IMPACT OF DIGITAL TECHNOLOGIES ON EMPLOYMENT PATTERNS IN DEVELOPING ECONOMIES: A KENYAN STUDY

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ABSTRACT

Digital technologies are transforming economies worldwide, reshaping the way people work and the types of jobs available. In developing countries such as Kenya, this transformation brings both opportunities and risks: while digital tools can expand access to employment and stimulate growth, they also threaten to displace workers who lack the necessary skills. This study examines how technological innovations, particularly mobile internet access and internet usage, affect employment patterns in Kenya. Using twenty years of national data, the analysis reveals that digital adoption is strongly associated with shifts in employment trends. Importantly, the results show that unemployment significantly mediates this relationship, amplifying both the opportunities and vulnerabilities created by digital change. The findings highlight the double-edged nature of technological advancement in developing economies: it can drive inclusion and productivity but also deepen inequalities if not carefully managed. The study underscores the urgent need for policies that expand affordable digital access, promote reskilling, and ensure that the benefits of technological progress are equitably shared across society.

KEYWORDS

Digital Technologies, Development Economies, Employment patterns,

1. INTRODUCTION

Digital innovations have become a defining force in the 21st century, profoundly impacting economic structures, social dynamics, and employment patterns across the globe. Among several dimensions of the digital transformation concept, organizations have decentralized, have become adaptable, new leadership models have evolved, coordination and teamwork have been enhanced. In the simplest of terms, the purposeful use of technological innovations to enhance workflows and productivity, provide better experiences for customers and employees, manage company risk, and keep expenses under control is known as digital transformation [1]. Key in this definition is the concept of "adoption" of digital technologies. The people are the ones who adopt, therefore digital transformation is more about people than it is about digital technologies.

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The fast pace of technological change is demanding that every business and its workforce evolve into a digital enterprise [2]. The swift development of digital technology has become a distinguishing feature of the global economy of the twenty-first century, significantly altering employment trends, production systems, and labor markets. The rise of digital technology offers both revolutionary possibilities and disruptive risks in developing nations like Kenya, where underemployment and unemployment continue to be major socioeconomic concerns [3].

A digital business or enterprise is a company that uses digital technologies as an integral part of its business model and operation. This is a digitally enabled business that can survive and adapt through technological disruption. The workforce inside a digital business shift from reacting to situations to creating the future [3]. In a digital business, innovation culture permeates all functions of the business where employees are encouraged to experiment with emerging technologies to create value. The basis for innovation, curiosity and delivering value for the organisation depends on the level of digital preparedness and digital aptitude of the workforce across the organisation. It is in this context that substantial shifts have been witnessed in employment patterns within the modern organisation [4]. In manufacturing and other sectors, complete shifts have been experienced where automation of routine tasks and services has led to the displacement of certain job categories, while simultaneously generating demand for high-skilled positions in technology-driven sectors.

Considering the foregoing, a critical question is then raised: What is the influence of digital technologies on employment sequence within developing nations? In this study, the above central question has emerged from literature which observes that the adoption of digital technologies presents a complex array of challenges that can disrupt traditional employment patterns. The main thrust of the issue confronting emerging nations today is this paradox: how to maximize the benefits of technology advancement while minimizing its negative consequences on workforce [5]. From the need that workers be tech-savvy to the actual replacement of workers by technology, there are many intricate issues. The loss of jobs brought about by automation and mechanization is one of the main issues, especially in industries that have traditionally generated a large number of jobs.

For instance, mechanized equipment and precise farming have improved agricultural productivity while decreasing the need for physical labor. In the manufacturing industry, robotics and artificial intelligence are also increasing productivity, but they are also displacing low-skilled people who are unable to swiftly switch to new tasks. To address these issues, this study offers a thorough examination of the ways in which technological innovation is affecting employment trends in developing nations. By looking at the effects on a particular sector, determining the skills needed for fresh job roles, and exploring the purpose of education and training, this research aims to offer actionable insights and recommendations for policymakers, business leaders, and educators. Evaluating the impact of mobile internet access on employment pattern in developing nations, a case study of Kenya. Ensuring that technical developments support equitable and continuous economic growth that benefits all facets of society is the aim. In light of the aforementioned issue and the main query, the following were the goals of this research:

- Evaluating the effect of mobile internet access on employment pattern in emerging nations, a case study of Kenya.
- Assessing the effect of internet-usage rate on employment pattern in developing countries, a case study of Kenya.
- Examining the mediating effect of unemployment on the relationship between technological innovation and employment patterns in developing countries, case study of Kenya.

2. RELATED LITERAURE

Historically, developed countries have been at the forefront of technical innovation, using it to increase productivity and economic prosperity. The labor markets in the US, Germany, and Japan have changed a lot since they started using new technology [6]. For instance, using AI in different fields has made things run more smoothly and created new jobs that require specific talents [7]. But this change also makes skill mismatches worse and means that a lot of money needs to be spent on education and retraining programs. Technological advancement brings with it many problems and chances, some industries lose jobs, while others see the rise of whole new ones.

[8] Significant changes in the demand for skills, labor mobility, and the overall makeup of employment have resulted from the spread of mobile internet, cloud computing, e-commerce, artificial intelligence, and platform-based gig work, which have reshaped the nature of job opportunities. Digital technologies have the ability to boost productivity and speed up economic growth, but their use has also been connected to informality, employment segregation, and a growing technological discrimination, especially in middle-income and low-income countries [9]. [10] although internet access has increased quickly and mobile phone adoption in Kenya has surpassed 130% by 2023, technological advancements are not equally dispersed, favoring high-skilled professionals and urban populations more than others.

According to [11], these discrepancies worsen socioeconomic inequality and produce a dual labor market in which digital technology threatens low-skilled employment through automation and technological displacement while simultaneously creating high-paying positions for a select few. [12] posited that policymakers, corporate executives, and educators must thus comprehend how digitalization affects employment patterns in developing nations. The gig economy, powered by digital platforms, provides adaptability and new earning opportunities for workers. However, this change underscores the necessity for digital abilities, which many workers in underdeveloped nations lack, widening the digital gap and potentially excluding them from advantages of technology developments. [13] underlines the importance of investing in training and development in order to fill the gap between present worker capabilities and fresh job opportunities. Without this investment, there is a risk of increasing inequality and social unrest, since many people may fall behind in the technological shift.

[14] highlights the dual nature of technology's impact on the informal economy, emphasizing the necessity for policies that assist informal workers during transitions and provide them with the tools they need to use technological improvements to their advantage. [15] Provides an exploratory evaluation of the utility of mobile phone-enabled services for smallholder farmers, illustrating how these technologies can improve accessibility to market information, banking services, and agricultural guidance, resulting in increased productivity and income. Precision farming, mobile agriculture information systems, and digital financial services are examples of technological breakthroughs in developing countries that show potential for increasing production and improving livelihoods. However, automating and mechanizing of agricultural operations carry the potential of decreasing employment possibilities in rural regions, demanding an equitable approach to embracing technology. Advances in technology are causing an unprecedented shift in the industrial sector in emerging economies.

Automation and robotics are increasing efficiency and reducing production costs, which can attract foreign investment and stimulate economic growth [16] However, these technologies are also leading to job losses in low-skill manufacturing positions, a prevalent employment source in many developing nations. The existing literature provides a nuanced understanding of the dynamics of employment patterns in developing countries amid technological innovation. While technological advancements offer significant opportunities for economic growth and improved livelihoods, they also present challenges that require careful management.[17] conducted a report on trade and development focusing on digital and macro context. The study adopted macro-policy analysis. The report revealed that policy choices mediate distributional outcomes of technology. However, the Micro-labor links in Kenya were not quantified in the report which was covered in this study.

Summary Table - Conceptual Framework Gaps

Author(s) & Year	**Topic**	**Main Variable**	**Methodology**	**Key Findings**	**Gaps Identified**	**Flling the Gap**
[1]	Digital transformation	Digital transformation (DT)	Industry white paper synthesis	DT spans technology, people, and processes; success depends on strategy and capability alignment	Limited labor-market evidence	The current study operationalizes DT basing on mobile internet & usage and connecting it to employment patterns in Kenya
[3]	Digital transformation for African development	Broadband, digital public infrastructure, skills	Policy report	Digitalization can boost growth but risks exclusion without complementary policies	Country-level causal pathways to employment outcomes underdeveloped	Kenya case quantifies links from access as well as usage to employment structures
[4]	Mobile-enabled services for smallholders	Information access; adoption	Exploratory literature review	Evidence of benefits but mixed and context-specific	Employment quality and transitions under-studied	Current study includes employment pattern analysis for Kenya
[5]	Second Machine Age and jobs	Automation; digital capital; skills	Conceptual synthesis	Digital tech can polarize jobs and increase skill premiums	Limited evidence from African labor markets	Tests polarization mechanisms in Kenyan context
[7]	Future of Work in Africa	Platform work; broadband; skills; regulations	Policy synthesis and descriptive analytics	Potential for inclusive growth if complemented by skills and protection	Micro-evidence on employment patterns and mediators is sparse	Introduces unemployment as mediator between digital adoption and employment patterns
[8]	Technology waves & development	Frontier tech readiness	Global indicator analysis	Diffusion uneven	National labor-market transmission channels not quantified	Estimates employment effects specifically in Kenya
[9]	Digital	Platform	Surveys	Platforms expand	Kenya-	Captures platform-adjacent

	labour platforms and work	participation; earnings; conditions	& case studies	opportunities but with precarity risks	specific platform effects on employment structure unclear	digital usage effects on employment patterns
[10]	ICT facts & figures	Penetration rates; broadband metrics	Descriptive statistics	Rapid mobile broadband growth globally	No correlational link to employment outcomes	Uses access/usage metrics as explanatory parameters for employment rates
[11]	Kenya communications sector statistics	Mobile subscriptions; data usage; coverage	Administrative statistics	High mobile penetration and rising data usage in Kenya	Link to labor-market outcomes not assessed	Combines digitization indicators with labor data to estimate employment impacts
[12]	Alternative work arrangements	Gig work prevalence	Survey-based measurement (US)	Sharp rise in alternative work arrangements	Evidence from Kenya and Sub-Saharan Africa lacking	Current study uses Kenyan data to infer shifts
[14]	Automation and employment	Automatable tasks; productivity; displacement	Task-based modeling	Substantial task automation potential	Country-specific labor-market net effects uncertain	Empirically estimates net effect on Kenyan employment patterns
[17]	Trade & Development Report digital & macro context	Global demand, policy	Macro-policy analysis	Policy choices mediate distributional outcomes of technology	Micro-labor links in Kenya not quantified	Country-level empirical evidence
[21]	CUSUM-based monitoring	CUSUM change detection	Methodological paper	CUSUM effective for detecting regime shifts	Limited adoption to socio-economic time series in labour market	Uses structural-break/robustness checks to detect stability of the model
[23]	Aging population & labour market in Kenya	Demographics; labor supply	Kenya-focused analysis	Aging influences labor supply and sectoral dynamics	Interplay with digital adoption not analyzed	Accounts for demographic factors when estimating digital effects
[14]	A Future That Works (report)	Automation potential; occupations; tasks	Global modeling & scenarios	Automation hinge on job creation	Specific occupational transitions uncertain	Documents Kenyan general employment reallocation associated with digital adoption

3. Methodology

The research study adopted descriptive and correlational designs to examine the effect of the dynamics of employment patterns in developing countries amid technological innovation. The study adopted quantitative secondary data from internationally recognized sources such as, World Development Indicators (WDI) by the World Bank. The study used annual time series data for a period of 20 years spanning from 2001to 2021 for the variables of interest, were technological innovation platforms (mobile internet access, internet usage rate, and employment trends (EMP) while unemployment was applied as a study mediating aspect. Technological innovation was measured by internet usage rates; employment pattern was indicated by labour participation rates while the moderator, unemployment was indicated by unemployment rates (UNEMP) in Kenya.

3.1. Empirical Case

Kenya has always been one of the flourishing technological hubs on the African continent. From Mobile Money and EdTech tools and e-government platforms to fintech innovations, technological innovations in Kenya have scaled beyond the continent. Through its focus on public and private partners, the Kenyan Government encourages technological innovations to both lower the barriers to techno entrepreneurs and spur the adoption of emerging technologies like the blockchain, AI, and others. The employment market has been affected by the adoption of technology in many ways. There is no study that captures the revolutionary effect of technology on the job market in Kenya. Job technology (JobTech) is being leveraged to train, reskill, and connect people to work opportunities in all sectors of the Kenyan economy. Innovative platforms like MESH and the JobTech Alliance are revolutionizing job placement by focusing on skills development and digital literacy, which are crucial for the current and near-future labour force. MESH, a Kenyan technology network platform with monthly users exceeding 275,000, connects job seekers with both formal and informal job opportunities in diverse emerging fields. Notably MESH has partnered with Unilever, which is a huge agri-processing company that supplies users of MESH with products for commerce. The current digital revolution, characterized by automation, artificial intelligence, and data-driven practices in government, service and manufacturing in Kenya, is at the forefront of transforming the economy and how labour is deployed across different value chains.

3.2. Econometric Model Specification

The study employed the correlation research approaches and regression model to estimate the nexus between technological innovation platforms and employment trends in developing countries. The following econometric model was adopted.

$$EP_t = \beta_0 + \beta_1 MI_t + \beta_2 IU_t + \mu_t \tag{1}$$

Where: EP=Employment pattern
MI=Mobile Internet access
IU=internet usage rate
μ= Error term.
T=time

Further under this study, hierarchical analysis was conducted to establish the mediating impact of unemployment rate (M) on the relationship between technological innovation employment pattern in developing countries. This research determined the mediator's relevance through comparisons of R-squared, adj R-squared, and significance levels prior to and after including the unemployment rate (M) in the regression model. The resulting model was created with an additional moderating variable.

$$EP_t = \beta_0 + \beta_1 MIM_t + \beta_2 IUM_t = \mu_t$$

Where:
- M- Unemployment rate (mediator)
- β_0 –constant
- $\beta_{1\text{-}2}$-coefficient
- μ- error term
- t- Time

Model above revealed the mediating effect of unemployment rate (M) on the predicted objective explored by explained variable understudy.

4. Results and Discussion

4.1. Stationarity Test

The Augmented Dickey-Fuller (ADF) test was used in the current research to check for the stationarity of the relevant variables. The findings for unit root test in Table 1 revealed that the pertinent variables had non-stationarity issue at levels where the MI, IU, and UR problem was resolved after second differencing in Table 2 while EP was found to be stationery at first difference and therefore, all were probability values less than 0.05 after differencing.

Table 1: Augmented Dickey Fuller, (ADF)

Variables	**t-statistics**	**Critical Values**			
		1%	**5%**	**Prob-value**	**Conclusion**
MI	-1.7032	-3.8085	-3.0207	0.4146	Unit root
IU	-1.6320	-2.8172	-3.0021	0.2451	Unit root
EP	-2.6034	-3.9204	-3.0656	0.1126	Unit root
UR	-1.9318	-3.8574	-3.0404	0.3115	Unit root

Table 2: Stationarity Test at difference

Variables	**t-statistics**	**Critical Values**				
		1%	**5%**	**Prob**	**Difference**	**Conclusion**
MI	-6.7104	-3.8315	-3.0210	0.0000	2nd	Stationary
IU	-5.6781	-3.3381	-3.4323	0.0020	2nd	Stationery
EP	-4.2034	-3.72035	-3.0646	0.0263	1st	Stationary
UR	-10.9107	-3.8574	-3.0403	0.0000	2nd	Stationary

4.2. Correlational Analysis

Pairwise correlation was conducted prior to stationarity test, and the results are shown in table 3 below. The findings from correlational summary below indicated the residuals were not highly collinear. The strength and direction of the nexus between the study objectives and the correlation was evaluated using correlational diagnostics. The correlation coefficient (R), which is also measured in this research and ranges from a positive 1 to a negative 1 value. From the results, mobile internet access (MI) had a positive significant (0.6275, $p<0.05$) relationship with employment pattern. It clearly shows that the EP rate rises by 0.6275 units when MI rises by a single unit, and the reverse is true. This could imply that mobile internet access facilitates creation of new job opportunities, fosters economic growth, and contributes to higher employment levels. Similarly, Internet usage rate revealed a positive statistically significant influence on employment trends (0.5943, $p=0.0012$).

Table 3: Correlational Analysis

Covariance Analysis. Sample: 2001-2021 Included Observations: 21				
Correlation t-statistics Probability	**EP**	**MI**	**IU**	**UR**
EP	1.0000			
MI	0.6275 3.513 0.0023	1.0000		
IU	0.5943 3.423 0.0012	0.4567 3.321 0.010	1.0000	
UR	0.7942 3.587 0.0000	0.5821 3.121 0.006	0.4456 3.213 0.023	1.0000

4.3. Regression Analysis

From the regression results in table 4a, the model was significant at 5% level with the pv $0.0023 < 0.05$. The Durbin- Watson statistics was 1.92 indicating that there is no autocorrelation problem which conquers with the findings of [22, 21]. The (R^2) value was 0.6001 showing that the explanatory variable included in the model explains 60% of employment pattern in developing nations. From the findings below it was noted that when all factors in the economy are held constant, (C) the employment pattern shifted by 9.19% while when the mobile internet access was considered, the coefficient shifted to 53.20%. This was a clear indication that TI had a strong significant relationship with EP such that when TI increases by one-unit EP fluctuated by 53.20%. This implies that, as MI increases, it leads to changes in job roles, skills requirements, and possibly job creation or displacement. Understanding this relationship is crucial for businesses, policymakers, and individuals to penetrate the changing job structure.

Table 4: Regression Analysis

Dep Var: Employment Pattern
Approach; OLS

Dep Var (EP)	**Parameter**	**t-statistic**	**Prob-value**
C	0.0919	3.529	0.0023
MI	0.5320	3.034	0.0000
IU	0.5024	2.501	0.0021
R-Squared 0.6001			
Adj. R-squared 0.4618			
Durbin-Watson stat 1.92			
Prob (F-statistic) 0.0023			

The goodness of fit (R-squared) rose from 0.6001 to 0.8901 (a high-positive effect of 29%) after unemployment was added as a mediator (M). This indicates that the R^2 increased by 29% as a result of the mediating effect of the unemployment rate increasing the variance of employment pattern explained by technological innovation. Additionally, the independent variables maintained their significance with a probability value <0.05 even when the unemployment rate (M) was included.

As a result, when the moderator, unemployment rate, was added, the probability value was 0.0020, which was below the significant level of 0.05. It suggests that changes in unemployment had a notable and measurable impact on the employment outcome. The null hypothesis was thus disproved, and it was determined that the unemployment rate significantly moderated the variables under investigation. Given that it falls between 1.5 to 2.5, the Durbin Watson value of 2.13 indicated the lack of serial autocorrelation.

Table 5: Regression Analysis with Moderator

Variable	**Coefficient**	**t-statistic**	**Prob**
C	-0.1343	-4.88	0.0001
MI	0.3820	2.89	0.0028
IU	0.4350	2.23	0.0021
UR (mediator)	0.1750	3.4732	0.0000
R-Squared 0.8901			
Adj-R Squared 0.7879			
Durbin-Watson 2.13			
Prob (F-statistic) 0.0020			

4.4. Test for Autocorrelation: Breusch-Godfrey Test

Table 5 below indicates the absence of serial correlation as the probability of chi-square > 0.05. The resulting time series data show autocorrelation when an error term crosses into another period [23].The values of subsequent error terms are implied to be sequentially independent by the linear regression error term, as stated in [16]. The Breasch-Godfry LM test for serial correlation was adopted to determine whether there was any link, with the null hypothesis being that there is no serial correlation. In the event that the p-value surpasses 0.05, the null hypothesis remains valid.

Table 6: Serial Correlation Test

F-statistic	3.804	prob. F (2, 26)	0.054
Obs* R^2	7.244	prob. Chi-square (2)	0.067

4.5. Normality Test

Considering the findings of the Jarque Berra test for normalcy (shown in figure 1), which revealed a p-value of 0.478292>0.05, the null hypothesis—that is, that residuals are normally distributed—was accepted at a 5% significance level.

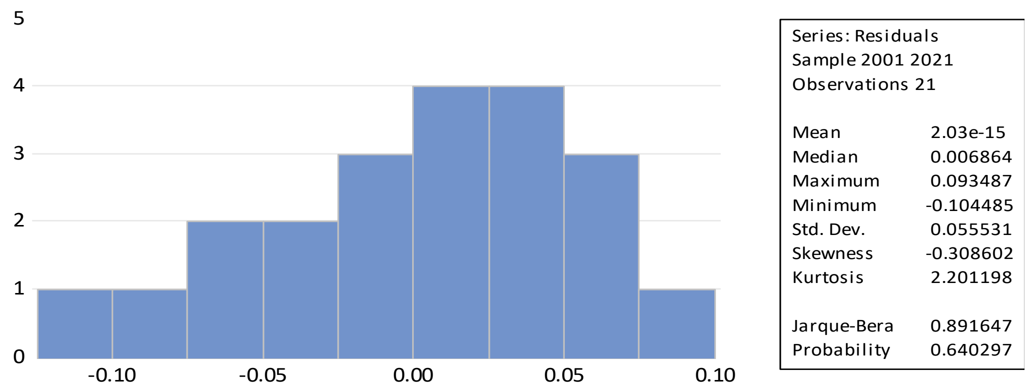

Figure 1: Normality test

4.6. Breusch-Pagan-Godfrey Test for Heteroscedasticity

The null hypothesis for the test was that there is no heteroscedasticity and that the variance is constant (homoscedasticity). According to [21,22] the null hypothesis is accepted if the probability value (p-value) is greater than 5%. Heteroscedasticity usually occurs when the variance of the error term varies for each value of the regressor. The null hypothesis was accepted since the revealed p-value was greater than 0.05.

Table 7: Heteroscedasticity Test

Heteroskedasticity Test Breusch -Pagan -Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.440621	Prob. F (3.38)	0.7258
Obs *R-squared	1.442595	Prob. Chi-squared (3)	0.6956
Scaled explained SS	1.046171	Prob. Chi-squared (3)	0.7901

4.7. Model Stability Test

If the sequence crosses the upper or lower critical line (0.05) following a few iterations of recursive regression, there is a problem with the model. Between the top and lower bounds of the significance level of 0.05, a stable model should be found. The stability of the resultant model (CUSUM) was assessed using the Cumulative Sum Test, according to [21, 22]. Every variable falls between the lower and higher boundaries of the 5% significance criterion, as shown in Figure 2 below. Since all the variables were contained inside the essential upper and lower bounds, as shown in Fig. 2 below, the model established in this study was confirmed to be stable.

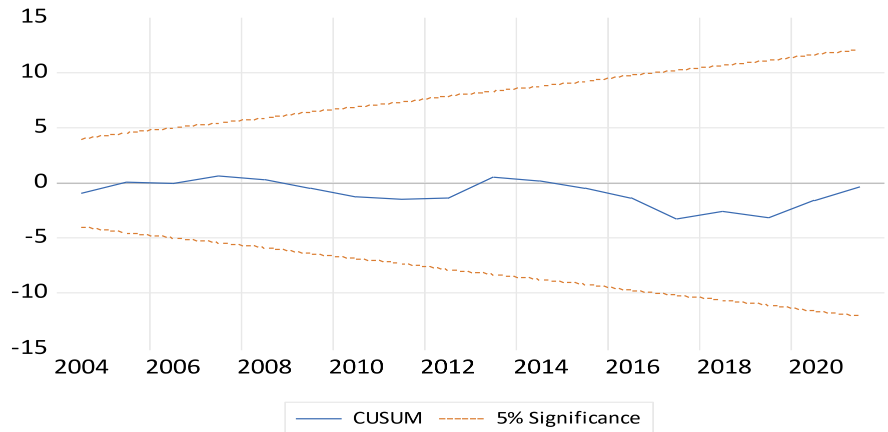

Figure 2: CUSUM Test

5. Conclusions

It can be concluded from the results and discussions that follow that there exists a connection between job patterns and technical advancements (such as mobile internet access and internet usage). The outcome demonstrates that the explanatory variable had a statistically significant impact on the explained variables over the course of the investigation. It was also concluded that the mediator, unemployment, had a strong, significant mediating impact on the nexus between technological innovation and employment pattern in developing countries.These findings illustrate the revolutionary impact of digital innovations, which have the capacity to both generate and replace jobs, emphasizing the critical need for policies in emerging economies that promote equitable digital inclusion, labor upgrading, and long-term economical adaptability.

5.1. Recommendations

The government should invest in digital infrastructure development to increase affordable broadband access and mobile internet usage, especially in rural and underserved areas. Public-private partnerships can help to bridge the digital divide and increase involvement in emerging digital economies. The study suggests that authorities improve technological skill acquisition by building community tech hubs and portable educational centers for informal sector workers and unemployed youth. Same way, promote tax breaks and subsidies for start-ups, fintech companies, and creative businesses that use digital tools. Likewise, the authorities should promote research and industrial collaboration by strengthening relationships among academic, government, and commercial sector organizations. The policymakers should ensure inclusive Policies and Social Protection Policies should be enacted to ensure that gig and platform-based sector employees have a right to social security and fair pay as well introduction of flexible labor policies that allow for new types of technological employment while maintaining rights for employees.

5.2. Areas For Future Studies

Future researchers should carry out further studies to:

i. Investigate gender inequities in getting access to technology-driven chances, particularly among women in rural and informal settings.
ii. Evaluate how technological advancement affects various sectors (agricultural, industry, and services), particularly in unstructured areas.
iii. Investigate the possible impact of artificial intelligence, robotics, and process automation on displacement of employment and reskilling necessities in Kenya.
iv. Examine the effects of platform-centered services (such as delivery applications and ride-hailing) on social safeguards, job fulfillment, and economic stability.

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