXIN) exhibit very high VIFs, indicating significant multicollinearity with other factors. This may affect the interpretation of their effects on the demand for AI-specialized profiles. Variables like Skill Complementarity (SKCM) and Firm Size (FRMS) also show high levels of correlation with other variables, though to a lesser extent. The other variables in the model, including Business Transformation (BSTR), Job Market Polarization (JMPZ), and Increasing Returns to Skills (IRSK), have moderate VIFs, suggesting they are less prone to strong redundancy. Nevertheless, these results highlight that certain control variables, such as GOVS and EXIN, require careful attention to avoid biases in the econometric analysis.

Outliers and influential observations pose a significant challenge in econometric estimations, as they can disrupt the accuracy and reliability of the results. Outliers are data points that deviate substantially from the general trend, while influential observations disproportionately impact the estimated model coefficients due to their specific position in the variable space. Their presence can introduce biases, distort relationships between variables, and reduce the precision of predictions.

Figure 1: Influence and leverage statistics according to the Hat Matrix.



Source: authors

Figure 1 of the Hat Matrix illustrates the leverage measure for each observation, indicating the extent to which a data point influences overall estimates. High leverage signals an observation that could significantly impact the regression. In this figure, several participants are positioned above the threshold, suggesting that they exert a notable influence on the model. Proper management of outliers and influential points may involve checking the data for potential errors or implementing robust estimation techniques to mitigate the impact of extreme values. Outliers and influential observations present a major issue in econometric estimations, as they can disrupt the precision and reliability of results. Outliers are data points that significantly deviate from the general trend, while influential observations have a disproportionate impact on the estimated model coefficients due to their specific position in the variable space. Their presence can introduce biases, distort relationships between variables, and reduce prediction accuracy.

Analyzing collinearity and Hat Matrix results justifies the use of Ridge Regression to improve estimates. The high collinearity identified by VIF indicates that some variables are highly correlated, making OLS coefficients unstable and less reliable. Additionally, high-leverage observations detected in the Hat Matrix exacerbate this issue, disproportionately influencing results. Ridge Regression mitigates these effects by adding a penalty to the coefficients, reducing their magnitude without eliminating variables. This method stabilizes estimates despite collinearity and limits the impact of identified influential points, providing more robust and reliable results for the model.

4. Results

4.1 Robustness analysis of the model

The Ramsey test (or Ramsey RESET test) is a crucial tool for evaluating whether the model is correctly specified. It detects specification errors that may arise from omitting relevant variables, improper transformation of variables, or incorrect relational structures between explanatory variables and the dependent variable. In other words, this test assesses whether the linear model is adequate or if additional nonlinear terms or interactions should be included to better capture relationships in the data. In the context of Ridge Regression, the Ramsey test is particularly important. Ridge Regression addresses multicollinearity effects by shrinking coefficient magnitudes, thereby improving estimation stability. However, if the base model is misspecified, even Ridge Regression cannot correct biases introduced by inadequate specification. For instance, if key variables or nonlinear forms are omitted, regularization will only shrink the existing coefficients without truly resolving the underlying problem.

Table 2: Ramsey RESET specification test for the ridge regression model

Omitted Variables: Squares of fitted values			
Specification: SPRD C SKCM RTRP BSTR JMPZ IRSK FRMS GOVS EXIN			
	Value	df	Probability
t-statistic	0.819574	228	0.4133
F-statistic	0.671701	(1, 228)	0.4133
Likelihood ratio	0.700131	1	0.4027

Source: authors

Table 2 presents the results of the Ramsey test for the model. The results of the Ramsey specification test indicate that there is no major issue with the Ridge regression model used. The value of the t-statistic, combined with a p-value of 0.4133, does not allow rejection of the null hypothesis of correct specification. Similarly, the values of the F-statistic and the Likelihood ratio, accompanied by comparable p-values greater than the 0.05 threshold, confirm this observation. These results suggest that the model adequately includes the variables and captures the essential relationships among them without significant omission of terms or nonlinear forms. The lack of statistical significance in these tests implies that the functional structure of the model is appropriate and that there is no need to add additional interactions or nonlinear terms to improve the fit.

The analysis of the results in Table 3 of the VIF shows that Ridge Regression has effectively corrected the collinearity problem. The values of the centered VIF, now all close to 1, indicate a significant reduction in the interdependence among the explanatory variables compared to the previously observed high values. This reduction in VIF demonstrates that Ridge Regression has stabilized the coefficients by mitigating the excessive influence of collinearity on the estimates.

Table 3: Variance Inflation Factors for the Ridge Regression.

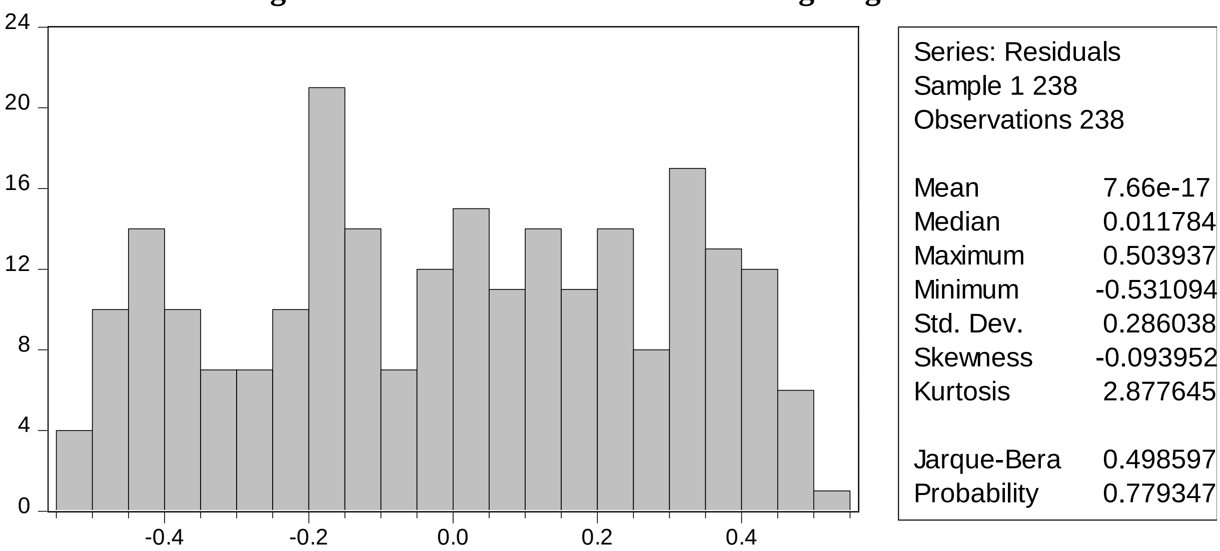
Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.009074	25.50410	NA
SKCM	0.004123	4.069324	1.050357
RTRP	0.005296	4.806899	1.027091
BSTR	0.005044	4.595900	1.034604
JMPZ	0.004698	4.549544	1.043621
IRSK	0.004924	4.190542	1.018603
FRMS	0.004744	3.988625	1.028588
GOVS	0.004960	4.274291	1.041257
EXIN	0.003933	3.526275	1.048354

Source: authors

The uncentered VIF values, which previously measured much higher, are also reduced, although the slightly higher values reflect the structural complexity of the model rather than direct interdependencies between variables. Ridge Regression has therefore not only improved the precision of the estimates but has also made the coefficients reliably interpretable, ensuring a robust and well-specified model for the data.

The analysis of the residual distribution for the Ridge Regression allows for the evaluation of the normality of errors, which is important to ensure the quality of the estimates. The figure shows the histogram of the residuals, with a mean close to zero (7.66e-17) and a standard deviation of 0.286308, which aligns with expectations for a normal distribution.

Figure 2: residual distribution of the Ridge regression



Source: authors

The coefficients of skewness (-0.0939525) and kurtosis (2.877645) indicate that the distribution is relatively symmetric and slightly flattened compared to a perfect normal distribution. The Jarque-Bera test, with a p-value of 0.779347, confirms this observation: the high p-value suggests that we do not reject the hypothesis of normality of the residuals. The normality of the residuals implies that the Ridge Regression model is well-fitted and that the estimates can be interpreted with confidence.

The analysis of heteroscedasticity in our Ridge Regression model, performed using the Harvey test, verifies whether the variance of the errors is constant across all values of the explanatory variables. A constant variance of the residuals (homoscedasticity) is an important assumption for the validity of statistical tests in a regression model.

Table 4: Harvey test results for heteroscedasticity

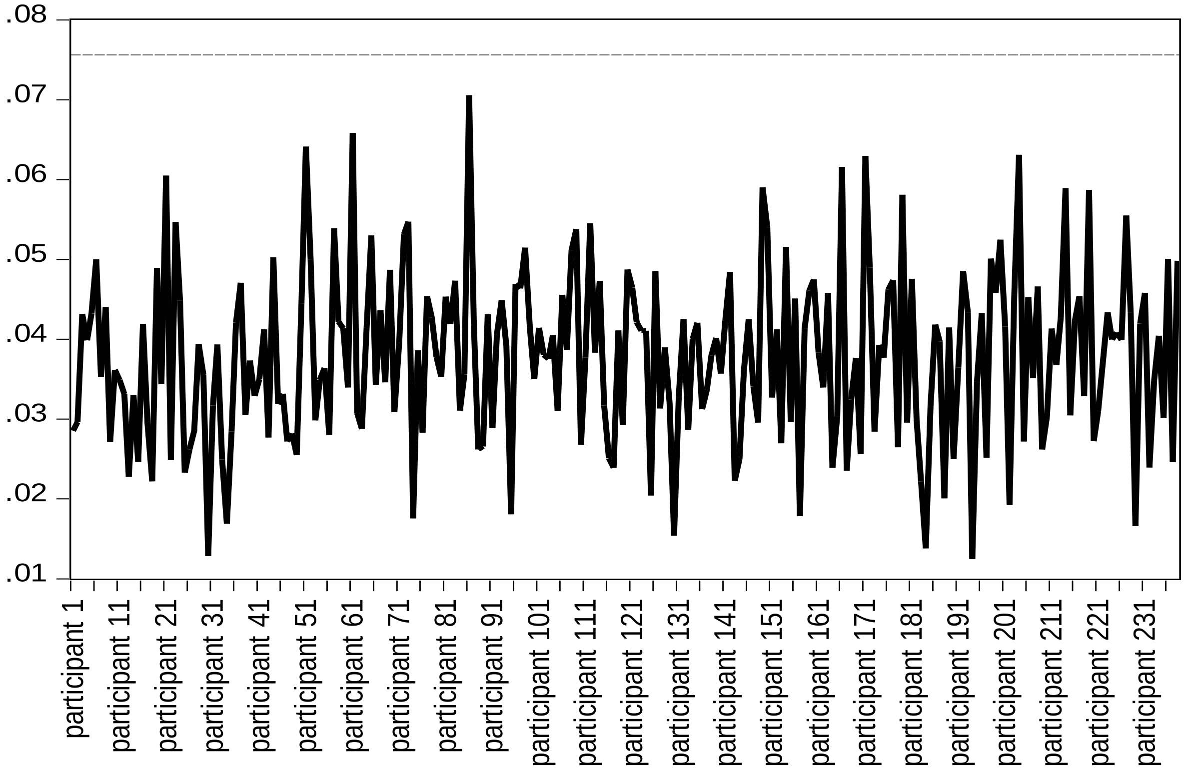
Test Statistic	Value	Probability	Degrees of Freedom
F-statistic	1.259130	0.2660	(8, 229)
Obs*R-squared	10.02783	0.2631	Chi-Square (8)
Scaled Explained SS	8.403819	0.3950	Chi-Square (8)

Source: authors

The results of the Harvey test show an F-statistic of 1.259130 with a p-value of 0.2660. This p-value, being greater than the 0.05 threshold, indicates that we do not reject the null hypothesis of homoscedasticity. Similarly, the Obs*R-squared is 10.02783 with a p-value of 0.2631, and the Scaled explained SS is 8.403819 with a p-value of 0.3950. All these high p-values confirm that there is no sign of heteroscedasticity in the residuals of the model. In other words, the variance of the residuals remains stable across different observations and does not systematically increase with the values of the predictors. These results suggest that the Ridge Regression model adequately satisfies the homoscedasticity assumption, enhancing the reliability of the estimates obtained.

Figure 3 presents the influence statistics for each observation of the model, illustrated by the Hat Matrix, following the application of Ridge Regression. Compared to the initial results of the OLS regression, where many observations had higher leverage values, this figure shows that Ridge Regression has corrected the problem of excessive influence. In the OLS regression, some observations exceeded the threshold of 0.08, exerting a disproportionate influence on the model's predictions, thereby increasing the risk of distortion in the estimates.

Figure 3: influence statistics after ridge regression (Hat Matrix)



Source: authors

Here, after the regularization brought by Ridge Regression, the leverage values are uniformly distributed and mostly remain below the critical threshold. This outcome demonstrates that Ridge Regression has not only reduced collinearity among variables but also stabilized the influence of observations by minimizing the impact of high-leverage points. Consequently, Ridge Regression enhances the robustness and reliability of the estimates, reducing the risks of instability observed in the OLS model.

4.2 Results of the Ridge regression

The empirical study is based on the theory of skill-biased technological change (SBTC), which posits that technological advancements, in our case AI, increase the demand for highly skilled workers. Five key dimensions (SKCM, RTRP, BSTR, JMPZ, IRSK) are incorporated into an econometric model to assess their impact on the labor market, accounting for control variables such as company size, government support, and export intensity. However, the model encounters challenges of high collinearity, detected through very high VIF values for variables like RTRP and EXIN, making OLS coefficients unstable. Additionally, the presence of outliers and high leverage points, revealed by the Hat Matrix, further compromises the precision of the estimates.

In response, Ridge Regression is employed to mitigate these effects, stabilizing the coefficients while retaining key variables. This method significantly reduces the VIF values and moderates the influence of extreme points, thereby improving the model's robustness. Residual analyses and the Ramsey test confirm the adequate specification of Ridge Regression, validating its reliability for capturing the impact of AI on the demand for advanced skills.

Table 5: Results of the ridge regression

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	***0,469680	0,102809	4,568472	0,0000
SKCM	***0,193540	0,069305	2,792579	0,0057
RTRP	**0,198600	0,078542	2,528585	0,0121
BSTR	*0,131337	0,076650	1,713460	0,0879
JMPZ	***0,201360	0,073974	2,722034	0,0070
IRSK	-0,013604	0,075733	-0,179625	0,8576
FRMS	**0,178040	0,074335	2,395098	0,0174
GOVS	0,096280	0,076008	1,266702	0,2065
EXIN	**0,139773	0,067688	2,064961	0,0400

Source: authors; ***Significant at 1%; **Significant at 5%; *Significant at 10%.

Table 5 presents the results of the Ridge regression. The variable SKCM is significant at 1% (p = 0.0057), supporting hypothesis H1. This indicates that companies with strong complementarity between AI and human skills actively seek specialized AI profiles. These companies are looking for talent capable of leveraging this complementarity to fully exploit advanced technologies. RTRP is significant at 5% (p = 0.0121), validating hypothesis H2. This demonstrates that companies automating many routine tasks experience an increased demand for skilled AI professionals. The need for workers who can design, manage, and optimize AI systems that replace repetitive processes is thus reinforced. For BSTR, the significance at the 10% level (p = 0.0879) allows for the acceptance of hypothesis H3. Companies incorporating AI into their business models require specialized profiles to support these transformations, thereby increasing demand for advanced AI skills.

The variable JMPZ is highly significant at 1% (p = 0.0070), confirming hypothesis H4. This means that labor market polarization drives companies to seek highly skilled AI profiles. The decreasing relevance of intermediate skills amplifies the demand for specialized workers. On the other hand, IRSK is not significant (p = 0.8576), leading to the rejection of hypothesis H5. This shows that in this case, companies do not feel the need to increase their demand for AI profiles due to the increasing returns on advanced skills. Among the control variables, FRMS is significant at 5% (p = 0.0174), indicating that large companies demand more specialized AI profiles, as their size allows them to manage teams that integrate these new skills. GOVS is not significant (p = 0.2065), suggesting that government support does not significantly stimulate AI skills demand. EXIN is significant at 5% (p = 0.0400), showing that exporting companies seek more specialized AI profiles to remain competitive in international markets.

5. Discussion

Companies benefiting from a complementarity between their human skills and advanced technologies are more actively recruiting specialized AI talent. This indicates that advanced sectors, such as finance, manufacturing, and telecommunications, will need to invest more in training and skill development to fully harness these technologies. Moreover, companies automating routine tasks are compelled to hire qualified workers to manage and improve these intelligent systems. This highlights an urgent need for Moroccan companies to adapt to technological advancements, requiring supportive policies that facilitate continuous training and worker reskilling. Thus, a national plan to support the technological transition becomes essential, ensuring that current employees can upskill in advanced competencies.

The transformation of business models through AI integration also increases the need for companies to have employees trained in these technologies. This points to a growing demand for advanced skills to manage complex organizational innovations. Moroccan companies must invest in developing their human capacities, which could strengthen the economy's overall competitiveness, provided there is appropriate support, especially for small and medium-sized enterprises. However, labor market polarization is also observed, with highly skilled profiles increasingly sought after, while workers with more general skills risk becoming less relevant. This reality poses a significant challenge for Morocco, necessitating educational and training policies that address the labor market's changing needs and prevent widening inequalities. Strengthening technical and vocational education, along with reskilling programs, could be crucial to bridging this gap.

On the other hand, the absence of significant results for certain hypotheses indicates that the expected effect of advanced skills is not yet clearly visible. This suggests that additional efforts are needed to enhance these skills and integrate them more effectively into corporate development strategies. Morocco could consider implementing specific incentives to encourage innovation and increase the demand for AI skills. Furthermore, large enterprises appear better equipped to adopt these technologies and recruit specialized profiles, potentially disadvantaging smaller firms. To overcome this barrier, targeted support policies may be necessary to make these technologies more accessible to SMEs. Additionally, export-oriented companies show a higher demand for skilled talent, highlighting the importance of a national strategy that promotes skills and innovation to compete successfully in international markets.

6. Conclusion

This study analyzed the determinants of demand from technology-intensive SMEs for profiles trained in artificial intelligence. The integration of AI within technology firms has led to a significant transformation in skill requirements, driving an increased need for workers with advanced expertise to develop, manage, and optimize AI-based solutions. This trend is driven by the necessity to maintain a competitive edge in an economic environment where technological innovation has become a central performance factor. The analysis reveals that companies investing in automation and the transformation of their business models face a heightened demand for specialized AI skills, which cannot be met by workers with general qualifications. The ability to innovate and adapt to ever-evolving technological environments requires talent capable of leveraging AI advancements to boost productivity, optimize internal processes, and manage complex projects.

Moreover, companies operating in international markets must remain competitive by recruiting profiles capable of meeting global market demands, underlining the importance of advanced skills for differentiation and adaptation to worldwide challenges. Conversely, the lack of a significant impact from government support on the increased demand for AI skills highlights a potential gap between current public policies and corporate needs. This suggests that more targeted support strategies might be required to promote broader adoption of advanced technologies in the entrepreneurial landscape, such as specific incentives, training subsidies, and public-private partnerships to develop tailored training programs. One of the major challenges identified is the growing labor market polarization exacerbated by AI. This polarization creates an increasingly pronounced gap between highly skilled workers, who are becoming more sought after, and those with less specialized skills, who risk marginalization.

This finding calls for educational interventions and reskilling initiatives to ensure that the Moroccan workforce is well-prepared for the future. Strengthening technical education, promoting lifelong learning, and encouraging professional retraining are solutions to bridge this gap and ensure that the entire labor force benefits from technological advancement. Ultimately, for Moroccan SMEs to fully capitalize on the opportunities presented by AI, an integrated approach is needed, encompassing support for the adoption of advanced technologies, the development of human skills, and the implementation of effective educational policies. By investing in these areas, Morocco can ensure that its entrepreneurial fabric remains not only competitive but also capable of contributing sustainably to the national economy in an era dominated by cutting-edge technologies.

Reference

[1] Ahmed, N., Wahed, M., & Thompson, N. C. (2023). The growing influence of industry in AI research. Science, 379(6635), 884-886.

[2] Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. Labour economics, 71, 102002.

[3] Autor, D. H. (2014). Skills, education, and the rise of earnings inequality among the “other 99 percent”. Science, 344(6186), 843-851.

[4] Bertello, A., Bogers, M. L., & De Bernardi, P. (2022). Open innovation in the face of the COVID-19 grand challenge: insights from the Pan-European hackathon ‘EUvsVirus’. R&d Management, 52(2), 178-192.

[5] Brekelmans, S. and G. Petropoulos. (2020) ‘Occupational change, artificial intelligence and the geography of EU labour markets’, Working Paper 03/2020, Bruegel

[6] Card, D., & DiNardo, J. E. (2002). Skill-biased technological change and rising wage inequality: Some problems and puzzles. Journal of labor economics, 20(4), 733-783.

[7] Du, J. (2024). The impact of artificial intelligence adoption on employee unemployment: A multifaceted relationship. International Journal of Social Sciences and Public Administration, 2(3), 321-327.

[8] Duch-Brown, N., Gomez-Herrera, E., Mueller-Langer, F., & Tolan, S. (2022). Market power and artificial intelligence work on online labour markets. Research Policy, 51(3), 104446.

[9] Felton, E., Raj, M., & Seamans, R. (2018). Linking Advances in Artificial Intelligence to Skills, Occupations, and Industries. AEA Papers & Proceedings.

[10] Ključnikov, A., Popkova, E. G., & Sergi, B. S. (2023). Global labour markets and workplaces in the age of intelligent machines. Journal of Innovation & Knowledge, 8(4), 100407.

[11] Liu, J., Chen, K., & Lyu, W. (2024). Embracing artificial intelligence in the labour market: the case of statistics. Humanities and Social Sciences Communications, 11(1), 1-14.

[12] Manyika, J. (2017). Jobs lost, jobs gained: Workforce transitions in a time of automation. McKinsey Global Institute, 150.

[13] Moniz, A. B., Candeias, M., & Boavida, N. (2022). Changes in productivity and labour relations: artificial intelligence in the automotive sector in Portugal. International Journal of Automotive Technology and Management, 22(2), 222-244.

[14] Pettersen, L. (2019). Why artificial intelligence will not outsmart complex knowledge work. Work, Employment and Society, 33(6), 1058-1067.

[15] Rani, U., Pesole, A., & González Vázquez, I. (2024). Algorithmic Management practices in regular workplaces: case studies in logistics and healthcare (No. JRC136063). Joint Research Centre.

[16] Seamans, R., & Raj, M. (2018). AI, labor, productivity and the need for firm-level data (No. w24239). National Bureau of Economic Research.

[17] Su, Z., Togay, G., & Côté, A. M. (2021). Artificial intelligence: a destructive and yet creative force in the skilled labour market. Human Resource Development International, 24(3), 341-352.

[18] Szczepański, M. (2019). Economic Impacts of Artificial Intelligence (AI). European Parliamentary Research Service. https://policycommons.net/artifacts/1334867/economic-impacts-of-artificial-intelligence-ai/1940720/

[19] Wilson, H. J., Daugherty, P., & Bianzino, N. (2017). The Jobs That Artificial Intelligence Will Create. MIT Sloan Management Review, 58(4), 14.