https://qeafbreview.org/
Review of Advanced Research on Quantitative Economics, Applied Finance and Business VOL. 1 Issue 3 (2026)
ISSN: 3119-6640

Digital Innovation And Employment Creation in Morocco : Econometric Modeling

SALMI Yahya[1]
[1] PhD in Economics, Faculty of Economics, Abdelmalek Essaâdi University, Tangier, Morocco.
salmiyahya14@gmail.com

Abstract

This study analyzes the effect of digital innovation on job creation in Morocco using a structural vector autoregressive (SVAR) model. The analysis is based on quarterly macroeconomic data covering the period Q1 1965 – Q4 2025 and focusing on five variables: job creation, digital innovation, investment, human capital, and foreign direct investment. The methodology employs ADF stationarity tests, Johansen cointegration tests, Granger causality tests, impulse response functions, and forecast error variance decomposition. The results show that the model is stable and that digital innovation has a positive, progressive, and sustained effect on job creation. They also highlight the decisive role of human capital in transmitting the effects of digital transformation, while the contributions of investment and foreign direct investment remain more modest. These results underscore the importance of strengthening digital infrastructure, workforce skills, and policies supporting innovation in order to promote sustainable, job-creating growth in Morocco.

Keywords: Digital innovation; Job creation; SVAR; Human capital; Morocco.

1. Introduction

From a theoretical perspective, innovation has mixed effects on employment. According to (Schumpeter's, 1934) theory of creative destruction, technological progress promotes growth by replacing obsolete activities with new, more productive ones. However, the ultimate impact depends on several compensatory mechanisms, such as expanding demand, the emergence of new markets, investment, and the development of human capital. In emerging economies, digital transformation is thus a key driver of modernization, provided it is accompanied by investments in skills and infrastructure.

In Morocco, digitalization is playing an increasingly important role in public policy. Despite the progress made, the labor market continues to face high unemployment, regional disparities, and a mismatch between available skills and the needs of businesses. Furthermore, econometric studies analyzing the dynamic effects of digital innovation on job creation remain limited, particularly those based on structural models such as SVAR.

In this context, this study analyzes the impact of digital innovation on job creation in Morocco using a structural vector autoregressive (SVAR) model. It examines the interactions between employment, digital innovation, investment, human capital, and foreign direct investment in order to identify the transmission mechanisms of technological shocks and their effects on the labor market. The results aim to contribute to the literature on emerging economies and to formulate economic policy recommendations that promote inclusive and job-creating growth.

The remainder of the article is organized as follows. The first section presents the literature review. The second describes the data, variables, and econometric methodology based on the SVAR model. The third section presents the empirical results, followed by a discussion and economic policy recommendations. Finally, the last section concludes the study by presenting its main contributions, limitations, and research prospects.

2. Literature Review

The relationship between technological innovation and employment is theoretically ambiguous. From a Schumpeterian perspective, innovation operates through creative destruction, whereby emerging technologies, products, firms, and production processes replace obsolete activities while generating new economic opportunities (Schumpeter, 1934). Innovation can consequently support employment by raising productivity, expanding markets, encouraging firm creation, and stimulating economic activity. However, these effects may vary across workers, sectors, and regions and may not materialize immediately.

The overall employment impact depends on the balance between job displacement and job creation. Technological change can stimulate employment through stronger demand, new products and markets, lower production costs, higher investment, and improved international competitiveness (Freeman and al., 1982). At the same time, innovation may temporarily reduce employment in activities rendered obsolete by technological progress (Aghion & Howitt, 1992). Hence, the net employment effect ultimately reflects the relative magnitude of these opposing mechanisms.

Digital innovation intensifies the ambiguity surrounding the employment effects of technological change because digital technologies simultaneously transform production, organizational structures, market access, communication, and work processes. Although automation may replace workers performing routine tasks, digital technologies can increase demand for analytical, creative, managerial, and technology-related skills, thereby reshaping rather than necessarily reducing overall employment (Autor, 2015).

This duality is further explained by the distinction between displacement and productivity effects. Automation can substitute for human labor, while productivity gains and lower production costs may expand output and stimulate labor demand (Acemoglu & Restrepo, 2018, 2020). The net employment outcome therefore depends on the relative strength of these mechanisms. This issue is particularly important in developing economies, where digital adoption interacts with structural transformation, extensive informal employment, and substantial disparities in education and digital skills.

Empirical evidence on the employment effects of innovation remains heterogeneous, reflecting differences in innovation types, analytical levels, sectors, and institutional contexts. At the firm and sectoral levels, product innovation generally produces stronger employment gains than process innovation, as new products can expand demand and create additional economic activities, whereas process innovation may raise efficiency while reducing labor requirements (Pianta, 2005 ; Calvino & Virgillito, 2018). The employment outcome consequently depends on both the nature of technological change and the economy's capacity to generate compensating demand and new activities (Vivarelli, 2014).

Evidence on automation further highlights this complexity. While technological advances can enhance productivity, they may reduce employment opportunities in routine occupations (Brynjolfsson & McAfee, 2014). Technological change may therefore contribute to labor-market polarization by reducing demand for middle-skilled routine jobs while increasing opportunities for highly skilled and selected non-routine occupations (Autor, 2015). Digitalization thus primarily reshapes the composition and structure of employment rather than producing a uniform increase or decline in jobs.

Recent studies emphasize that the employment effects of technological change are highly heterogeneous and depend on the technology, sector, occupation, institutional context, and level of analysis (Calvino & Virgillito, 2018 ; Hötte and al., 2022). Consequently, evidence from advanced economies should not be directly generalized to developing and emerging economies.

The relationship between technological change and employment also depends critically on human capital. Digital technologies are more likely to create employment when workers possess complementary skills, whereas skill shortages may limit technology adoption and restrict access to emerging employment opportunities. Unequal access to education, training, digital infrastructure, and technology may therefore reinforce existing socioeconomic disparities.

Moreover, digital technologies can foster organizational innovation and employment growth when firms develop the capabilities required to reorganize production and exploit technological opportunities (Opland and al., 2022). Thus, technological progress alone is insufficient to ensure broad-based and sustainable employment gains; complementary investments in human capital, organizational capabilities, infrastructure, and institutional quality are essential.

A recent meta-analysis by (Arenas Díaz and al., 2024) further emphasizes the distinction between product and process innovation, finding that product innovation generally has a more favorable employment effect than process innovation. Such evidence reinforces the argument that the employment consequences of digital innovation depend not only on the intensity of technological adoption but also on the mechanisms through which innovation affects demand, productivity, and the organization of production.

Human capital conditions the employment effects of technological innovation by determining workers' capacity to complement emerging technologies. Digitalization tends to increase demand for advanced digital, cognitive, and non-routine skills, while skill mismatches may limit employment gains. Technological change therefore simultaneously displaces routine tasks and expands opportunities in activities requiring problem-solving, creativity, communication, judgment, and technological competencies. The overall employment impact of digital innovation consequently depends on the ability of workers and education systems to adapt to evolving labor-market skill requirements.

This issue is particularly critical in developing economies, where education, vocational training, and lifelong learning systems may respond slowly to technological change. Evidence from the ILO (2022), World Bank (2016), and OECD (2019) indicates that the economic and employment benefits of digital transformation are greater when supported by adequate skills, infrastructure, institutions, and complementary investments. Human capital should therefore be viewed not merely as a control variable but as a key transmission mechanism linking digital innovation to productivity, occupational mobility, and employment creation.

Morocco provides a relevant context for examining the innovation–employment nexus, given its rapid progress in digital connectivity alongside persistent labor-market challenges, including unemployment, informality, skills mismatches, segmentation, and regional disparities. These structural features may generate heterogeneous employment responses to technological change. While digital adoption can create skilled occupations and new employment opportunities, automation may reduce demand for routine labor, particularly among workers with limited access to digital training.

Recent evidence supports this heterogeneous effect. (Benaini & Ouarraoui, 2024) show that digital transformation is reshaping recruitment and employment in Morocco while increasing demand for digital competencies. Persistent skill shortages, however, may limit the extent to which digitalization translates into broad-based employment gains.

Digital innovation generates employment effects through complementarities with human capital, firms' technological capabilities, investment, and FDI. These effects depend on workforce adaptability, skill alignment, local production linkages, and firms' capacity to absorb technological spillovers. In Morocco, this interaction is especially relevant in technology-intensive sectors integrated into global value chains. Nevertheless, empirical evidence remains limited for emerging economies, particularly at the macroeconomic level. This study addresses this gap by jointly examining digital innovation, employment, investment, human capital, and FDI within an integrated dynamic framework.

For Morocco, empirical evidence on the macroeconomic transmission of digital innovation to employment remains limited. Existing research has largely examined digital transformation, skills, recruitment, and digital economy development without identifying the dynamic effects of technological shocks. This study addresses this gap through a multivariate SVAR framework linking employment, digital innovation, investment, human capital, and FDI. Using impulse response functions and forecast error variance decomposition, the analysis evaluates the magnitude, persistence, and relative contribution of structural shocks to employment dynamics. The study contributes long-run macroeconomic evidence and highlights the complementary roles of investment, human capital, and FDI in shaping the employment effects of digital transformation in Morocco.

3. Data and Methodology

3.1. Data and Variables

This study investigates the dynamic relationship between digital innovation and job creation in Morocco using a structural vector autoregressive (SVAR) framework. The empirical model includes five endogenous variables: job creation (EMP), digital innovation (DIG), investment (INV), human capital (HC), and foreign direct investment (FDI).

The functional relationship underlying the empirical analysis can be expressed as follows :

$$EMP_t = f\,(DIG_t,\ INV_t,\ HC_t,\ FDI_t) \qquad (1)$$

The corresponding long-run relationship is represented by :

$$EMP_t = \beta_0 + \beta_1 DIG_t + \beta_2 INV_t + \beta_3 HC_t + \beta_4 FDI_t + \varepsilon_t \qquad (2)$$

ISSN: 3119-6640

Where, β : model parameters to be estimated;

EMP : Job creation measured by the employment rate as a percentage of GDP;

DIG : Digital innovation, measured by the digitization index and the number of Internet users;

INV : Investment, measured by gross fixed capital formation as a percentage of GDP;

HC : Human capital, measured by public education spending as a percentage of GDP;

FDI : Foreign direct investment, measured by FDI flows as a percentage of GDP.

ε : error term.

The empirical analysis covers the period from the first quarter of 1965 to the fourth quarter of 2025. The study therefore relies on a long quarterly time series designed to capture both short-term dynamics and longer-term changes in Morocco's economic and technological environment. The data are obtained from recognized national and international statistical sources, including the World Bank, the High Commission for Planning and Foreign Exchange Office. The use of several institutional sources is intended to improve the reliability and consistency of the series over the study period.

3.1.1. Definition and measurement of the variables

Job creation (EMP) : is measured using the employment indicator available in the macroeconomic database. Given the conceptual distinction between employment and GDP, its precise construction should be clearly documented, including the original data source, transformation, frequency conversion, and normalization procedures. EMP is intended to capture changes in labor-market absorption associated with economic activity and technological transformation.

Digital innovation (DIG) : constitutes the main variable of interest. In the original manuscript, DIG is defined as a composite measure combining a digitization index and the number of Internet users.

Investment (INV) : Investment is measured by gross fixed capital formation as a percentage of GDP. This indicator captures the contribution of physical capital accumulation to productive capacity and employment creation.

Human capital (HC) : Human capital is measured by public education expenditure as a percentage of GDP. This variable is intended to capture the accumulation of productive capabilities that allow workers to adapt to technological change and benefit from digital transformation.

Foreign direct investment (FDI) : Foreign direct investment is measured by FDI flows as a percentage of GDP. The variable captures the potential contribution of foreign capital to domestic investment, technology transfer, productivity, and employment creation.

3.1.2. Data transformation and comparability

Given the extended sample period, particular attention is devoted to maintaining consistency across observations. The empirical analysis covers quarterly data from 1965Q1 to 2025Q4, with all temporal aggregation, interpolation, rebasing, benchmarking, and splicing procedures explicitly documented where applicable. To ensure comparability, INV, HC, and FDI are expressed as ratios to GDP, while EMP and DIG are transformed according to their respective measurement definitions. The time-series properties of all variables are subsequently assessed using unit-root tests prior to estimation.

Descriptive evidence reveals substantial variability in digital innovation, whereas investment and human capital display relatively lower dispersion. FDI exhibits greater volatility, consistent with its sensitivity to domestic and international economic conditions.

3.2. Econometric Methodology

3.2.1. SVAR framework

A structural vector autoregressive model is employed to identify the dynamic effects of structural shocks on employment in Morocco. The SVAR framework is appropriate because the variables included in the system may be jointly determined and can influence one another over time. Unlike a single-equation regression, the VAR/SVAR framework does not impose an ex ante distinction between dependent and explanatory variables.

The vector of endogenous variables is defined as :

$$Y_t = \begin{pmatrix} \mathrm{EMP} \\ \mathrm{DIG} \\ \mathrm{INV} \\ \mathrm{HC} \\ \mathrm{FDI} \end{pmatrix} \qquad (3)$$

The structural form of the SVAR model is given by :

$$A_0 Y_t = A_1 Y_{t-1} + \varepsilon_t \qquad (4)$$

where A_0 is the contemporaneous-impact matrix, A_1 is the matrix of lagged coefficients, and ε_t is the vector of mutually orthogonal structural shocks.

Multiplying Equation (4) by A_{0-1} yields the reduced-form representation:

$$Y_t = A_{0-1} A_1 Y_{t-1} + A_{0-1}\, \varepsilon_t \qquad (5)$$

Defining the reduced-form coefficient matrix as : $B_1 = A_{0-1} A_1$

and the reduced-form innovations as : $u_t = A_{0-1} \varepsilon_t$

Equation (5) can be written more compactly as : $Y_t = B_1 Y_{t-1} + u_t$ (6)

The structural identification problem therefore consists of recovering the economically interpretable structural shocks εt from the reduced-form residuals ut. This requires imposing appropriate restrictions on the contemporaneous relationships among the variables.

3.2.2. Lag-order selection and preliminary tests

Before estimating the structural model, the time-series properties of the variables are examined. The Augmented Dickey–Fuller test indicates that EMP, DIG, INV, HC, and FDI are non-stationary in levels but become stationary after first differencing, implying that the variables are integrated of order one, I(1).

Standard information criteria—Akaike, Schwarz, and Hannan–Quinn—consistently indicate one optimal lag, supporting a VAR(1) and corresponding SVAR(1) specification. Johansen's trace and maximum-eigenvalue tests reveal no conventional cointegration at the 5% significance level. The analysis therefore focuses on the dynamic transmission of structural shocks within the stationary VAR framework.

3.2.3. Structural identification and contemporaneous restrictions

SVAR identification relies on recursive restrictions reflecting differences in the adjustment speed of the variables. Employment is treated as relatively slow-moving, while digital innovation is assumed to be largely predetermined in the short run. Investment, human capital, and FDI are allowed to respond more rapidly to current economic and technological conditions, subject to their respective institutional and market constraints.

The precise recursive ordering, however, must correspond to the ordering actually implemented in EViews. Since the current specification does not explicitly report the Cholesky ordering or the estimated (A_0) matrix, the final manuscript should state the exact ordering used to generate the impulse response functions and forecast error variance decompositions. This consistency is essential for the validity and reproducibility of the structural identification.

3.2.4. Economic interpretation of the structural ordering

The identification strategy assumes that contemporaneous restrictions should reflect economically plausible differences in adjustment speeds. Digital innovation may influence employment through productivity gains, new activities, changes in labor demand, and production reorganization, but these effects are unlikely to materialize instantaneously because technology adoption and workforce adaptation require time. Human-capital accumulation is similarly characterized by gradual adjustment due to the longer horizons of education and training.

Investment and FDI may respond more rapidly to changing economic conditions, although their effects on employment can remain delayed because capital formation and technology transfer require implementation periods. These considerations provide an economic rationale for the recursive identification scheme. Nevertheless, the resulting structural shocks depend on the validity of the imposed contemporaneous restrictions; hence, the recursive ordering should be interpreted as an identifying assumption rather than a directly observable empirical fact.

3.3. Diagnostic and Stability Tests

Several diagnostic tests are conducted to assess the adequacy and stability of the estimated model. The inverse roots of the characteristic polynomial lie within the unit circle, confirming system stability. The LM test provides no evidence of residual serial correlation, as the reported probabilities exceed the 5% significance level. However, the residual diagnostics indicate deviations from normality and the presence of heteroskedasticity. These results are plausible given the long sample period and the structural changes affecting Morocco's economic environment, policy regimes, technological development, and exposure to external shocks. Accordingly, these deviations are not interpreted as evidence of model invalidity, but they warrant caution when interpreting the impulse responses and variance decompositions, which remain conditional on the underlying structural identification assumptions.

3.4. Impulse Response Functions and Forecast Error Variance Decomposition

Impulse response functions are used to identify the direction, magnitude, and persistence of employment responses to structural shocks in digital innovation, investment, human capital, and FDI, with particular emphasis on digital innovation. Forecast error variance decomposition complements this analysis by quantifying the contribution of each shock to employment fluctuations over different horizons. Together, these methods provide a comprehensive assessment of the dynamic transmission and relative importance of structural shocks in explaining employment dynamics.

4. Results and Discussion

4.1. Empirical Results

4.1.1. Descriptive statistics

Table 1. Descriptive Statistics

	EMP	DIG	INV	HC	FDI
Mean	40.60588	57.53231	24.12089	22.26422	1.366731
Median	38.34411	60.88947	25.26251	22.24400	1.253210
Maximum	47.63128	91.20000	31.95474	25.76847	6.444129
Minimum	35.53703	0.003710	10.61662	17.29529	-0.265782
Std. Dev.	4.503922	30.41058	5.139118	2.182609	1.093184
Skewness	0.512734	-0.744885	-1.142825	-0.488217	0.961655
Kurtosis	1.604737	2.317054	3.417224	2.959388	4.502099
Jarque-Bera	30.10838	26.97021	54.20762	9.590533	59.80238
Probability	0.000000	0.000001	0.000000	0.008269	0.000000
Sum	9786.018	13865.29	5813.134	5365.678	329.3821
Sum Sq. Dev.	4868.476	221952.9	6338.529	1143.307	286.8123
Observations	244	244	244	244	244

Source: Authors' calculations using EViews 14

Table 1 reports the descriptive statistics of the variables. EMP exhibits a mean of 40.61 and relatively limited dispersion (SD = 4.50), suggesting a comparatively stable evolution. DIG records a mean of 57.53 and the highest standard deviation (30.41), reflecting substantial changes in Morocco's digital transformation over the sample period. INV and HC average 24.12% and 22.26%, respectively, with moderate variability, whereas FDI averages 1.37% of GDP and displays greater dispersion, indicating its sensitivity to domestic and international conditions. The skewness and kurtosis statistics reveal departures from perfect symmetry and normality across some distributions. Consistently, the Jarque–Bera test rejects normality for all variables ($p < 0.05$), a common feature of long macroeconomic time series that does not, by itself, invalidate the SVAR estimation.

4.1.2. Stationarity and lag selection

Table 2. Augmented Dickey–Fuller (ADF) Unit Root Test Results

Variable	Level	p-value	First Difference	p-value	Order of Integration
EMP	-1.550645	0.5062	-4.592114	0.0002***	I(1)
DIG	-1.951038	0.3086	-4.739860	0.0001***	I(1)
INV	-2.806459	0.1965	-3.552468	0.0007***	I(1)
HC	-0.133488	0.6367	-4.612555	0.0003***	I(1)
FDI	-1.700022	0.4299	-3.461143	0.0006***	I(1)

***: significant at the 1% level; **: 5%; *: 10%

Source: Authors' calculations using EViews 14

ISSN: 3119-6640

Table 2 reports the Augmented Dickey–Fuller (ADF) test results for assessing the stationarity properties of the variables. At levels, EMP, DIG, INV, HC, and FDI exhibit unit roots, with p-values above the 5% significance threshold. After first differencing, all series become stationary, with ADF statistics significant at the 1% level ($p < 0.01$), indicating that the variables are integrated of order one, I(1).

The common integration order supports the use of cointegration tests to assess potential long-run relationships among the variables and provides a basis for examining their dynamic interactions within the structural VAR framework.

Table 3. Information criteria for selecting the optimal number of delays

Lag	AIC	SC	HQ
0	25.80503	25.87819	25.83452
1	4.496219*	4.301043*	4.820614*
2	5.266267	5.705262	5.443210
3	4.609109	5.779763	5.080957
4	4.577133	6.113616	5.196433

* indicates lag order selected by the criterion. AIC: Akaike information criterion
SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion
Source: Authors' calculations using EViews 14

Table 3 reports the lag-order selection results for the VAR model. The Akaike (AIC), Schwarz (SC), and Hannan–Quinn (HQ) information criteria consistently identify one lag as optimal, supporting the specification of a VAR(1) and, consequently, an SVAR(1). This parsimonious specification captures the relevant dynamic interactions among employment, digital innovation, investment, human capital, and FDI while preserving sufficient degrees of freedom for reliable estimation. The selected lag structure is therefore used for the subsequent structural analysis, including impulse response functions and forecast error variance decomposition.

4.1.3. Model stability and diagnostic results

Table 4. VAR Granger Causality and Block Exogeneity Wald Tests

Excluded	Chi-sq	df	Prob.
DIG	0.535653	2	0.7650
INV	2.843857	2	0.2412
HC	4.448176	2	0.1082
FDI	3.282619	2	0.1937
All	14.81130	8	0.0629

Source: Authors' calculations using EViews 14

Table 4 reports the Granger causality (Wald) tests for employment dynamics. None of the individual variables—DIG, INV, HC, or FDI—exhibits statistically significant Granger

https://qeafbreview.org/
Review of Advanced Research on Quantitative Economics, Applied Finance and Business VOL. 1 Issue 3 (2026)
ISSN: 3119-6640

causality at the 5% level. However, the joint block exogeneity test is significant at the 10% level ($\chi^2 = 14.8113$; $p = 0.0629$), indicating that these variables collectively contribute to explaining employment dynamics.

These findings suggest that employment is influenced by the combined interaction of technological, investment, human-capital, and external-financing factors rather than by any single determinant in isolation. They therefore support the use of a multivariate SVAR framework to examine the transmission and dynamic effects of structural shocks.

Table 5. Unrestricted Cointegration Rank Test (Trace)

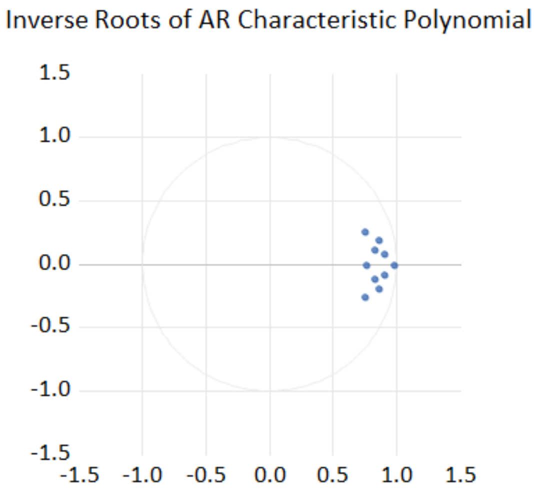
Hypothesized No. of CE(s) Hypothesized	Eigen value	Statistic Trace	Critical Value 0.05	Critical Value Prob.**
None	0.120500	62.84500	69.81889	0.1586
At most 1	0.055143	32.54221	47.85613	0.5822
At most 2	0.043315	19.15602	29.79707	0.4818
At most 3	0.018788	8.705741	15.49471	0.3933
At most 4 *	0.017763	4.229643	7.841465	0.3097
No. of CE(s) Hypothesized	Eigen value	Statistic Max-Eigen	Critical Value 0.05	Critical Value Prob.**
None	0.120500	30.30278	33.87687	0.1260
At most 1	0.055143	13.38620	27.58434	0.8625
At most 2	0.043315	10.45028	21.13162	0.7016
At most 3	0.018788	4.476097	14.26460	0.8060
At most 4 *	0.017763	4.229643	7.841465	0.3097

Trace test indicates no cointegration at the 0.05 level
Max-eigenvalue test indicates no cointegration at the 0.05 level.
* denotes rejection of the hypothesis at the 0.05 level. **MacKinnon Haug-Michelis p-values
Source: Authors' calculations using EViews 14

Table 5 reports the Johansen cointegration results for EMP, DIG, INV, HC, and FDI. Both the Trace and Maximum Eigenvalue tests fail to reject the null hypothesis of no cointegration at the 5% significance level, as the test statistics remain below their critical values and the associated p-values exceed 0.05. Thus, no evidence of a stable long-run equilibrium relationship is found among the variables.

Given the absence of cointegration, the analysis focuses on short-run dynamics and structural shock transmission. Accordingly, a first-difference SVAR framework is employed, with impulse response functions and forecast error variance decomposition used to characterize the dynamic effects of the identified shocks.

Figure 1. Stability Test



Source: Authors' calculations using EViews 14

Figure 1 reports the SVAR stability test based on the inverse roots of the autoregressive characteristic polynomial. All roots lie within the unit circle, confirming the dynamic stability of the estimated system. This result indicates that the effects of structural shocks are transitory and that the system remains dynamically stable following a disturbance. The stability condition therefore supports the interpretation of the impulse response functions (IRFs) and forecast error variance decomposition (FEVD) as measures of the dynamic transmission of structural shocks among employment, digital innovation, investment, human capital, and FDI in Morocco.

Table 6. Diagnostic Tests on Residues

Lag	LRE* stat	df	Prob.	Rao F-stat	Df	Prob.
1	21.73917	25	0.6508	0.868844	(25, 815.1)	0.6508
2	12.28063	25	0.9842	0.488007	(25, 815.1)	0.9842
3	10.40750	25	0.9954	0.413103	(25, 815.1)	0.9954

VAR Residual Serial Correlation LM Tests. Null hypothesis: No serial correlation at lag h
Source: Authors' calculations using EViews 14

Table 6 reports the LM test results for residual serial correlation in the SVAR model. The p-values for the three tested lags (0.6508, 0.9842, and 0.9954) exceed the 5% significance level, so the null hypothesis of no serial correlation cannot be rejected. The residuals therefore show no evidence of temporal dependence, supporting the adequacy of the model's dynamic specification and the subsequent interpretation of the impulse response functions and forecast error variance decomposition.

Table 7. SVAR Residual Normality Tests

Component	Skewness	Chi-sq	df	Prob.*
1	1.695578	114.5202	1	0.0000
2	-1.342098	71.74885	1	0.0000
3	-0.278624	3.092318	1	0.0787
4	-1.232449	60.50408	1	0.0000
5	0.263247	2.760403	1	0.0966
Joint		252.6258	5	0.0000
Component	Kurtosis	Chi-sq	df	Prob.
1	75.84134	52837.52	1	0.0000
2	19.72881	2786.872	1	0.0000
3	17.24260	2020.066	1	0.0000
4	15.94130	1667.793	1	0.0000
5	24.19876	4475.152	1	0.0000
Joint		63787.41	5	0.0000
Component	Jarque-Bera	df	Prob.	
1	52952.04	2	0.0000	
2	2858.621	2	0.0000	
3	2023.158	2	0.0000	
4	1728.297	2	0.0000	
5	4477.912	2	0.0000	
Joint	64040.03	10	0.0000	

Source: Authors' calculations using EViews 14

Table 7 reports the residual normality tests based on skewness, kurtosis, and the Jarque–Bera statistic. The Jarque–Bera p-values are below 1%, leading to rejection of the normality hypothesis. This departure from normality may reflect the occurrence of structural changes, economic shocks, and macroeconomic fluctuations over the extended sample period. However, non-normal residuals do not, by themselves, invalidate the SVAR specification, particularly given the evidence of system stability and the absence of residual serial correlation. The structural results should nevertheless be interpreted with appropriate caution.

Table 8. SVAR Residual Heteroskedasticity Tests (Levels and Squares)

Chi-sq	Df	Prob.
814.6343	300	0.0000

Source: Authors' calculations using EViews 14

Table 8 reports the SVAR residual heteroskedasticity test. The chi-square statistic (814.6343) is associated with a p-value of 0.0000, leading to rejection of the null hypothesis of homoskedasticity and indicating time-varying residual variance. This result may reflect structural changes, policy reforms, and external shocks over the extended sample period.

Review of Advanced Research on Quantitative Economics, Applied Finance and Business
https://qeafbreview.org/
Review of Advanced Research on Quantitative Economics, Applied Finance and Business VOL. 1 Issue 3 (2026)
ISSN: 3119-6640

Although heteroskedasticity warrants caution in interpreting the estimates, the model remains dynamically stable and free from residual serial correlation. The IRF and FEVD results can therefore be interpreted as evidence on the dynamic transmission of structural shocks, subject to the underlying identification assumptions.

Table 9. SVAR Model Estimation

	EMP	DIG	INV	HC	FDI
EMP(-1)	0.991021	-0.060342	0.003069	0.010430	-0.014754
DIG(-1)	0.930772	0.963206	-0.001781	0.001570	-0.001392
INV(-1)	0.710761	0.109958	0.983391	-0.017125	0.005084
HC(-1)	0.223512	0.195148	0.070969	0.981989	-0.006689
FDI(-1)	0.817545	0.324791	0.016239	0.018673	0.933960
C	1.077824	-2.495154	-1.156498	0.288550	0.801237
R-squared	0.995101	0.993757	0.988628	0.960218	0.917297
Adj. R-squared	0.994996	0.993623	0.988385	0.959368	0.915530
Sum sq. resids	23.62451	1364.949	69.99728	45.25832	23.65861
S.E. equation	0.317741	2.415184	0.546931	0.439786	0.317970
F-statistic	9505.861	7449.351	4068.687	1129.614	519.0809
Log likelihood	-62.34275	-549.1332	-192.6833	-140.3550	-62.51585
Akaike AIC	0.569523	4.626110	1.655695	1.219625	0.570965
Schwarz SC	0.656539	4.713126	1.742711	1.306641	0.657981
Mean dependent	40.57758	57.77202	24.17716	22.27410	1.370319
S.D. dependent	4.491813	30.24513	5.074921	2.181762	1.094045

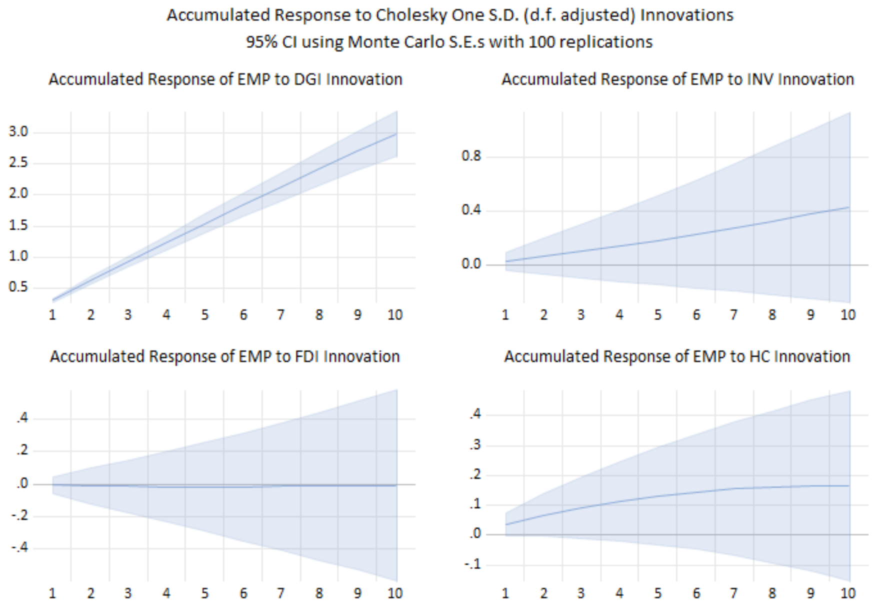
Source: Authors' calculations using EViews 14

Table 9 reports the SVAR estimation results for EMP, DIG, INV, HC, and FDI. The coefficients indicate substantial temporal persistence, with several lagged terms close to unity, suggesting that the variables are strongly influenced by their past dynamics. The cross-equation coefficients also reveal interactions among digital innovation, investment, human capital, FDI, and employment, consistent with interconnected transmission mechanisms.

The equations display high explanatory power, with R^2 values ranging from 0.917 to 0.995 and statistically significant F-statistics. Nevertheless, these goodness-of-fit measures should not be interpreted as evidence of causal validity. The economic significance and dynamic effects of structural shocks are therefore examined more directly through impulse response functions (IRFs) and forecast error variance decomposition (FEVD).

4.2. Dynamic Response of Employment to Structural Shocks

Figure 2. Impulse response of employment to a digital innovation shock



Source: Authors' calculations using EViews 14

4.2.1. Response of employment to a digital innovation shock

Figure 2 shows that employment responds positively and persistently to a structural shock in digital innovation. The gradual strengthening of the response suggests that the employment effects of digitalization materialize through an adjustment process rather than instantaneously. Firms may initially require complementary investments in digital infrastructure, organizational capabilities, and worker training before productivity gains and new digital activities translate into higher labor demand.

This finding is consistent with the compensation mechanisms identified in the innovation–employment literature, whereby productivity improvements, lower transaction costs, market expansion, and new products or services can offset part of the labor displacement associated with automation. The persistence of the response further suggests that digital transformation may generate employment effects beyond the initial adoption phase as firms reorganize production and workers acquire complementary skills.

However, the positive aggregate response should not be interpreted as a uniform employment effect. It may reflect the net outcome of simultaneous job creation and displacement, with benefits likely to be greater for workers possessing relevant digital and cognitive skills, while routine occupations may remain more exposed to substitution.

4.2.2. Response of employment to an investment shock

A positive investment shock generates a favorable but more moderate employment response than digital innovation. This effect is consistent with the conventional investment–employment mechanism, whereby higher investment expands productive capacity, stimulates demand, and increases labor requirements.

The relatively limited magnitude of the response suggests that employment effects depend not only on investment volume but also on its sectoral and technological composition. Capital-intensive investment may increase productivity without generating substantial employment, whereas investment in labor-intensive activities, services, digital infrastructure, and innovative sectors can produce stronger job creation. In Morocco, the employment impact of investment is therefore likely to be enhanced when it is complemented by technological upgrading, skills development, and integration into expanding value chains.

4.2.3. Response of employment to a human capital shock

Employment responds positively and increasingly to a human-capital shock, highlighting the importance of skills in translating digital transformation into employment gains. Human capital facilitates technology adoption, raises worker productivity and occupational mobility, and enables firms to implement technological and organizational innovations requiring more advanced capabilities.

The gradual response is consistent with the delayed effects of education and training, as skill acquisition, workplace integration, and labor reallocation require time. This finding suggests that digital infrastructure and technology adoption alone are insufficient to maximize employment creation in Morocco. Complementary investments in education, training, and digital competencies are essential for converting technological progress into sustained employment gains.

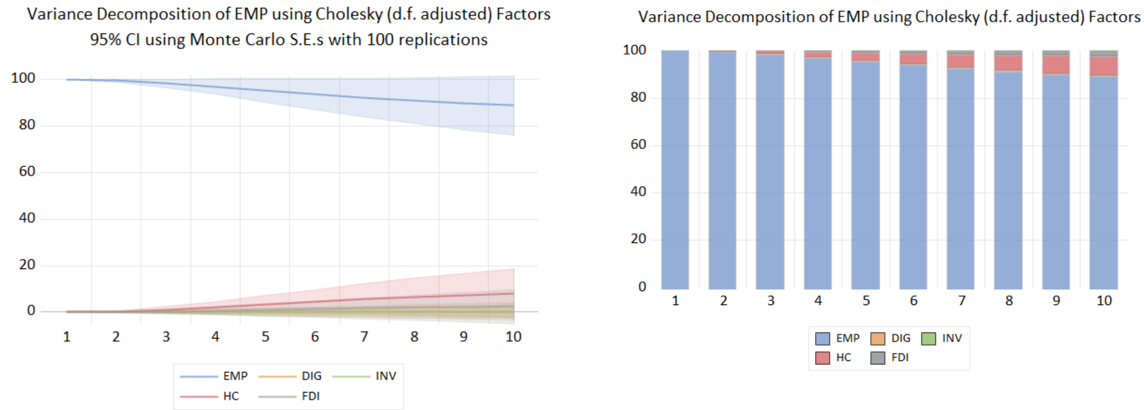
4.2.4. Response of employment to a foreign direct investment shock

Employment exhibits a relatively modest response to an FDI shock, suggesting that its short-run employment effects are weaker than those associated with digital innovation and human capital. This result may reflect the sectoral composition of FDI, particularly when foreign capital is concentrated in capital-intensive or highly automated activities.

Moreover, the employment benefits of FDI may materialize gradually through technology transfer, supplier linkages, productivity gains, exports, and knowledge spillovers rather than through immediate job creation. In Morocco, strengthening domestic linkages and local firms' absorptive capacity could therefore increase the employment impact of FDI. Policies that attract investment toward skill-intensive activities with stronger technology-transfer potential may enhance its contribution to sustainable employment creation.

4.3. Forecast Error Variance Decomposition

Figure 3. Decomposition of the variance in forecast errors



Source: Authors' calculations using EViews 14

Figure 3 reports the forecast error variance decomposition of employment over a ten-period horizon. In the short run, employment fluctuations are largely explained by its own structural innovations, reflecting substantial labor-market persistence. As the horizon extends, the contribution of external shocks increases, with human capital emerging as the most important determinant, followed by digital innovation.

The rising contribution of digital innovation over time is consistent with the gradual diffusion of technologies across firms, production processes, and labor markets. Meanwhile, the strong role of human capital suggests that skills development is a key enabling condition for translating technological progress into employment opportunities. By contrast, investment and FDI account for relatively smaller shares of employment fluctuations, consistent with their more moderate or delayed employment effects.

Overall, the IRF and FEVD results indicate that digital innovation constitutes an important driver of employment dynamics, while human capital plays a complementary role in determining the economy’s capacity to absorb and convert technological change into sustainable employment gains.

4.4. Discussion and Policy Implications

The empirical evidence indicates a positive and persistent relationship between digital innovation and employment in Morocco. The response to a digital innovation shock suggests that, at the aggregate level, productivity gains, demand expansion, new activities, and technological opportunities outweigh the direct displacement effects over the estimated horizon. This finding is consistent with the Schumpeterian view of technological change and with compensation mechanisms emphasized in the innovation–employment literature.

However, the positive aggregate effect does not imply uniform benefits across workers or sectors. Digitalization may simultaneously displace routine tasks and increase demand for workers with complementary technological and cognitive skills. The strong contribution of human capital to employment fluctuations reinforces this interpretation, indicating that skills are a critical channel through which the economy absorbs and converts technological change into employment opportunities.

The relatively limited contribution of FDI compared with human capital can be explained by the sectoral and technological composition of foreign investment. Capital-intensive or highly automated activities may generate substantial output without proportional employment gains, while technology transfer and knowledge spillovers often require time and strong domestic absorptive capacity. Human capital therefore appears to play a complementary role in enhancing the broader employment effects of FDI.

The FEVD results support this interpretation, with human capital accounting for a larger share of employment fluctuations than FDI, while the contribution of digital innovation increases over longer horizons. These findings suggest that Morocco’s employment and investment policies should be integrated: digital transformation should be accompanied by sustained investment in education, vocational training, lifelong learning, and digital skills, while FDI strategies should prioritize projects generating domestic linkages, technology transfer, skills development, and knowledge spillovers.

The empirical findings provide several policy implications for Morocco. First, continued investment in digital infrastructure and technology access is essential, given the positive and persistent employment response to digital innovation. However, technological adoption should be accompanied by substantial investment in human capital, particularly in digital skills, data analysis, artificial intelligence, cybersecurity, programming, and other emerging competencies.

Second, policies should facilitate digital adoption among firms, especially SMEs and startups, through targeted financial support, technical assistance, digital platforms, and innovation incentives. Third, FDI policies should focus increasingly on investment quality by prioritizing projects that generate domestic supplier linkages, technology transfer, workforce training, and knowledge spillovers.

Fourth, stronger cooperation between universities, vocational institutions, research centers, and firms is necessary to align skills development with evolving labor-market requirements and strengthen domestic technological absorptive capacity. Labor-market policies should also support retraining, occupational mobility, and lifelong learning to facilitate workers' transition from declining to emerging activities.

Overall, the results indicate that digital innovation is an increasingly important driver of employment dynamics in Morocco, with its contribution becoming more pronounced over longer horizons. Nevertheless, technology alone does not guarantee broad-based employment creation. Human capital emerges as a critical transmission mechanism, while the relatively limited contribution of FDI highlights the importance of sectoral composition, domestic linkages, and absorptive capacity. Morocco's digital transformation should therefore be pursued through an integrated strategy combining technological adoption, skills development, productive investment, innovation, and institutional support to promote sustained and inclusive employment creation.

5. Conclusion

This study analyzed the impact of digital innovation on job creation in Morocco using a structural vector autoregressive (SVAR) model. By incorporating investment, human capital, and foreign direct investment, it assessed the dynamic effects of technological shocks on the labor market. The results show that the variables are first-order integrated and that the model satisfies the main validity tests, notably stability and the absence of autocorrelation in the residuals. The impulse response functions indicate that a positive digital innovation shock gradually and sustainably stimulates job creation. The variance decomposition also highlights the growing role of human capital and digital innovation in explaining fluctuations in employment, while the effect of foreign direct investment remains more limited.

These results underscore that the benefits of digital transformation depend on the quality of human capital and an environment conducive to innovation. They argue in favor of strengthening digital infrastructure, developing digital skills, supporting business innovation, and better directing investment toward technology-intensive sectors.

This study does, however, have certain limitations related to the limited number of variables selected and the use of aggregated macroeconomic data, which do not allow for an understanding of sector-specific characteristics. Future research could incorporate more detailed indicators of the digital economy, such as artificial intelligence, e-commerce, or research and development spending, as well as employ more advanced dynamic models, notably TVP-VAR or DSGE approaches.

Ultimately, this study shows that digital innovation is a major driver of economic transformation and job creation in Morocco. However, its positive effects can only be fully realized through coherent public policies that promote skills development, technological investment, and an institutional environment conducive to innovation.

References

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy, 128*(6), 2188–2244. https://doi.org/10.1086/705716

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica, 60*(2), 323–351. https://doi.org/10.2307/2951599

Arenas Díaz, F., Guerrero, M., & Heijs, J. (2024). Innovation and employment: A meta-analysis of product and process innovation effects. *Technological Forecasting and Social Change*, *203*, 123456.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3–30.https://doi.org/10.1257/jep.29.3.3

Benaini, N., & Ouarraoui, B. (2024). The digital revolution in Morocco: What effects on employment? *Management Control, Auditing and Finance Review*, *1*(4), 155–165.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Calvino, F., & Virgillito, M. E. (2018). The innovation-employment nexus: A critical survey of theory and empirics. *Journal of Economic Surveys, 32*(1), 83–117.

Freeman, C., Clark, J., & Soete, L. (1982). Unemployment and technical innovation: A study of long waves and economic development. Frances Pinter.

Hötte, K., Somers, M., & Theodorakopoulos, A. (2022). Technology and employment: A systematic review of the literature. *Research Policy, 51*(8), 104555.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*(2–3), 231–254. https://doi.org/10.1016/0165-1889(88)90041-3

Opland, J., Børing, P., Cappelen, Å., & Raknerud, A. (2022). Digital technologies, organizational innovation and employment growth: Evidence from European firms. *Research Policy, 51*(6), 104472.

Pianta, M. (2005). Innovation and employment. Dans J. Fagerberg, D. Mowery, & R. Nelson (Eds.), *The Oxford Handbook of Innovation* (pp. 568–598). Oxford University Press.

Schumpeter, J. A. (1934). The Theory of Economic Development. Harvard University Press.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, *48*(1), 1–48. https://doi.org/10.2307/1912017

Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues, 48*(1), 123–154.