economies

Article

Investigating the Impact of Digital Transformation on the Labor Market in the Era of Changing Digital Transformation Dynamics in Saudi Arabia

Masahina Sarabdeen * and Hind Alofaysan

Department of Economics, College of Business and Administration, Princess Nourah bint Abdulrahman University, Riyadh 11617, Saudi Arabia
* Correspondence: msarabdeen@pnu.edu.sa

Abstract: In Saudi Arabia, limited studies have developed models related to measuring the impact of the digital economy on the labor market. This model concerns the agricultural, service, and industrial sectors in Saudi Arabia. This study further investigates the relationship between digitalization, labor productivity, and unemployment using the ARDL error correction method for time-series data obtained from the World Bank database for the period of 2001–2019. The findings of this study illustrate, digital variables such as fixed broadband subscriptions (LNFBS), mobile cellular subscriptions (LNMCS), and computer, communications, and other services (LNCCO) do not significantly affect the labor market in the agricultural sector. LNMCS and LNCCO do not influence the service sector. However, they are negatively influencing the industrial sector and labor productivity. In contrast, LNFBS has a positive impact on both the service and industrial sectors. Interestingly, all three digital variables significantly reduce unemployment in the long run in Saudi Arabia. However, in the short run, digitalization does not have a positive impact on the economy. This study hopes to benefit policymakers in considering how to reorganize the socioeconomic infrastructure to balance economic growth through greater technology and the utilization of the country's human resources.

Keywords: digital transformation; labor market; labor productivity; unemployment; Saudi Arabia

Citation: Sarabdeen, Masahina, and Hind Alofaysan. 2023. Investigating the Impact of Digital Transformation on the Labor Market in the Era of Changing Digital Transformation Dynamics in Saudi Arabia. *Economies* 11: 12. https://doi.org/10.3390/economies11010012

Academic Editors: Renata Korsakienė, Laima Jesevičiūtė-Ufartienė and Neringa Vilkaitė-Vaitonė

Received: 9 November 2022
Revised: 20 December 2022
Accepted: 26 December 2022
Published: 4 January 2023

1. Introduction

The phrase "digital economy" refers to how the technological revolution is transforming value chains in revolutionary ways and opening new opportunities for value addition and structural change (Digital Economic Report 2019). Meantime, Bukht and Heeks (2017) define it as "part of economic output derived solely or primarily from electronic technologies with a business model based on digital goods or services". Knickrehm et al. (2016) defined simplicity as the proportion of economic output derived from broad "technological inputs", such as "computer talents, computer equipment (hardware, software, and communications equipment), and intermediary digital goods and services. Such broad endeavors are the foundations of the digital economy.

Digitalization has the potential to support economic growth throughout the world. Moreover, it is expected that greater efficiency in production due to digital transformation would lead to lower costs and increased productivity. This would lead to higher aggregate demand, higher employment, and potentially higher wages, thus making up for the underlying interruption. Since a significant number of firms and associations are adopting advanced digital technologies to reshape plans of action and associations (Ping and Ying 2018), technological innovations require workforces to possess a wide range of expertise, such as self-direction, critical thinking, correspondence skills, and web management.

With the advent of digitalization, certain aspects of the marketplace have undergone massive changes. These changes in demand for skills and employment caused bound employment to disappear. This changed the positions of companies in terms of development, market capitalization, and many more. In the innovative era, the most effective strategies are still in progress or uncertain (Walwei 2016).

An OECD report published in 2016 suggests the long-term effects of digitalization on labor are ambiguous, as mechanical manipulation should be minimal. Meantime, it is believed that digital competence has not resulted in the creation of modern jobs on a large enough scale to replace traditional jobs. An additional 2018 OECD report shows that digitalization and robotization do not constitute a threat to widespread employment in the indefinite future (Nedelkoska and Quintini 2018).

The studies of Kvochko (2013) and Katz and Koutroumpis (2016) investigated the impact of digital transformation on the labor market. The findings show that digital transformation is expected to create 22% of new employment (760,000) by 2020 in the USA alone, and 25,000 innovative jobs annually in Australia. Moreover, the study of Katz and Koutroumpis (2016) revealed that a 1% increase in digitization of the consumption index would lead to a 0.07% reduction in unemployment worldwide between 2004 and 2015. This result is in line with the study of Kunming (2019) which found that every additional score in the Digital China Index has prompted more than 660,000 job opportunities.

The effects of technological innovation on employment were investigated by Su et al. (2022). A correlation was found between patents and jobs created between 2013 and 2021. Employment is positively impacted by technological innovation. Technological innovation may also have a negative impact on employment because it tends to have a greater substitution effect than a creation effect in Chinese society.

The study of Ping and Ying (2018) shows that the devastating impact of digitalization on employment would in general require significant changes in working style, executives, and decision-making processes. As a result, a company's lower costs of production would increase its labor income. Therefore, an increase in income would increase expectations of living, expand labor efficiency, and advance the economic progress of events and collective improvement.

A study by Aly (2020) reviewed the association between the digital revolution and employment among 25 developing countries in 2017. Malaysia, Chile, and China succeeded in converting the digital revolution into more extensive working opportunities. However, Turkey, South Africa, and even Jordan were absent from creating the ideal number of vacancies.

In the meantime, the study of Autor et al. (1998) shows that the demand for computers and skilled laborers is high, which leads to polarization in the USA. The studies of Acemoglu and Autor (2011); Goos et al. (2014); Michaels et al. (2014); and Ju (2014) found that as technology advances, the demand for "middle-skilled" labor declines while high and "low-skilled" labors continue to grow. Moreover, Sachs and Kotlikoff (2019) propose that insolent innovations accompany untalented work by youth, resulting in lesser earnings for incompetent youth and impeded efforts to obtain skills. However, digitalization and the demand for skilled labor have a positive impact, as digitalization and the exchange have not yet prompted polarization of the work market among lower–middle-income countries (Ugur and Mitra 2017). Meanwhile, the study of Banga and Velde (2018) shows that digitalization does not affect the labor market in 12 African countries. At the same time, the study of Arntz et al. (2016) found that pioneering digital innovations have a minimal impact on absolute business rates yet lead to enormous developments in labor among occupations and enterprises.

Despite this, the industrial revolution did not have the same impact on employment across different sectors. A recent study by Chinoracký et al. (2019) examined OECD countries' employment in agricultural, services, and industrial sectors and the probability of job automation. Sector-specific job automation risks were identified in the results. The agricultural and industrial sectors are more susceptible to job automation than the service sector. Therefore, countries that have a highly tensive labor force in agriculture and industry will experience high risk from job automation.

The literature is clear in showing that digitalization of the economy helps to boost economic development by taking the skilled labor force while victimizing the low and middle-skilled laborers. Several studies have been conducted in developed countries. The impacts are different from country to country. However, there is still a lack of literature in developing countries, specifically in the Middle East. There is no evidence to show how digital transformation impacts job creation in Saudi Arabia. It is still debatable and not predictable.

Saudi Arabia has prioritized the development of the digital economy, as it contributes significantly to achieving one of the primary goals of "Vision 2030", which is to create jobs. The government is especially optimistic regarding decreasing the young unemployment rate and expanding the participation of women in the workforce (SABR 2021).

On the other hand, it is noted that Saudi Arabia faces significant challenges in moving towards a digital transformation or knowledge-based economy. First, there is a mismatch in skills between jobs. Second, the unemployment rate among Saudis is 12.3%, and youth unemployment and female unemployment were 25.55% and 42%, respectively, in 2019 (SAMA 2020). The high unemployment rate among Saudi youth remains a component of the Saudi economy.

Considering the above challenges existing in the Saudi Arabian labor market, there is a need to do in-depth research on to what extent digital transformation dynamics affect the labor market by sectors in Saudi Arabia. Therefore, this research intends to develop a model for investigating the impact of digital transformation on the labor market by sector in Saudi Arabia. It will contribute to filling the knowledge gap.

To realize the objectives of this study, secondary data from the World Bank database and digital reports has been utilized. Eviews were used as a research tool for data analysis. It is useful to study the short- and long-term effects of digital transformation on the Saudi labor market using the ARDL error correction method. It is expected that the findings of this study will contribute to the empirical findings on the impact of digital transformation on the labor market and will help monitor emerging labor market trends in Saudi Arabia. Moreover, this study hopes to benefit policymakers in considering how to reorganize the socioeconomic infrastructure. This is to balance economic growth through greater technology and the utilization of the country's human resources.

Having said that, this paper is structured as follows: A detailed introduction including the impact of digital transformation on the labor market is discussed in Section 1 followed by the methodology in Section 2. Section 2 provides details of data and model specification and technical details on the statistical methods of the study. In Section 3, empirical findings and discussions are presented while Sections 4 and 5 consist of the conclusion and the policy implications followed by limitations and future research directions.

2. Methodology

Eviews software was used to measure the impact of the digital economy on the labor market. This was done using secondary time-series data collected from the World Bank from 2001 to 2019. ARDL error correction method was used, as it is useful to study the short- and long-term effects of digital transformation on the Saudi labor market. Moreover, the ARDL approach can easily be expanded to include multiple data and can accept general lag patterns (Econometric Approach Report 2010). Therefore, ARDL approach was utilized in this study.

This section is divided into two portions. First portion discusses the data and the variables used in the model specification. Meanwhile, the second portion explains the technical details of the statistical methods employed in the study.

2.1. Data and Model Specification

As a measure of digital expansion in a country, variables such as 'mobile cellular subscriptions' and 'fixed broadband subscriptions' were selected from the literature (Duasa and Ramadan 2019). Enrollment in tertiary education reflects human capital capability (absorption of digital transformation), which is the root of succeeding technical inventions (Jafari-Sadeghi et al. 2021). Gross domestic product per person represents the labor productivity of an economy. It hopes to investigate how ICT empowers an economy by combining labor and capital inputs more efficiently, enhancing total factor productivity (Aly 2020; Duasa and Ramadan 2019). Unemployment is an independent indicator of the impact of the digital revolution on vulnerable employment in the country. The variable 'computer, communications, and other services' (LNCCO) was chosen to examine the relationship between diversification in trade and digitalization (Matthess and Kunkel 2020). As expected in the literature, the creation of intermediate input and services trade, notably modern services trade, are positively connected to digitalization. We also treated LNCCO as one of the digital development variables in this study (Matthess and Kunkel 2020; WTO 2017, 2019).

Five models were used to achieve the objectives of this study. The first three models examine the relationship between digital transformation and employment rate in the agricultural, service, and industrial sectors, respectively. The fourth model refers to the link between digital transformation and labor productivity. The last equation intends to investigate the association between the technological revolution and unemployment in Saudi Arabia. Table 1 shows the variables and the data used in the research models.

Table 1. Variables and data used in the research models specifications.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	
Dependent variables	LF-AGR	LF-SEV	LF-IND	TLF	UEM	
Variable description	Labor force participation rate in agriculture	Labor force participation rate in the service sector	Labor force participation rate in industries	Total labor force	Unemployment	
Independent variables	LNGDPP	LNCCO	LNSE	LNFBS	LNMCS	TLF
Variable description	Gross domestic product per person employed	Computer, communications, and other services (% of commercial service imports)	Enrollment in tertiary education (numbers)	Fixed broadband subscriptions (per 100 people)"	Mobile cellular subscriptions (per 100 people)"	Total labor force (numbers)

Source of data: World Bank Database.

2.2. Technical Details on the Statistical Methods

The following technical processes were taken for the data analysis in this study.

2.2.1. Unit Root Test

As a first stage in the analysis, a unit root test was performed with "Augmented Dickey-Fuller (ADF)", "DF-GLS", and "Phillips Perron (PP)" through "Akaike Information Criterion (AIC)" with constants to assure the order of integration of each variable.

2.2.2. Lag Length Criterion

The second step was to check the appropriate lag order. The appropriate lag order is one of the criteria for the ARDL method, and appropriate lag selection would help to eliminate the serial correlation of the error correction terms.

2.2.3. Bound Test

When the model meets all the criteria for an optimal fit, the bound test was performed to confirm the long-run relationship among the variables. ARDL, the most suitable model, was selected using "least Akaike Information Criteria", which has leased residual. From 2001–2019, cointegration tests were conducted on a long-run basis according to the following hypothesis.

H0: *There is no cointegration among the variables.*

H1: *There is cointegration among the variables.*

2.2.4. Long-Run and Short-Run Relationship

Long-run and short-run parameters were gained using the error correction model as stated in base model where λ is the speed of adjustment parameter with a negative sign, ECT is the error correction term, and X is the variable in the regression.

$$\Delta Y_t = \alpha_{0i} + \sum_{i=1}^{P} \gamma i Y_{t-i} + \sum_{i=0}^{q} \alpha_1 X_{t-i} + \lambda ECT_{t-1} + U_t \text{ (Base Model)}$$

2.2.5. Pairwise Granger Causality Test

This study used pairwise Granger causality tests to investigate the short-run relationship between the variables.

2.2.6. Diagnostic Test

Moreover, the adequacy of the models was verified using numerous diagnostic tests, such as Breusch–Godfrey Serial Correlation LM test, Ramsey RESET test, normality test, and CUSUM of squares.

3. Findings and Discussions

In the analysis of unit root test, we used mixed order variables and found that they remained stationary at the level and first difference between I(0) and I(1) at 1%, 5%, and 10% (Refer Appendix A). So, this study enables the use of ARDL-bound test models.

We used LR, FPE, AIC, SC, and HQ criteria to select the optimal lag length, as shown in Table 2. It shows that the maximum appropriate lag length is 1.

Table 2. Lag Length Criterion.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	178.82	NA	9.05×10^{-16}	−20.44	−20.20	−20.42
1	221.63	55.40 *	1.30×10^{-16} *	−22.54 *	−21.07 *	−22.39 *
2	294.81	51.65	1.32×10^{-18}	−28.21	−25.51	−27.94

* "Indicates lag order selected by the criterion. LR: sequentially modified LR test statistic; FPE: final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan–Quinn information criterion".

From 2001–2019, cointegration tests were conducted. There is a cointegration relationship between variables in five models in the long run as the F-statistic is greater than the critical value of the lower and upper bounds of I(0) and I(1), as stated by Pesaran et al. (2001) (Refer to Appendix B Bound test).

The further analysis illustrates how the selected variables affect the long run and short run in the following sections.

3.1. Long-Run Relationship

Long-run and short-run parameters were gained using the error correction model as presented in Tables 3 and 4, respectively. Table 3 denotes how the selected variables affect them in the long run (refer to the models in Appendix C). In Model 1, LNGDPP significantly affects the labor market in the agricultural sector. Other factors do not influence LNLF-AGR. In Model 2, LNGDPP, LNMCS, and LNSE have a negative relationship while LNFBS has a positive relationship with LNLF_SER in the long run. LNGDPP has significance at a 10% level. This implies that LNLF_SER decreases by 0.654 percent for every 1 percent increase in LNGDPP. Moreover, a 1% increase in "education level" and "mobile cellular subscriptions" would reduce the demand for the labor force in the service sector by 0.0024% and 0.008%, correspondingly. At the same time, LNLF-SER increases by 0.03 percent for every 1 percent increase in LNFBS at a 5% significance level. Nevertheless, LNSE has a negative relationship with LNLF-SER, which is not in line with this theory. However, in Model 3 LNSE has a positive impact on LNLF-IND. An increase in LNSE by 1 percent would increase LNLF-IND by 0.26%. Therefore, we could mention that since the existing educational system is suitable for adopting digital transformation in the industrial sector rather than the service or agricultural sectors, all levels of educational institutions should ensure that their courses meet the labor market demand in the era of digital transformation.

Moreover, independent digital development variable LNCCO significantly increases the LNLF-IND by 0.03%. Meantime LNFBS has a negative impact on LNLF-IND in Model 3, which is in contrast with the finding of Duasa and Ramadan (2019).

Table 3. Estimates of Long Run Relationship.

Dependent Variables	**LNLF-AGR**	**LNLF-SEV**	**LNLF-IND**	**LNTLF**	**LNUEM**
Independent Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
LNGDPP (Coefficient) (Prob)	23.529 0.0960 ***	−0.6540 0.0661 ***	−0.4086 0.1310	−0.4337 0.2110	0.6177 (0.4007)
LNCCO (Coefficient) (Prob)	−0.3273 (0.5051)	−0.0018 0.8882	0.0439 0.0895 ***	−0.0089 0.0481 **	−0.0916 (0.4811)
LNSE (Coefficient) (Prob)	2.0683 (0.1393)	−0.1574 0.0024 *	0.2575 0.0003 *	0.0899 0.5657	−0.2326 (0.4434)
LNFBS(Coefficient) (Prob)	−0.2063 (0.4148)	0.0177 0.0341 **	−0.0284 0.0245 **	0.0122 0.0238 **	−0.0804 0.0115 **
LNMCS(Coefficient) (Prob)	0.2527 (0.1121)	−0.0083 0.0464 **	−0.0041 0.4797	−0.0173 0.0134 **	−0.0316 0.0467 **
C(Coefficient) (Prob)	−303.78 (0.0968) ***	14.188 0.0087 *	4.2471 0.2388	17.596 0.0004 *	−1.7999 0.4521

Note: Significant at * 1%, ** 5%, and *** 10%.

In Model 4, digital development variables LNCCO and LNMCS negatively influence GDPP at the 5% significant level while LNFBS is positively significant at the 5% level. In Model 5, the digital variables LNFBS and LNMCS influence unemployment. The unemployment rate decreased by 0.09%, 0.08%, and 0.032% for every 1 percent increase in LNCCO, LNFBS, and LNMCS, respectively. This finding shows evidence of the importance of digital transformation to reduce unemployment rates and increase productivity. Some economic sectors have benefited more from digitalization than others. Therefore, this study recommends empowering digitalization and enhancing ICT readiness in all sectors to boost economic diversification, job creation, and economic development. In particular, the agricultural sector should conduct a thorough study to identify the challenges and opportunities of using digital technology in KSA to meet the food demands of its citizens.

In Saudi Arabia, the adoption of digitization can act as a catalyst for long-term growth in the postoil sector and serve as a crucial pillar for welfare, transparency, and enhancing citizens' access to public services. Saudi Arabia should establish a sound economic foundation, acknowledge the importance of education in this era, and increase its investments in human capital to help young people develop their abilities. This could help increase the employment and production of the country.

3.2. Short-Run Estimates of the ARDL Approach

The result of the error correction model and short-run relationship is discussed in Table 4. In Model 1, the estimated results show that the sign of the error correction term (ECM_{t-1}) is negative and statistically significant. ECT_{t-1} is −2.2534, which indicates that adjustments are corrected by 225.34% from the short run to the long run of the period over every year.

Table 4. Estimates of Short Run Relationship.

Model 1	**Dependent Variable: D(LNLF_AGR)**	
Independent Variables	**Lag Order**	
	0	1
D(LNLF_AGR)		1.5497 ** (0.0290)
D(LNGDPP)	3.2025 (0.101)	5.8509 ** (0.0472)
D(LNCCO)	0.3174 ** (0.0414)	−0.6643 ** (0.025)
D(LNSE)	−0.5355 (0.5330)	
D(LNFBS)	−1.2798 ** (0.0282)	1.0922 ** (0.0194)
D(LNMCS)	0.0226 (0.4389)	0.0487 (0.1275)
ECT(−1)	−2.2534 ** (0.0435)	
Model 2	Dependent variable: D(LNLF_SER)	
D(LNLF_SER)		−0.5598 (0.2525)
D(LNGDPP)	0.0519 (0.7319)	0.0054 (0.9806)
D(LNCCO)	−0.0030 (0.7552)	−0.0153 (0.3971)
D(LNSE)	−0.2086 ** (0.0401)	
D(LNFBS)	−0.0184 (0.5641)	0.0231 (0.4296)
D(LNMCS)	−0.0027 (0.4056)	
ECT(−1)	−0.048464 ** (0.02786)	
Model 3	Dependent variable: D(LNLF_IND)	
D(LNLF_IND)		−0.3377 (0.8712)
D(LNGDPP)	−0.4514 (0.4439)	−0.2545 (0.7372)
D(LNCCO)	0.0019 (0.9528)	0.0571 (0.3156)
D(LNSE)	0.3326 (0.1661)	
D(LNFBS)	0.0670 (0.5189)	−0.1109 (0.2506)
D(LNMCS)	−0.0044 (0.6763)	0.0009 (0.9218)
ECT(−1)	0.040149(0.7795)	
Model 4	Dependent variable: D(LNGDPP)	
D(LNGDPP)		−0.0632 (0.8297)
D(LNTLF)	0.7393 (0.5203)	−1.9361 (0.1318)
D(LNCCO)	−0.0106 (0.5554)	
D(LNSE)	−0.0741 (0.7949)	0.4396 (0.1143)
D(LNFBS)	0.0185 (0.5867)	−0.0039 (0.8695)
D(LNMCS)	−0.0120 ** (0.0500)	
ECT(−1)	−0.1103 *** (0.0774)	
Model 5	Dependent variable: D(LNUNE)	
D(LNUNE)		−0.0996 (0.7796)
D(LNTLF)	−0.0371 (0.9876)	−0.3989 (0.8091)
D(LNCCO)	−0.0129 (0.7050)	−0.0738 *** (0.0595)
D(LNSE)	0.0709 (0.09012)	
D(LNFBS)	−0.1028 (0.1227)	
D(LNMCS)	−0.0097 (0.4576)	−0.0129 (0.3409)
D(LNGDPP)	−0.4364 (0.6400)	−0.2104 (0.7964)
ECT(−1)	−0.4813 *** (0.0978)	

Note: Significant at ** 5%, and *** 10%.

The greater the error term activists, the faster the economies correct to the stable growth rate. Moreover, in Models 2, 3, 4, and 5, the lagged error correction is negative and statistically significant. However, the coefficient of $ECM_{t\text{-}1}$ representing the slow adjustments toward equilibrium is corrected by 5%, 4%, 11%, and 4.8% in Models 2, 3, 4, and 5, respectively.

Most of the digital transformation variables have shown negative implications in the short run. In Model 1, LNGDPP and LNFBS have positive and LNCCO has a negative relationship with LNLF_AGR at order 1. However, LNCCO shows a positive relationship at lag order 0. In Model 2, only LNSE has a negative impact on LNLF_SER. In Models 2, 3, 4, and 5, the digital development variables LNCCO, LNFMS, and LNMCS are insignificant in the short run. These results are consistent with the study of Duasa and Ramadan (2019).

However, in Model 4, LNMCS has a negative implication on LNGDPP. Meanwhile, in Model 5, LNCCO has a negative implication on LNUNE in the short run. These outcomes could be attributed to the country's digital divide. The digital gap is a significant difficulty for economies in the digital revolution period due to significant variations in the development and quality of life between and within countries.

The results of the pairwise Granger causality tests show that unidirectional causality takes place among the variables. In Models 1 and 3, there is no causal relationship between the variables. In Model 2, LNLF_SER has a relationship with LNSE but the LNSE has no Granger cause with LNLF_SER. Thus, we can conclude that there is a unidirectional relationship between these variables. In Model 4, LNGDPP has a relationship with LNCCO, LNFBS, and LNMCS, but LNCCO, LNFBS, and LNMCS have no Granger cause with LNGDPP. This shows that there is a unidirectional relationship between these variables. In Model 5, LNFBS has a relationship with LNUNE. However, LNUNE has no Granger cause with LNFBS. LNUNE has a relationship with LNMCS and LNGDPP. However, the LNMCS and LNGDPP have no Granger cause with LNUNE. Therefore, there is a unidirectional relationship between these variables (refer to Appendix D).

Moreover, the results of the diagnostic tests indicate the stability of the specified models of the study, as shown in Table 5.

Table 5. Estimates of Diagnostic tests.

Models	Ramsey Reset Test	Normality Test	Serial Correlation LM Test
		F Statistic (Prob)	
Model 1	0.605	0.551	0.552
Model 2	0.657	0.516	0.053
Model 3	0.917	0.653	0.821
Model 4	0.330	0.884	0.268
Model 5	0.917	0.871	0.932

4. Conclusions

For a country's economic growth and flexibility, technological capabilities are essential. As a result, a country's economy must comprehend its current state as well as the trajectory of its technological development and its economic influence. The purpose of this study was to examine the impact of digital transformation on the labor market in a variety of sectors. In the short-term, digital transformation in the labor market has negative effects probably because of the nation's digital divide, which affects network availability and connectivity. However, in the long run, digital transformation in the labor market is profound in Saudi Arabia. The main findings of this study are:

- LNGDPP significantly affects the labor market in the agricultural sector. However, the digital variables do not significantly affect the labor market in the agricultural sector.
- An increase in labor productivity (LNGDPP) by 1% would decrease the demand for labor by 0.65%. Meanwhile, an increase in digital development, LNFBS, by 1% would increase the demand for labor by 0.03% in the service sector.

- An increase in digital development variables such as LNCCO and LNMCS has a negative impact on the demand for labor in the industrial sector while LNFBS and human capital have a positive impact.
- The unemployment rate is decreased by 0.09%, 0.08%, and 0.032% for every 1 percent increase in LNCCO, LNFBS, and LNMCS, respectively. Therefore, it is evident that digital variables LNCCO, LNFBS, and LNMCS are influencing the unemployment rate in Saudi Arabia.

5. Policy Implications

Saudi Arabia ranked second among the G20 countries in technological competitiveness, up 20 places from the previous year according to the Digital Riser Report (Digital Riser Report 2021). This advancement reflects the ambition and progress of Saudi Arabia's strategy in developing the country's telecommunications infrastructures. Since 2016, when Saudi Vision 2030 was initiated, several digital programs have been administered in collaboration between the government and service providers to improve telecommunications infrastructure, both fixed and mobile, and to optimize fixed and mobile broadband network performance to reduce the digital divide between densely populated and rural areas.

In 2017, Saudi Arabia's Ministry of Communications and Information Technology made an agreement with IBM to teach and qualify more than 38,000 people in information and communication technology (ICT) programs over the next four years through 30 new educational institutions. Around 19,000 trainees were projected to receive certification in the profession by 2020. The ministry's fundamental concerns, particularly "the shortage of specialized human capital" and "low user skills in the communication and information technology industry," was addressed through a deal with IBM. Through the ministry, "the Kingdom launched five upcoming programs involving the training, qualification, and recruiting of ICT experts" (Saudi Arabia: Political, Economic & Social Development Report 2017).

Furthermore, in 2021, the Saudi government established the Digital Government Authority to regulate the work of digital government in its agencies and to develop a technologically advanced and proactive government capable of providing highly efficient electronic services, such as e-education, e-government, and e-commerce to consumers, enterprises, and society. The government aims at accelerating digital transformation by adopting and implementing telecommunication systems and ICT technology. This would provide access to the internet for all regardless of their economic status.

The more extensive the use of ICT and other computerized apparatuses, the more enlightening and effective the residents will be. The Saudi Master Plan 2030 should achieve its goal by cooperating with the International Telecommunication Union (ITU), portable administrators, banks, retailers, and other specialist organizations.

This joint effort will improve worldwide interoperability and drive economies of scale to increase opposition and interest in ICT ventures in the area. A strong administrative strategy is also necessary to stimulate competition in the ICT markets of the locale. A government could direct the market to ensure that the positive ramifications of digital change on the way of life are acknowledged in the short and long term.

This research concludes with a call for active state intervention in promoting R&D, investing in infrastructure and education, and introducing regulatory practices that ensure that technology-induced organizational arrangements generate decent jobs while remaining mindful of possible government overreach with new technologies. Saudi Arabia, the use of digitization can constitute a catalyst for sustainable development in the post oil area and become a key pillar of transparency, welfare, and improving citizens' access to public services. To accomplish digital transformation, Saudi Arabia must base the economy on the recognition that education plays a key role in this phase, and the Saudi government should make greater investments in human capital to enhance skills among youth.

6. Limitation and Future Research Directions

Based on the results of this study, there are several directions for further investigation. To begin with, rather than investigating the impact of technological transformation within different sectors of the country, this study focused on the impact of technological transformation on the labor market at the sector level. The impact of technological transformation on the labor market varies by sector. Therefore, this impact can be the focus of upcoming research, which would be fantastic to investigate within the sector. The next study can investigate the impact of technological transformation among households. Finally, future studies can be carried out using primary data rather using limited secondary data within sectors to investigate the microlevel effect. All of these upcoming and current research endeavors can be improved by taking into account the capacity for alternative technological transformation of different businesses.

Author Contributions: Conceptualization, M.S. and H.A.; methodology, M.S.; software, M.S.; validation, M.S., H.A.; formal analysis, M.S.; investigation, H.A.; resources, H.A.; data curation, M.S.; writing—original draft preparation, M.S.; writing—review and editing, H.A.; visualization, M.S.; supervision, H.A.; project administration, M.S. and H.A.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Unit root test.

Variables	*p*-Value: ADF Test (Intercept Only)		*p*-Value: PP Test (Intercept Only)	
	Level	**1st Diff**	**Level**	**1st Diff**
LNGDPP	0.8156	0.0114 **	0.8786	0.0007 *
LNCCO	0.0000	0.0103 **	0.0832	0.0008 *
LNSE	0.4110	0.1000 ***	0.6599	0.0800 ***
LNUNE	0.0928	0.0414 **	0.0207	0.0037 *
LNFBS	0.0601	0.0655 ***	0.0852	0.0008 *
LNTLF	0.8330	0.1000 ***	0.6065	0.0120 **
LNMCS	0.0000	0.0064 *	0.0002	0.0064 *
LNLF_IND	0.9198	0.0093 *	0.9187	0.0093 *
LNLF_ AGR	0.1332	0.0516 ***	0.5576	0.1000 ***
LNLF_SER	0.7473	0.0289 **	0.6557	0.0289 **

Note: Significant at * 1%, ** 5%, and *** 10%.

Appendix B

Table A2. Bound test.

		Model 1		
Test Statistic	**Value**	**Sign**	**I(0)**	**I(1)**
F-statistic	3.840882	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
		Model 2		
F-statistic	4.027924	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
		Model 3		
F-statistic	3.773361	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
		Model 4		
F-statistic	8.177814	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
		Model 5		
F-statistic	4.854579	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

Appendix C

Model specification:
Model (1)

$$\begin{aligned}\Delta logLFAGR_t = \quad & \alpha_0 + \sum_{i=1}^{P} \gamma i \Delta logLFAGR_{t-i} \\ & + \sum_{i=0}^{q} \alpha_1 \Delta logGDPP_{t-1} + \sum_{i=0}^{q} \alpha_2 \Delta logCCO_{t-i} \\ & + \sum_{i=0}^{q} \alpha_3 \Delta logSE_{t-i} + \sum_{i=0}^{q} \alpha_4 \Delta logFBS_{t-i} + \sum_{i=0}^{q} \alpha_5 \Delta logMCS_{t-i} \\ & + \beta_1\ logLFAGR_{t-1} + \beta_2\ logGDPP_{t-1} + \beta_3\ \ logCCO_{t-1} \\ & + \beta_4\ logSE_{t-1} + \beta_5\ logFBS_{t-1} + \beta_6\ logMCS_{t-1} + U_t\end{aligned}$$

Model (2)

$$
\begin{aligned}
\Delta logLFSER_t = \; & \alpha_0 + \sum_{i=1}^{P} \gamma i \Delta logLFSER_{t-i} \\
& + \sum_{i=0}^{q} \alpha_1 \Delta logGDPP_{t-1} + \sum_{i=0}^{q} \alpha_2 \Delta logCCO_{t-i} + \sum_{i=0}^{q} \alpha_3 \Delta logSE_{t-i} + \sum_{i=0}^{q} \alpha_4 \Delta logFBS_{t-i} \\
& + \sum_{i=0}^{q} \alpha_5 \Delta logMCS_{t-i} + \beta_1 \, logLFIND_{t-1} + \beta_2 \, logGDPP_{t-1} + \beta_3 \; logCCO_{t-1} + \beta_4 \, logSE_{t-1} \\
& + \beta_5 \, logFBS_{t-1} + \beta_6 \, logMCS_{t-1} + U_t
\end{aligned}
$$

Model (3)

$$
\begin{aligned}
\Delta logLFIND_t = \; & \alpha_0 + \sum_{i=1}^{P} \gamma i \Delta logLFIND_{t-i} \\
& + \sum_{i=0}^{q} \alpha_1 \Delta logGDPP_{t-1} + \sum_{i=0}^{q} \alpha_2 \Delta logCCO_{t-i} + \sum_{i=0}^{q} \alpha_3 \Delta logSE_{t-i} + \sum_{i=0}^{q} \alpha_4 \Delta logFBS_{t-i} \\
& + \sum_{i=0}^{q} \alpha_5 \Delta logMCS_{t-i} + \beta_1 \, logLFIND_{t-1} + \beta_2 \, logGDPP_{t-1} + \beta_3 \; logCCO_{t-1} + \beta_4 \, logSE_{t-1} \\
& + \beta_5 \, logFBS_{t-1} + \beta_6 \, logMCS_{t-1} + U_t
\end{aligned}
$$

Model (4)

$$
\begin{aligned}
\Delta logGDPP_t = \; & \alpha_0 + \sum_{i=1}^{P} \gamma i \Delta logGDPP_{t-i} \\
& + \sum_{i=0}^{q} \alpha_1 \Delta logTLF_{t-1} + \sum_{i=0}^{q} \alpha_2 \Delta logCCO_{t-i} + \sum_{i=0}^{q} \alpha_3 \Delta logSE_{t-i} \\
& + \sum_{i=0}^{q} \alpha_4 \Delta logFBS_{t-i} + \sum_{i=0}^{q} \alpha_5 \Delta logMCS_{t-i} + \beta_1 \, logGDPP_{t-1} \\
& + \beta_2 \, logTLF_{t-1} + \beta_3 \; logCCO_{t-1} + \beta_4 \, logSE_{t-1} \\
& + \beta_5 \, logFBS_{t-1} + \beta_6 \, logMCS_{t-1} + U_t
\end{aligned}
$$

Model (5)

$$
\begin{aligned}
\Delta logUNE_t = \; & \alpha_0 + \sum_{i=1}^{P} \gamma i \Delta logUNE_{t-i} \\
& + \sum_{i=0}^{q} \alpha_1 \Delta logGDPP_{t-1} + \sum_{i=0}^{q} \alpha_2 \Delta logCCO_{t-i} \\
& + \sum_{i=0}^{q} \alpha_3 \Delta logSE_{t-i} + \sum_{i=0}^{q} \alpha_4 \Delta logFBS_{t-i} + \sum_{i=0}^{q} \alpha_5 \Delta logMCS_{t-i} \\
& + \sum_{i=0}^{q} \alpha_6 \Delta logTLF_{t-i} + \beta_1 \, logUNE_{t-1} + \beta_2 \, logGDPP_{t-1} \\
& + \beta_3 \; logCCO_{t-1} + \beta_4 \, logSE_{t-1} + \beta_5 \, logFBS_{t-1} \\
& + \beta_6 \, logMCS_{t-1} + \beta_7 \, logTLF_{t-1} + U_t
\end{aligned}
$$

Appendix D

Table A3. Pairwise Granger Causality Test.

Null Hypothesis	Probability Value
Model 2	
D(LNLF_SER) does not Granger cause D(LNSE)	0.0640 **
Model 4	
D(LNGDPP) does not Granger cause D(LNCCO)	0.0236 **
D(LNGDPP) does not Granger cause D(LNFBS)	0.0204 **

Table A3. *Cont.*

Null Hypothesis	Probability Value
D(LNMCS) does not Granger cause D(LNGDPP) D(LNGDPP) does not Granger cause D(LNMCS)	0.0946 * 0.0952 *
Model 5	
D(LNFBS) does not Granger cause D(LNUNE)	0.0557 *
D(LNUNE) does not Granger cause D(LNMCS)	0.0353 **
D(LNUNE) does not Granger cause D(LNGDPP)	0.0120 **

Note: Significant at * 1% and ** 5%.

References

Acemoglu, Daron, and David Autor. 2011. Skills, tasks, and technologies: Implications for employment and earnings. In *Handbook of Labor Economics*. Amsterdam: Elsevier, vol. 4, pp. 1043–171.

Aly, Heidi. 2020. Digital transformation development and productivity in developing countries: Is artificial intelligence a curse or a blessing? *Review of Economics and Political Science*. Available online: https://www.emerald.com/insight/2631-3561.htm (accessed on 20 December 2022). [CrossRef]

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. 2016. The risk of automation for jobs in OECD countries: A comparative analysis. In *OECD Social, Employment and Migration Working Papers*. No. 189. Paris: OECD.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. Computing inequality: Have computers changed the labor market? *The Quarterly Journal of Economics* 113: 1169–213. [CrossRef]

Banga, Karishma, and Dirk Willem Velde. 2018. Digitalization and the Future of African Manufacturing, SET Supporting Economic Transformation. Available online: https://setodi2020.wpenginepowered.com/wp-content/uploads/2018/03/SET_Future-of-manufacturing_Brief_Final.pdf (accessed on 20 December 2022).

Bukht, Rumana, and Richard Heeks. 2017. *Defining, Conceptualizing and Measuring the Digital Economy*. GDI Development, Informatics Working Papers, no. 68. Manchester: University of Manchester.

Chinoracký, Roman, Stanislava Turská, and Lucia Madleňáková. 2019. Does Industry 4.0 have the same impact on employment in the sectors? *Management (18544223)* 14: 5–17.

Digital Economic Report. 2019. New York: United Nations Publications.

Digital Riser Report. 2021. European Center for Digital Competitiveness, ESCP Business School. Available online: https://digital-competitiveness.eu/wp-content/uploads/Digital_Riser_Report-2021.pdf (accessed on 20 December 2022).

Duasa, Jarita, and Aisha Elalim Ramadan. 2019. Digital development and economic growth in selected Asian countries: Applying response surfaces for critical bounds of co-integration test. *Journal of Southeast Asian Studies* 24: 1–18. [CrossRef]

Econometric Approach Report. 2010. *How Has the Preferred Econometric Modal Been Derived?* Oxera: Department for Transport, Transport Scotland, and the Passenger Demand Forecasting Council.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. Explaining job polarization: Routine baised technological change and offshoring. *American Economic Review* 104: 2509–26. [CrossRef]

Jafari-Sadeghi, Vahid, A. García-Pérez, E. Candelo, and Jerome Couturier. 2021. Exploring the impact of digital transformation on technology entrepreneurship and technological market expansion: The role of technology readiness, exploration, and exploitation. *Journal of Business Research* 124: 100–11. [CrossRef]

Ju, Jaeuk. 2014. The effects of technological change on employment: The role of ICT. *Korea and the World Economy* 15: 289–307.

Katz, Raul L., and Pantelis Koutroumpis. 2016. *Assessment of the Economic Impact of Telecommunications in Senegal (2003–2014)*. Columbia Institute for Tele-Information Working Paper. New York: Columbia Institute for Tele-Information.

Knickrehm, Mark, Bruno Berthon, and Paul Daugherty. 2016. *Digital Disruption: The Growth Multiplier*. Dublin: Accenture.

Kunming, He Wei In. 2019. Digital Industry Plays a Bigger Role in Economic Growth. China Daily. Available online: http://www.chinadaily.com.cn/a/201905/23/WS5ce5f791a3104842260bd477.html (accessed on 20 December 2022).

Kvochko, Elena. 2013. Five Ways Technology Can Help the Economy. World Economic Forum. Available online: https://www.weforum.org/agenda/2013/04/five-ways-technology-can-help-the-economy/ (accessed on 20 December 2022).

Matthess, Marcel, and Stefanie Kunkel. 2020. Structural change and digitalization in developing countries: Conceptually linking the transformations. *Technology in Society* 63: 101428. [CrossRef]

Michaels, Guy, Ashwini Natraj, and John Van Reene. 2014. Has ICT polarized skill demand? Evidence from eleven countries over twenty five years. *The Review of Economics and Statistics* 96: 60–77. [CrossRef]

Nedelkoska, Ljubica, and Glenda Quintini. 2018. *Automation, Skills Use and Training, OECD Social, Employment and Migration Working Papers, No. 202*. Paris: OECD Publishing. [CrossRef]

Pesaran, M. Hashem, Yongcheol Shin, and Richard J. Smith. 2001. Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics* 16: 289–326. [CrossRef]

Ping, He, and Gao Yao Ying. 2018. Comprehensive view on the effect of artificial intelligence on employment. *Topics in Education, Culture and Social Development (TECSD)* 1: 32–35.

SABR. 2021. Saudi Arabia Budget report. A review of the Saudi Arabia 2021 Budget in the Context of Recent Economic Developments. KSA. Available online: https://home.kpmg/sa/en/home/insights/2020/12/saudi-arabia-2021-budget-report.html (accessed on 20 December 2022).

Sachs, Jeffrey D., and Laurence J. Kotlikoff. 2019. Smart machine and long-term misery 0898-2937, national bureau of economic. *Journal of Economic Literature* 57: 3–43.

SAMA. 2020. Saudi Central Bank, Saudi Arabia Economic Report. Available online: https://www.sama.gov.sa/en-us/economicreports/pages/yearlystatistics.aspx (accessed on 20 December 2022).

Saudi Arabia: Political, Economic & Social Development Report. 2017. Ministry of Foreign Affairs. Available online: https://www.saudiembassy.net/sites/default/files/WhitePaper_Development_May2017.pdf (accessed on 20 December 2022).

Su, Chi-Wei, Yuan Xi, Umar Muhammad, and Lobont Oana-Ramona. 2022. Does technological innovation bring destruction or creation to the labor market? *Technology in Society* 68: 101905. [CrossRef]

Ugur, Mehmet, and Arup Mitra. 2017. Technology adaptation and employment in less developed countries: A mixed-method systematic review. *World Development* 9: 1–18. [CrossRef]

Walwei, Ulrich. 2016. *Digitalization and Structural Labor Market Problems: The Case of Germany*. ILO Research Paper No 17. Geneva: International Labour Organization, pp. 1–31.

WTO, World Trade Report. 2017. *Trade, Technology and Jobs*. Geneva: WTO.

WTO, World Trade Report. 2019. *The Future of Service Trade*. Geneva: WTO.