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Social Protection Policies as a Moderator Between Digital Economy and Labor Market Dynamics in the North African States

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Abstract:

This study examines the interplay between the digital economy, social protection policies, and labor market dynamics in North African states. Using a quantitative research design and Structural Equation Modeling (SEM), data from a survey conducted among policymakers, business leaders, and labor market experts are analyzed. The results indicate a significant positive impact of the digital economy on labor market dynamics, emphasizing the role of technology adoption in driving job creation and economic growth. Furthermore, effective social protection policies are found to independently influence labor market outcomes and moderate the effects of digitalization on employment patterns. These findings underscore the importance of adopting comprehensive policy frameworks that leverage the opportunities presented by the digital economy while ensuring inclusivity, fairness, and social protection for all segments of society

Keywords:

Digital economy, Social protection policies, Labor market dynamics.

1. Introduction:

The digital economy, characterized by the widespread use of digital technologies in economic activities, has emerged as a significant driver of growth and transformation in modern economies. In North African states, the digital economy is rapidly evolving, influencing various aspects of economic development, including labor market dynamics. Labor market dynamics encompass changes in employment rates, job creation, and labor force participation, all of which are crucial indicators of economic health. However, the extent to which the digital economy impacts these labor market variables can be influenced by various moderating factors, such as social protection policies. Social protection policies, which include unemployment benefits, social security, and other forms of social safety nets, play a critical role in cushioning the labor market against economic shocks and uncertainties. This study aims to explore the interaction between the digital economy and labor market dynamics in North African states, with a specific focus on the moderating role of social protection policies.

Despite the growing body of literature on the digital economy and labor markets, there is limited research addressing the moderating effect of social protection policies in this context, particularly in North African countries. This study seeks to fill this gap by investigating how social protection policies influence the relationship between the digital economy and labor market dynamics. The primary research questions guiding this study are: How does the digital economy affect labor market dynamics in North African states? And, what is the moderating role of social protection policies in this relationship? The hypotheses of this study posit that the digital economy positively impacts labor market dynamics and that social protection policies enhance this positive relationship. The objectives are to empirically assess these relationships using data collected from North African states and to provide insights for policymakers on optimizing social protection policies to leverage the benefits of the digital economy for labor market improvements

2. Literature Review:

2.1. The Relationship between Digital Economy and Labor Market Dynamics:

The digital economy has a profound impact on labor market dynamics, leading to both opportunities and challenges. As highlighted in various research papers, the transition to digitalization significantly transforms the labor market by changing the requirements for specialists, improving efficiency, and increasing the demand for high-skilled labor (Shakizada, 2023) (Riazantseva & Parshukova, 2022). This shift results in the creation of new job opportunities in areas such as accounting, sales, and research and development, while also altering the structure of employment by decreasing the need for low- and medium-skilled labor (Zhibek et al., 2022). However, the rapid pace of digital transformation can lead to job cuts due to automation, contributing to social insecurity among workers (Wu & Ma, 2023). Despite these challenges, embracing digital technologies can enhance the overall employment scale of companies, demonstrating the positive correlation between digital economic development and job creation [(Babakulov et al., 2022). Ultimately, navigating the complexities of the digital economy is crucial for effectively managing labor market dynamics and ensuring sustainable employment opportunities.

First hypothesis (H1): There is no statistically significant relationship between Digital Economy and Labor Market Dynamics at a 5% significance level.

2.2. The relationship between Social Protection Policies and the relationship of Digital Economy to Labor Market Dynamics:

Social protection policies play a crucial role in shaping the relationship between the digital economy and labor market dynamics. Labor unions are actively engaging in campaigns to influence state investments, data protection, and AI regulation, while also negotiating for labor market protections for new worker groups (Virginia, 2022). The digital transformation is driving changes in labor protection laws and practices, emphasizing the importance of ensuring safe working conditions for effective business development (S. et al., 2022). The digitalization of the economy is reshaping industrial labor relations, emphasizing the need for modernization and non-standard approaches to address structural issues and enhance production processes (Shakizada, 2023). The COVID-19 pandemic has highlighted the disparities in social protection globally, with digital technologies further transforming labor markets and necessitating new regulations to address these challenges (I.V. et al., 2022). Countries like the Netherlands, Germany, and Italy are preparing their welfare states for increased technological changes, focusing on social investment to adapt to the evolving labor market dynamics (Eichhorst et al., 2022).

Second Hypothesis (H2): Social Protection Policies have no significant role in reducing the relationship between Digital Economy and Labor Market Dynamics at a 5% significance level.

2.3. Gaps in existing literature :

The digital economy has a profound impact on labor market dynamics, leading to both opportunities and challenges. Various research papers highlight the transition to digitalization, significantly transforming the labor market by changing the requirements for specialists, improving efficiency, and increasing the demand for high-skilled labor (Shakizada, 2023; Riazantseva & Parshukova, 2022). This shift results in the creation of new job opportunities in areas such as accounting, sales, and research and development, while also altering the structure of employment by decreasing the need for low- and medium-skilled labor (Zhibek et al., 2022). However, the rapid pace of digital transformation can lead to job cuts due to automation, contributing to social insecurity among workers (Wu & Ma, 2023). Despite these challenges, embracing digital technologies can enhance the overall employment scale of companies, demonstrating the positive correlation between digital economic development and job creation (Babakulov et al., 2022). Ultimately, navigating the complexities of the digital economy is crucial for effectively managing labor market dynamics and ensuring sustainable employment opportunities.

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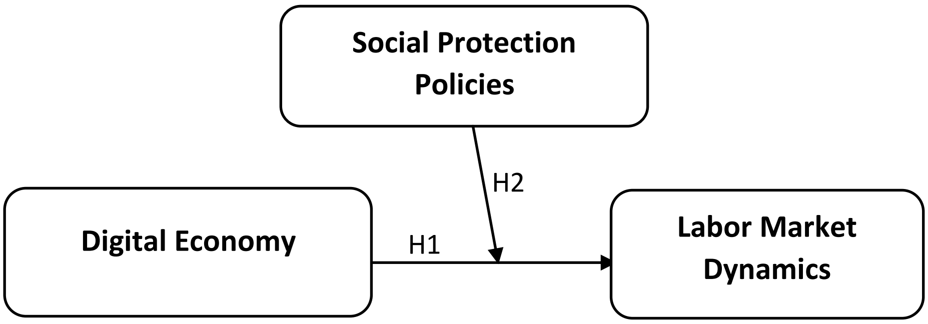


Figure 1. Theoretical framework.

3. Methodology:

3.1. Research Design and Approach

This study employs a quantitative research design, utilizing a cross-sectional approach to collect and analyze data at a single point in time. The research will focus on examining the relationship between the digital economy and labor market dynamics, with social protection policies as a moderating variable, within

North African states. Structural Equation Modeling (SEM) will be used to analyze the data, leveraging the SmartPLS software for its robust handling of complex variable interactions and moderating effects.

3.2. Data Collection Methods

3.2.1. Survey Questionnaire:

Development: A structured questionnaire will be developed, comprising items designed to measure the three main variables: digital economy indicators, labor market dynamics, and social protection policies.

Pretesting: The questionnaire will undergo a pretesting phase with a small sample to ensure clarity and reliability.

Distribution: The final questionnaire will be distributed electronically to a representative sample of participants from various sectors within North African countries. The target respondents will include policymakers, business leaders, and labor market experts.

3.2.2. Secondary Data:

Sources: Relevant secondary data will be sourced from governmental databases, international organizations such as the World Bank and International Labour Organization (ILO), and academic publications.

Indicators: Data will include digital economy metrics (e.g., internet penetration, digital transaction volumes), labor market indicators (e.g., employment rates, job creation statistics), and social protection measures (e.g., social security coverage, unemployment benefits).

3.3. Rationale for the Chosen Methods

3.3.1. Quantitative Research Design:

Objectivity and Generalizability: The quantitative approach allows for objective measurement and statistical analysis, providing generalizable findings that can inform policy and practice.

Complex Relationships: The use of SEM and SmartPLS is ideal for analyzing complex relationships between multiple variables and understanding the moderating effects of social protection policies.

3.3.2. Survey Questionnaire:

Direct Insights: The questionnaire will provide direct insights from key stakeholders, capturing current perceptions and experiences regarding the digital economy, labor market dynamics, and social protection policies.

Large Sample Size: Electronic distribution enables reaching a large and geographically dispersed sample, enhancing the representativeness of the data.

3.3.3. Secondary Data:

Comprehensive Context: Secondary data complements survey findings by providing a broader context and historical trends.

Validity: Utilizing established databases ensures the validity and reliability of the indicators used in the study

4. Data Presentation and Analysis:

First: Assessment of measurement Model:

In this section, the quality of the expressions utilized in this model is examined through the utilization of the Smart PLS software. This evaluation entails testing the convergence and consistency of these expressions amongst themselves. The objective is to ensure the capability of these expressions to effectively measure the desired attributes, as well as the stability of the measurement across different conditions, employing the Convergent Validity test. Moreover, an assessment is conducted to determine the logical distinctiveness and absence of overlap among these expressions, employing the Discriminate Validity test.

4.1. Convergent Validity:

Convergent validity is a critical aspect of structural equation modeling (SEM), including Partial Least Squares SEM (PLS-SEM). Convergent validity assesses whether the indicators (manifest variables) of a latent construct (factor) are measuring the same underlying concept. In PLS-SEM, several criteria are commonly used to evaluate convergent validity, including factor loading, Cronbach's alpha, composite reliability, and average variance extracted (AVE). Here's an explanation of each criterion:

Factor Loading:

Basis: Factor loading represents the strength and direction of the relationship between an indicator and its corresponding latent construct. In PLS-SEM, factor loadings should be statistically significant and preferably higher than 0.7 to indicate a strong relationship.

Cronbach's Alpha:

Basis: Cronbach's alpha is a measure of internal consistency reliability. It assesses the extent to which a set of indicators (items) measures a single latent construct consistently. In PLS-SEM, a high Cronbach's alpha (typically above 0.7) suggests good internal consistency.

Composite Reliability:

Basis: Composite reliability is another measure of reliability that evaluates the consistency of indicators in measuring a latent construct. In PLS-SEM, composite reliability should ideally exceed 0.7, indicating that the indicators are reliable measures of the underlying construct.

Average Variance Extracted (AVE):

Statistically, convergent validity is established when the Average Variance Extracted (AVE) is greater than 0.50 (Sarstedt et al., 2021). Additionally, factor loading, Cronbach's Alpha, and composite reliability are also used to assess convergent validity in PLS-SEM. Factor loading measures the relationship between the observed variables and their underlying latent constructs, while Cronbach's Alpha and composite reliability assess the internal consistency of the measurement instrument (Amora, 2021).

Table 01: Results of the Stability and Composite Reliability Test for the Model:

variables	Items	Loadings	Cronbach's Alpha	Composite Reliability	The average variance extracted
Labor Market Dynamics	LMD_1	0.925	0.891	0.932	0.822
	LMD_2	0.898			
	LMD_3	0.897			
Social Protection Policies	SPP_1	0.678	0.885	0.908	0.553
	SPP_2	0.801			
	SPP_3	0.754			
	SPP_4	0.711			
	SPP_5	0.796			
	SPP_6	0.698			
	SPP_7	0.752			
	SPP_8	0.752			
Digital Economy	DE_1	0.593	0.866	0.896	0.555
	DE_2	0.822			
	DE_3	0.758			
	DE_4	0.803			
	DE_5	0.814			
	DE_6	0.709			
	DE_7	0.689			

Source: Compiled by researchers based on the outputs of Smart PLS4.

The stability and composite reliability test results for the model, as presented in Table 01, indicate strong reliability and validity for the constructs of Labor Market Dynamics, Social Protection Policies, and Digital Economy. Labor Market Dynamics demonstrates excellent internal consistency, with high item loadings (ranging from 0.897 to 0.925), a Cronbach's Alpha of 0.891, composite reliability of 0.932, and an average variance extracted (AVE) of 0.822, indicating that over 82% of the variance is explained by the latent construct. Social Protection Policies also show good reliability, with item loadings from 0.678 to 0.801, a Cronbach's Alpha of 0.885, composite reliability of 0.908, and an AVE of 0.553, suggesting moderate to high item consistency and acceptable variance extraction. The Digital Economy construct, while slightly lower in some item loadings (0.593 to 0.822), maintains adequate reliability with a Cronbach's Alpha of 0.866, composite reliability of 0.896, and an AVE of 0.555, indicating over 55% of the variance is explained by the construct. Overall, the results affirm the reliability and validity of the measurement model, supporting its use in further analysis.

4.2. discriminate Validity :

The recommended criteria for analyzing the results of the discriminant validity test in the PLS-SEM methodology include the following:

Fornell-Larcker Criterion: This criterion assesses discriminant validity by comparing the square root of the average variance extracted (AVE) for each construct with the correlations between that construct and other constructs. Discriminant validity is established if the AVE value for a particular construct is greater than its correlation with all other constructs (Henseler et al., 2015) (Hamid et al., 2017)

Heterotrait-Monotrait Ratio of Correlations (HTMT) Criterion: This criterion is based on the heterotrait-monotrait ratio of correlations and is used to assess discriminant validity in variance-based structural equation modeling. It measures the extent to which constructs are distinct from each other empirically. A threshold of 0.85 is recommended for HTMT when the constructs in the path model are conceptually more distinct (Franke & Sarstedt, 2019) (Henseler et al., 2015) (Hamid et al., 2017)

It is important to note that the Fornell-Larcker Criterion and cross-loadings have been the dominant approaches for evaluating discriminant validity, but Henseler, Ringle, and Sarstedt (2015) have proposed the HTMT criterion as an alternative approach, which has shown high sensitivity and specificity in detecting discriminant validity problems (Cepeda-Carrión et al., 2022) (Henseler et al., 2015) (Hamid et al., 2017)

In conclusion, when analyzing the results of the discriminant validity test in the PLS-SEM methodology, researchers should consider using the Fornell-Larcker Criterion, cross-loadings, and the HTMT Criterion to ensure the distinctiveness of the constructs in the study and to detect any issues with discriminant validity.

Table 02: Fornell-Larcker Criterion

variables	Digital Economy	Labor Market Dynamics	Social Protection Policies
Digital Economy	0.745		
Labor Market Dynamics	0.655	0.906	
Social Protection Policies	0.703	0.571	0.744

Source: Compiled by researchers based on the outputs of Smart PLS4.

The Fornell-Larcker Criterion results presented in Table 02 provide evidence of discriminant validity for the constructs in the model. The diagonal values represent the square root of the average variance extracted (AVE) for each construct, with Digital Economy, Labor Market Dynamics, and Social Protection Policies having AVE square roots of 0.745, 0.906, and 0.744, respectively. These values are greater than the off-diagonal correlations with other constructs, indicating that each construct shares more variance with its measures than with those of other constructs. Specifically, the correlation between Digital Economy and Labor Market Dynamics is 0.655, between Digital Economy and Social Protection Policies is 0.703, and between Labor Market Dynamics and Social Protection Policies is 0.571. These correlations are all below the respective AVE square roots, thereby confirming the discriminant validity of the constructs and supporting the integrity of the model's measurement.

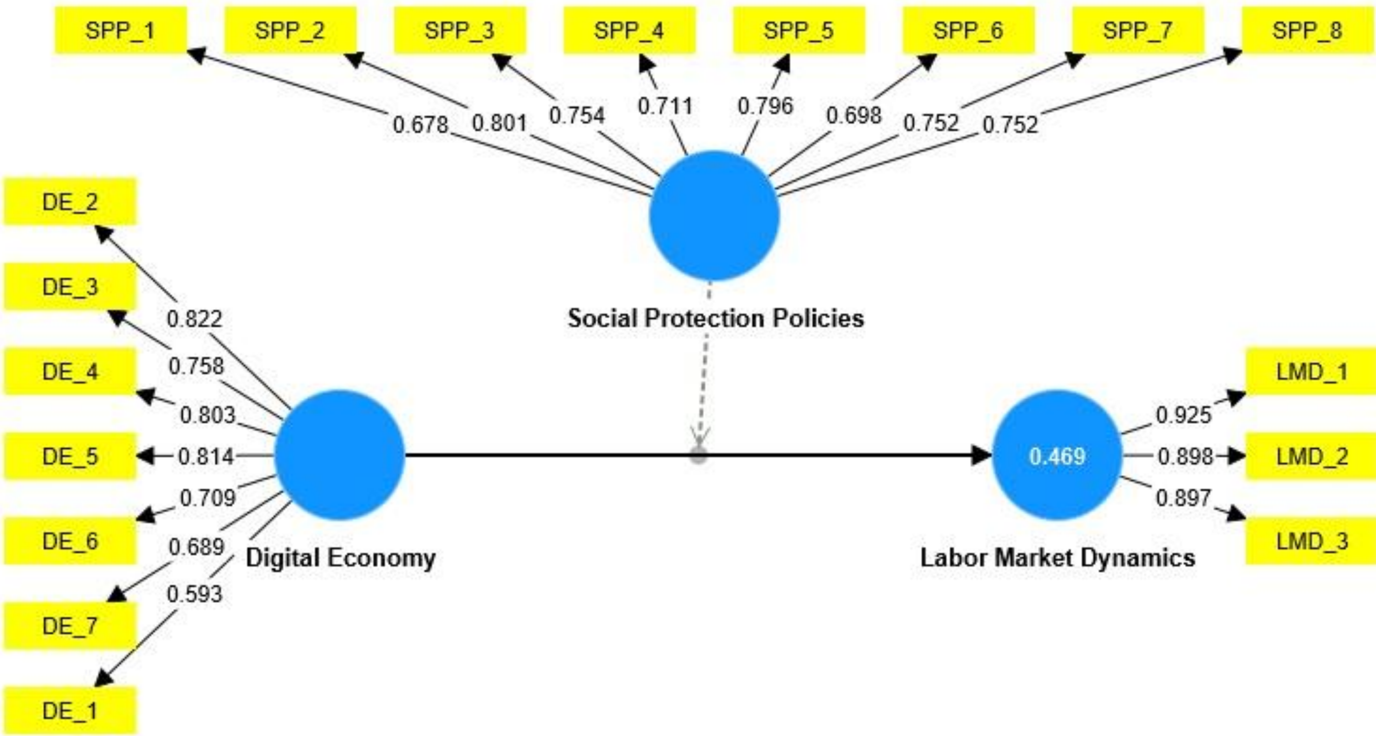
Table 03: the heterotrait-monotrait ratio of correlations (HTMT)

variables	Digital Economy	Labor Market Dynamics	Social Protection Policies
Digital Economy			
Labor Market Dynamics	0.716		
Social Protection Policies	0.804	0.629	

Source: Compiled by researchers based on the outputs of Smart PLS4.

Table 03 presents the Heterotrait-Monotrait Ratio of Correlations (HTMT) for the constructs of Digital Economy, Labor Market Dynamics, and Social Protection Policies. The HTMT values indicate the degree of correlation between constructs, where values below 0.85 are generally considered acceptable for establishing discriminant validity. The HTMT ratio between Digital Economy and Labor Market Dynamics is 0.716, between Digital Economy and Social Protection Policies is 0.804, and between Labor Market Dynamics and Social Protection Policies is 0.629. Since all these values are below the threshold of 0.85, the results confirm that the constructs are distinct from one another, providing further evidence of discriminant validity in the model. This validation supports the robustness of the measurement model and its suitability for subsequent structural analysis.

Figure 2: General Structural Model for the Study



Source: Compiled by researchers based on the outputs of Smart PLS4.

Secondly: Testing the Internal Model (Structural Model)

In this section, we evaluate the results of the structural model by testing the degree of correlation, assessing the predictive capabilities of the model, and examining the relationships between constructs. Additionally, we conduct the necessary tests to evaluate the model.

1. Validity of the Structural Model:

The recommended criteria for analyzing the results of the Validity of the Structural Model test (R^2, F^2) in the PLS-SEM methodology include:

Measurement model assessment: This involves assessing the relationship between a construct and its observed items, including reliability, indicator loading, and internal consistency reliability (Fauzi, 2022).

Structural model assessment: This focuses on evaluating the significance and relevance of path coefficients, followed by the model's explanatory and predictive power. Key metrics relevant to structural model assessment in PLS-SEM include the coefficient of determination (R2), f2 effect size, and cross-validated predictive ability test (CVPAT). (Hair Jr et al., 2021).

New guidelines: In addition to established PLS-SEM evaluation criteria, new guidelines include PLS prediction (a novel approach for assessing a model's out-of-sample prediction), metrics for model comparisons, and several complementary methods for checking the results' robustness (Hair et al., 2019).

Table 04: Validity of the Structural Model

Variables	Coefficient of Determination (R2)	Explanatory size (F2)
Labor Market Dynamics	0.469	/
Digital Economy	/	0.247
Social Protection Policies	/	0.056

Source: Compiled by researchers based on the outputs of Smart PLS4.

Table 04 presents the validity indicators for the structural model, focusing on the coefficient of determination (R^2) and the explanatory size (f^2). The R^2 value for Labor Market Dynamics is 0.469, indicating that 46.9% of the variance in Labor Market Dynamics is explained by the predictor variables within the model, suggesting a moderate level of explanatory power. The explanatory size (f^2) indicates the impact of one construct on another. The f^2 value for Digital Economy is 0.247, signifying a substantial effect size in explaining Labor Market Dynamics. In contrast, the f^2 value for Social Protection Policies is 0.056, indicating a small but notable impact. These results demonstrate that while both Digital Economy and Social Protection Policies significantly contribute to explaining Labor Market Dynamics, the Digital Economy has a more pronounced effect. This supports the model's structural validity and highlights the critical role of the digital economy in shaping labor market dynamics, moderated by social protection policies.

2. Discussion of testing the study hypotheses

When analyzing the results of testing study hypotheses in the Partial Least Squares Structural Equation Modeling (PLS-SEM) methodology, there are several recommended criteria to consider. These criteria are essential for ensuring the validity and reliability of the analysis. Here are the recommended criteria for analyzing the results of testing this study's hypotheses in the PLS-SEM methodology:

Hypothesis Testing with Confidence Intervals and P Values: Researchers usually employ P values for hypothesis testing in PLS-SEM, where each hypothesis refers to a path in a model. P values may be one-tailed or two-tailed (Kock, 2016).

Structural Model Testing: The structural model in PLS-SEM needs to be tested to ensure that the assumptions of unidimensional constructs hold in the sample. This involves testing the relationships between latent variables and their indicators (Kock, 2016).

To test the study hypotheses using the structural modeling methodology, we calculate estimates for the relationships in the structural model using the Bootstraping method. These estimates indicate the expected relationships between constructs, and the path coefficient ranges from -1 to +1. Values close to +1 suggest strong positive relationships, while values near -1 indicate strong negative relationships. Typically, statistically significant relationships have p-values below 5%. Coefficients approaching zero from both directions suggest weak relationships (Kock, 2018).

2.1. Hypotheses:

2.1.1. First hypothesis (H1): There is no statistically significant relationship between Digital Economy and Labor Market Dynamics at a 5% significance level.

2.1.2. Second Hypothesis (H2): Social Protection Policies have no significant role in reducing the relationship between Digital Economy and Labor Market Dynamics at a 5% significance level.

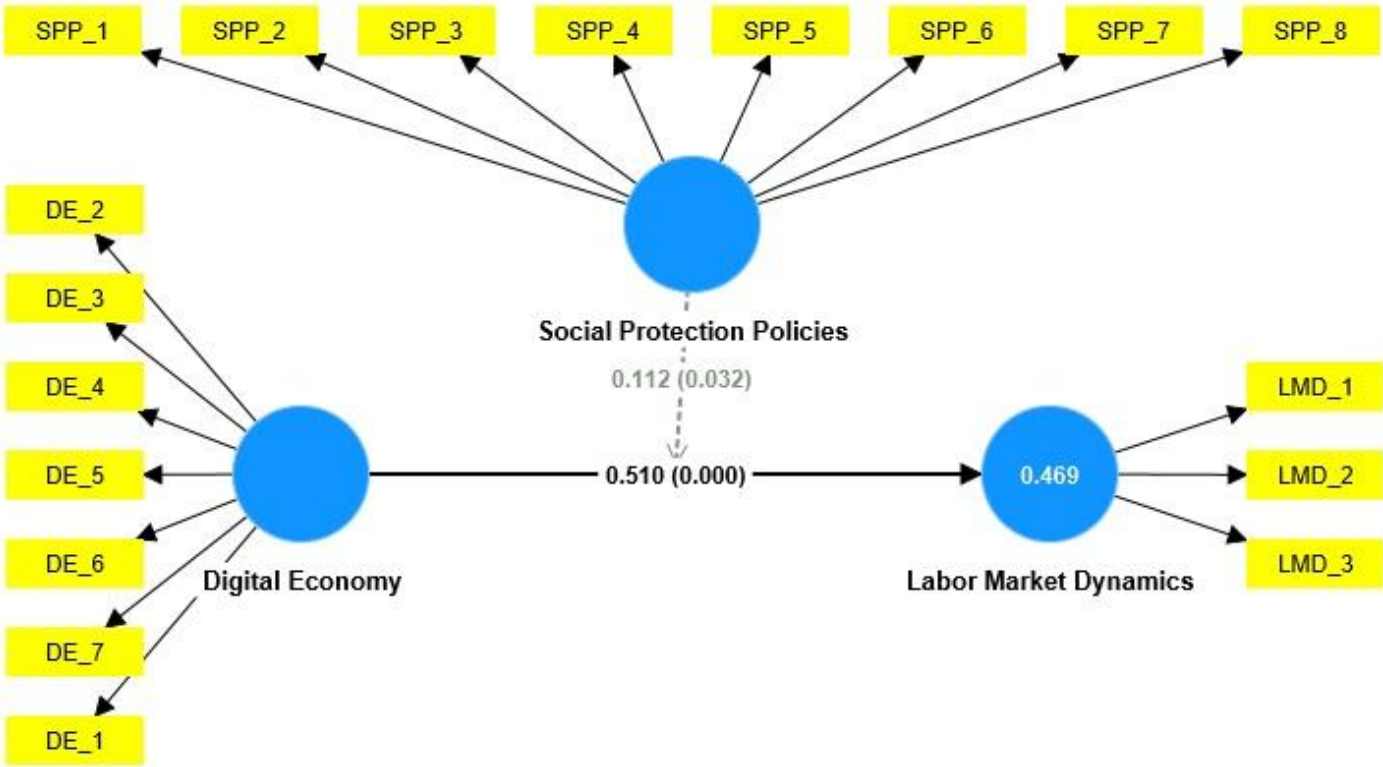
Table 5: Testing the Hypotheses for the Study (H_1, H_2)

Hypothesis	Paths	Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values	Decision
H_1	DE -> LMD	0.510	0.512	0.116	4.398	0.000	Accepted
H_2	(DE * SPP) -> LMD	0.112	0.112	0.052	2.144	0.032	Accepted

Source: Compiled by researchers based on the outputs of Smart PLS4.

Table 5 presents the results of hypothesis testing for the study, focusing on Hypotheses H1 and H2. Hypothesis H1, which posits a direct relationship between the Digital Economy (DE) and Labor Market Dynamics (LMD), is supported by the data, with a significant path coefficient of 0.510. The T statistics value of 4.398 and the associated p-value of 0.000 indicate a strong statistical significance, leading to the acceptance of the hypothesis. This finding suggests that the digital economy has a positive and substantial impact on labor market dynamics in the context of the study. Hypothesis H2, which proposes an interaction effect between the Digital Economy and Social Protection Policies (SPP) on Labor Market Dynamics, is also supported by the data. The path coefficient of 0.112, accompanied by a T statistics value of 2.144 and a p-value of 0.032, demonstrates statistical significance, leading to the acceptance of the hypothesis. This result suggests that the interaction between the digital economy and social protection policies further influences labor market dynamics, highlighting the importance of considering both factors in policy formulation and economic planning.

Figure 3: Results of path coefficients



Source: Compiled by researchers based on the outputs of Smart PLS4.

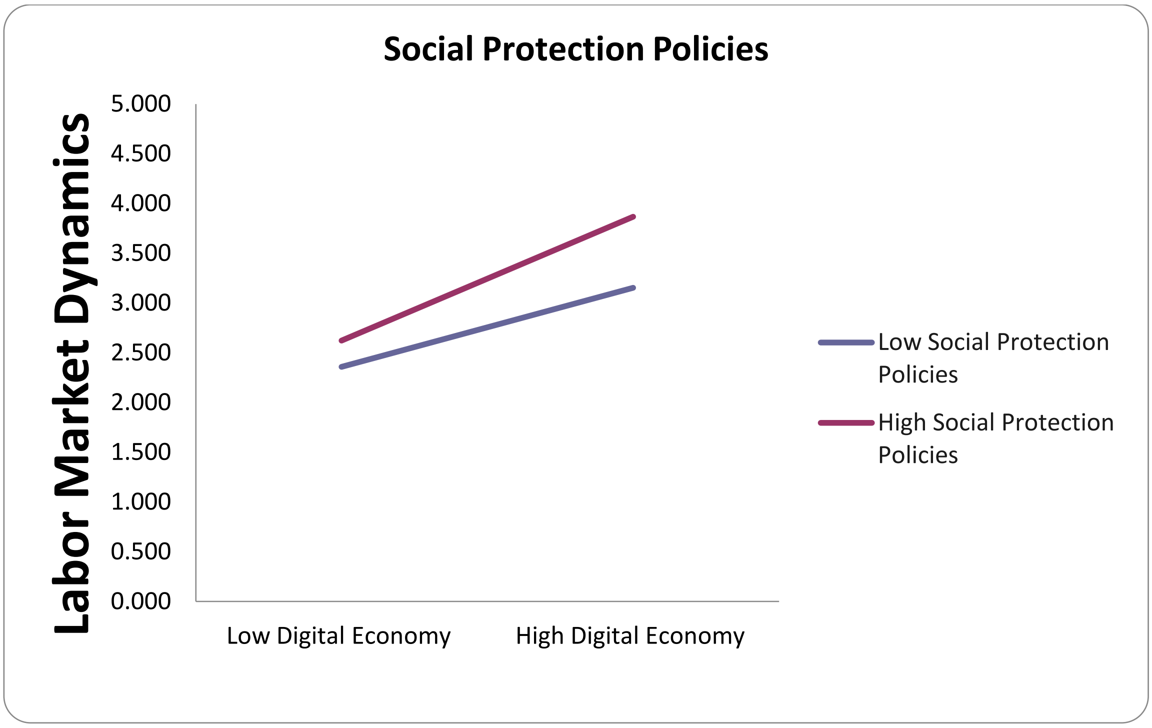
Table 6: Testing the effectiveness of the moderating variable (Social Protection Policies) in reducing the effect of Digital Economy on Labor Market Dynamics

Relationship	Path Coefficient	P Values	Hypothesis
Digital Economy --> **Labor Market Dynamics**	0.510	0.000	Accepted
Social Protection Policies --> **Labor Market Dynamics**	0.245	0.024	Accepted
The Interaction (**DE * SPP**) --> **Labor Market Dynamics**	0.112	0.032	Accepted

Source: Compiled by researchers based on the outputs of Smart PLS4.

Table 6 provides insights into the effectiveness of the moderating variable, Social Protection Policies (SPP), in reducing the effect of the Digital Economy (DE) on Labor Market Dynamics (LMD). The path coefficient for the direct relationship between the Digital Economy and Labor Market Dynamics is 0.510, with a statistically significant p-value of 0.000, indicating a strong positive impact of the digital economy on labor market dynamics, a result consistent with previous findings. Additionally, the path coefficient for the relationship between Social Protection Policies and Labor Market Dynamics is 0.245, with a significant p-value of 0.024, suggesting that social protection policies independently contribute to shaping labor market dynamics. Furthermore, the interaction term (DE * SPP) has a path coefficient of 0.112 and a significant p-value of 0.032, indicating that the interaction between the digital economy and social protection policies further influences labor market dynamics. These results demonstrate that while the digital economy has a significant impact on labor market dynamics, the presence of effective social protection policies moderates this effect, highlighting the importance of comprehensive policy frameworks in mitigating the potential challenges posed by digitalization on labor markets.

Figure 4: Path coefficients of The Interaction (DE * SPP) --> Labor Market Dynamics



Source: Compiled by researchers based on the outputs of Microsoft Excel.

8. Discussion:

8.1. Interpretation of findings

The findings of this study shed light on the intricate relationship between the digital economy, social protection policies, and labor market dynamics in the context of North African states. The results indicate a significant positive impact of the digital economy on labor market dynamics, as evidenced by the strong path coefficient (0.510) and the statistically significant p-value (0.000) in the direct relationship between the Digital Economy (DE) and Labor Market Dynamics (LMD). This suggests that the adoption and advancement of digital technologies contribute to job creation, skill enhancement, and overall economic growth in the region. Moreover, the study reveals that Social Protection Policies (SPP) independently influence labor market dynamics, with a path coefficient of 0.245 and a significant p-value of 0.024. This underscores the importance of effective social protection measures in ensuring labor market stability and safeguarding workers' rights amidst technological transformations. Furthermore, the interaction term (DE * SPP) demonstrates a moderating effect on labor market dynamics, emphasizing the role of social protection policies in mitigating the potential disruptive impacts of digitalization on employment patterns.

8.2. Comparison with prior research :

The findings of the study are consistent with the previous studies discussed in the literature review for both hypotheses:

The findings of this study are consistent with previous research highlighting the positive correlation between the digital economy and job creation. Studies by Shakizada (2023) and Riazantseva & Parshukova (2022) have similarly emphasized the transformative effects of digitalization on labor markets, leading to the creation of new employment opportunities and shifts in skill requirements. Additionally, the findings align with the literature emphasizing the role of social protection policies in shaping labor market outcomes. Virginia (2022) and S. et al. (2022) have discussed the evolving landscape of labor protection laws and the importance of ensuring safe working conditions in the digital era. However, this study contributes novel insights by specifically examining the moderating role of social protection policies in the relationship between the digital economy and labor market dynamics in North African states. The results provide empirical evidence supporting the efficacy of social protection measures in mitigating the potential adverse effects of digitalization on employment, thereby enriching the existing body of literature on this topic.

9. Conclusion:

In summary, this study has provided valuable insights into the relationship between the digital economy, social protection policies, and labor market dynamics in North African states. Key findings indicate a significant positive impact of the digital economy on labor market dynamics, highlighting the role of technology adoption in driving job creation and economic growth. Additionally, effective social protection policies were found to independently influence labor market outcomes and moderate the effects of digitalization on employment patterns.

The importance of the digital economy and social protection policies in shaping labor market dynamics cannot be overstated. The digital economy presents unprecedented opportunities for innovation, productivity enhancement, and job creation. However, it also poses challenges such as job displacement and skills mismatches. In this context, social protection policies play a crucial role in mitigating these challenges by providing safety nets, upskilling opportunities, and support for vulnerable workers. By ensuring inclusive and sustainable growth, social protection policies contribute to fostering a resilient and dynamic labor market that benefits all segments of society.

Moving forward, policymakers, businesses, and other stakeholders must prioritize investments in digital infrastructure, education, and social protection systems to harness the full potential of the digital economy while addressing its associated risks. By fostering an enabling environment that promotes digital innovation and equitable access to opportunities, North African states can achieve more inclusive and resilient labor markets that drive sustainable economic development and improve the well-being of their citizens

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