Research Article

Queen Arwa University Scientific Refereed Journal
مجلة جامعة الملكة أروى العلمية المحكمة
QAUSRJ

Research Article Data:	
PUBLISHER	Queen Arwa University
DOI	10.58963/qausrj.v28i28.305
P-ISSN	2226-5759
E-ISSN	2959-3050
Reception Date	01 Dec 2024
Accepted Date	20 Dec 2024
Published Date	31 Dec 2024
License ©	(CC BY 4.0)

Citation:
Mana'a, S. A. yahya ., Alsabry, A., & Algawani, R. S. . (2024). The Impact of Technology Advancement on Unemployment in Yemen Manufacturing Companies. *Queen Arwa University Journal*, 28(28), 13. https://doi.org/10.58963/qausrj.v28i28.305

Main contact:
Author: *Rana Saleh Algawani*
Phone: 967776018376+
Published Email: dr.sadekmanaa77@gmail.com

Organization/University/ Center:
Affiliation: *Sa'ada University, International University of Technology Twintech.*
Research funder: *Not found.*

Research field/specialization:
Economic, General Management

QR code:
Scan QR code to visit this journal on your mobile device.
امسح الكود لزيارة موقع المجلة

The Impact of Technology Advancement on Unemployment in Yemen Manufacturing Companies

Dr. Sadeq Mana'a [1,2], Dr. Ayman Alsabry [2], Rana Saleh Algawani [3]

[1] Sa'ada University, Sa'ada, Yemen.
[2] International University of Technology Twintech, Sana'a, Yemen.
[3] Federation of Yemen Chambers of Commerce and Industry, Sana'a, Yemen.

2024

Abstract:

This study examines the relationship between Unemployment and three independent sub-variables: Productivity Enhancement, Operational Efficiency, and Skill Requirement. The objective is to gain insights into the factors influencing the Unemployment and their significance in explaining its variability. The study employs various statistical analyses, including correlation analysis, multiple regression analysis, ANOVA, and t-tests, to analyze the data. The findings reveal a moderate positive correlation between Technological Advancement and Unemployment, suggesting that as Technological Advancement increases, the Unemployment tends to moderately increase. However, further investigation is needed to establish a causal relationship. The multiple regression analysis demonstrates that approximately 23.4% of the variability in the Unemployment can be explained by the independent sub-variables: Productivity Enhancement, Operational Efficiency, and Skill Requirement. Specifically, Productivity Enhancement and Skill Requirement exhibit a positive and significant impact on the.

Keywords:
Technology Advancement, Unemployment, Productivity Enhancement, Operational Efficiency, Skill Requirement.

ROR: 03ygqq617
ISSN : 2226 - 5759

ترجمة الى العربية

تأثير التقدم التكنولوجي على البطالة في الشركات الصناعية اليمنية

د. صادق مناع[1,2]، د. ايمن الصبري[2]، رنا صالح الجعوني[3]

[1] جامعة صعدة، صعدة، اليمن.
[2] جامعة تونتك الدولية للتكنولوجيا، صنعاء، اليمن.
[3] الاتحاد العام للغرف التجارية والصناعية اليمنية، صنعاء، اليمن.

2024

الملخص

تتناول هذه الدراسة العلاقة بين البطالة وثلاثة متغيرات مستقلة فرعية: تعزيز الإنتاجية، الكفاءة التشغيلية، ومتطلبات المهارات. يهدف البحث إلى تقديم رؤى حول العوامل المؤثرة في البطالة وأهميتها في تفسير التغيرات فيها. تستخدم الدراسة تحليلات إحصائية متنوعة، بما في ذلك تحليل الارتباط، التحليل الانحداري المتعدد، تحليل التباين (ANOVA)، واختبارات T لتحليل البيانات. تكشف النتائج عن وجود ارتباط إيجابي معتدل بين التقدم التكنولوجي والبطالة، مما يشير إلى أنه مع زيادة التقدم التكنولوجي، تميل البطالة إلى الزيادة بشكل معتدل. ومع ذلك، هناك حاجة إلى مزيد من التحقيق لتحديد العلاقة السببية. يوضح التحليل الانحداري المتعدد أن حوالي 23.4% من التباين في البطالة يمكن تفسيره بالمتغيرات المستقلة الفرعية: تعزيز الإنتاجية، الكفاءة التشغيلية، ومتطلبات المهارات. بشكل خاص، يظهر أن تعزيز الإنتاجية ومتطلبات المهارات لهما تأثير إيجابي وملحوظ على البطالة، في حين أن الكفاءة التشغيلية ليس لها تأثير إحصائي ذو دلالة. تؤكد اختبارات الفرضيات أهمية العلاقات بين المتغيرات المستقلة الفرعية والبطالة.

الكلمات المفتاحية

التقدم التكنولوجي، البطالة، تعزيز الإنتاجية، الكفاءة التشغيلية، متطلبات المهارات.

Introduction

Yemen, a country located in the Middle East, has been grappling with various economic challenges due to political instability and armed conflict in recent years. The country's economy has been significantly affected, leading to high unemployment rates and an urgent need for economic revitalization (Almaliki, 2023; ALSHAMI, 2024). Yemen's economy has been severely affected by ongoing conflicts, disruptions in infrastructure, and political instability (Nugroho & Kartono, 2024) . These factors have hindered economic growth and led to a decline in various economic indicators. The Gross Domestic Product (GDP) of Yemen has experienced a significant downturn in recent years, reflecting the adverse effects of the conflict on the country's overall economic performance (Mukashov et al., 2022). The labor market in Yemen faces numerous challenges, with high unemployment rates being one of the prominent issues. The lack of job opportunities has resulted in increased economic vulnerability and poverty among the population. The unemployment rate has been a pressing concern, particularly among the youth, who represent a significant portion of the labor force (Dahlgren, 2014). Furthermore, the Yemeni economy is characterized by a heavy reliance on imports, limited diversification, and a weak industrial base. The manufacturing sector, despite its potential for employment generation and economic growth, has been constrained by various factors, including limited access to capital, inadequate infrastructure, and a lack of technological advancements (Saleh & Manjunath, 2020).

Addressing the economic challenges and high unemployment rates in Yemen requires a comprehensive understanding of the economic context. It necessitates the identification of key economic indicators, such as GDP growth rates, inflation rates, and foreign direct investment (FDI) inflows, to assess the overall economic performance and trends in the country. Moreover, it is important to acknowledge the need for economic development and the potential role of the manufacturing sector in achieving this goal. Strengthening the manufacturing industry can contribute to job creation, income generation, and economic

diversification, ultimately fostering sustainable economic growth in Yemen (Schmitz, 2012).

In this context, the manufacturing sector plays a crucial role in Yemen's economy. It contributes to employment generation, income generation, and overall economic growth (Abualrejal et al., 2017). However, the impact of technology advancement on unemployment in Yemeni manufacturing companies remains a topic of concern and requires further exploration. However, the impact of technology advancement on unemployment in Yemeni manufacturing companies remains a topic of concern and requires further exploration.

Technological advancements have been transforming industries worldwide, including the manufacturing sector (Goldmann & Knörzer, 2023). While these advancements have the potential to enhance productivity and efficiency, they also raise concerns about job displacement and the potential impact on unemployment rates, particularly in developing countries such as Yemen.

By examining the historical context, theories, and concepts related to the impact of technological advancement on unemployment in Yemeni manufacturing companies, the study aims to achieve the following objectives:

1. To investigate the impact of technology advancement on unemployment in Yemeni manufacturing companies.
2. To identify and analyze the factors that influence the relationship between technology advancement and employment opportunities in Yemeni manufacturing companies.
3. To contribute to the existing body of knowledge by providing insights into the impact of technology advancement on unemployment in developing countries, with a specific focus on the context of Yemen.
4. To establish a foundation for future research and studies on the subject, facilitating further exploration and understanding of the complex dynamics between technology advancement and unemployment in the manufacturing sector of Yemen.

Based on this, the research questions are:

1. What is the relationship between Technological Advancement and Unemployment?
2. To what extent do the independent sub-variables (Productivity Enhancement, Operational Efficiency, and Skill Requirement) explain the variability in the Unemployment?
3. Do the independent sub-variables have a significant overall effect on the Unemployment?
4. Do the results support the alternative sub-hypotheses related to the effects of the independent sub-variables on the Unemployment?

Literature Review

1. Technological Advancement

1.1.Productivity Enhancement

Productivity enhancement in the workplace refers to strategies and techniques implemented to improve the efficiency and effectiveness of employees and teams in achieving their goals and tasks. By enhancing productivity, businesses can optimize their resources, increase output, and achieve better results (Tuttle, 1983). One of the outcomes of adopting technology in organizations is the enhancement of productivity (Juhász et al., 2024). The integration of digital technologies such as artificial intelligence, robotics, big data, and business analytics, along with virtual and augmented reality, provides new possibilities for effective study and management (Aithal, 2023; Zeebaree et al., 2020). Suitable technology can enhance market efficiency, employee productivity, communication, and responsibility, leading to improved overall performance (Hafizji et al., 2022). Lean manufacturing principles and tools like kanban and 6s system can be implemented to improve efficiency and quality, reduce lead time, and streamline the production process (J. Johny, 2019; Sordan et al., 2024). Building Information Modeling (BIM) and SAP tools optimize quality and productivity by providing an integrated environment and minimizing errors (LINGAN, 2018). Technological advancements also enhance entrepreneurship by facilitating the flow of creative ideas and employee participation (Mohammed, 2019). Overall, technological advancements play a crucial role in enhancing organizational productivity in manufacturing organizations by improving

processes, reducing costs, and increasing innovation.

1.2.Skill Requirement

Another outcome of technology adoption in organizations is the changing skill requirements for employees. Technological advancements often require workers to possess a new set of skills and competencies to effectively operate and leverage the technology. For example, engineers in the agri-food and energy network industries in the Netherlands require digital, analytical, and communicative skills, as well as the ability to learn new things (Oeij et al., 2023). Additionally, advanced technology enhances the flow of creative ideas in organizations and requires the participation of employees for effective idea generation (Mohammed, 2019). Virtual training modules can be used to enhance the productivity and skill sets of individuals in the domain of Mechanical Engineering, particularly in developing economies where access to expensive equipment may be limited (Chandrashekar et al., 2021). Technological change also affects skill accumulation among workers, with higher rates of technological change leading to increased formal company training, particularly for less educated workers (Dina, 1994).

1.3.Operational Efficiency

Operational efficiency is another significant outcome of adopting technology in organizations. The use of advanced technologies can improve economic results, efficiency, and return on equity and sales (Handoyo et al., 2023; Janeček & Hynek, 2015). It also enhances the flow of creative ideas and promotes entrepreneurship within the organization (Mohammed, 2019). Collaboration between developers, manufacturers, customers, and academia is crucial for creative advancement in manufacturing engineering methods (Bargelis & Mankute, 2010; Malhotra et al., 2023). Advanced Manufacturing Technology (AMT) offers benefits such as faster machine cycles, greater reliability, reduced inventory, labor savings, flexibility, and improved quality (Nyori & K'Obonyo). The adoption of manufacturing technologies and lean practices has unique and complementary effects on operational performance dimensions, including quality, lead-time, flexibility, and cost (Khanchanapong et al., 2014). Building strong manufacturing technologies and lean practices can maximize operational performance in manufacturing firms.

2. Unemployment factor

1.4.Job Losses

Job losses in the manufacturing sector have a significant impact on unemployment rates (Schweitzer, 2017; Townsend, 2024). The decline in manufacturing jobs has been a major factor in the economic struggles of the industrial Midwest, also known as the Rust Belt (Gavin, 2013). Studies have shown that the loss of manufacturing employment is correlated with declines in economic performance, including nonmanufacturing employment, unemployment rates, population, and per capita income levels (Beale & Nethercott, 1985; Schweitzer, 2017). The consequences of job loss extend beyond just unemployment, as it has been found to have negative effects on health and increase healthcare costs (Jarosch, 2014; Picchio & Ubaldi, 2024). Job loss not only leads to unemployment but also results in large and persistent earnings reductions (Illing et al., 2024; Maxwell, 1989). Workers with higher levels of human capital are less likely to experience wage loss and unemployment after job termination. Overall, job losses in manufacturing organizations have a significant impact on unemployment rates and have far-reaching consequences for individuals and the economy as a whole.

1.5.Job Security

Job security has a significant impact on the unemployment rate. Studies have shown that job security provisions, such as severance payments and dismissal restrictions, can influence the age-composition of employment and lead to a decline in the employment-to-population rate of young workers (Ellonen & Nätti, 2015). However, job security does not have a significant impact on overall aggregate employment, participation, or unemployment rates (Montenegro, 2007). Additionally, the effects of job security on unemployment can vary depending on other factors such as wage setting institutions and minimum wage policies (Cahuc & Zylberberg, 1999). High

redundancy transfers and administrative dismissal restrictions have a negligible effect on unemployment when wages are flexible or when the minimum wage is low, but can have a dramatic positive impact on unemployment when there is a high minimum wage (Cahuc & Zylberberg, 1999).

1.6.Skill Demand

Skill demand is a significant factor in measuring unemployment in manufacturing organizations. Several studies have examined this relationship. Weaver and Osterman found that the demand for higher-level skills in manufacturing establishments is generally modest, with three-quarters of establishments not experiencing hiring difficulties (Weaver & Osterman, 2017). Weaver and Osterman used a search and matching framework to measure unemployment due to skill mismatch and found that skill mismatch increased during the Great Recession but returned to pre-recession levels (Weaver & Osterman, 2013).

1.7.Labor Market Dynamics

Labor market dynamics can be used as a factor to measure unemployment in manufacturing organizations (Finamor & Scott, 2021). By analyzing the transition rates between labor market states, it is possible to decompose fluctuations in the unemployment rate into inflow and outflow driven components (Fiaschi & Tealdi, 2021). Additionally, labor market reforms such as placement and employment services, UI benefit reduction, and product market deregulation have been found to be effective policy levers for reducing unemployment (Murtin & Robin, 2018). Furthermore, a footloose entrepreneur model with job search and matching frictions in the manufacturing sector can capture both within-sector and regional unemployment adjustment (Yang, 2014). Finally, a dynamic trade model that considers labor mobility frictions, goods mobility frictions, geographic factors, and input-output linkages can quantify the effects of trade shocks on manufacturing employment in different labor markets (Caliendo et al., 2019).

Previous Research

Technological advancements have a significant impact on unemployment in manufacturing companies. These advancements lead to job losses and changes in job security, as new technologies often replace traditional roles (Angyridis & Zhou, 2022; DAĞLI, 2022). However, technological advancements also create new job opportunities, as companies require new skills to operate and benefit from increased productivity and operational efficiency (Hiilamo, 2022). The demand for skills in the labor market is affected by technological advancements, with certain skills becoming more in demand while others become obsolete (Kim, 2022). Overall, the impact of technology on unemployment in manufacturing companies is complex and depends on various factors such as the level of technology, investment in research and development, and the specific industry context (Lydeka & Karaliute, 2021) .

(DAĞLI, 2022) conducted research entitled "The Rise of Technology for the Future Labor Force: The Nexus between Technology and Unemployment in OECD Countries" , the impact of technology on employment was analyzed with the S-GMM estimator in 33 OECD member countries for the years 2005-2018, and the empirical results showed that a 1% increase in technology reduces unemployment by 0.07%.

(Angyridis & Zhou, 2022) conducted research entitled "In this article” Search, technology choice, and unemployment". A search-theoretic framework for finding the optimal technology choice for a firm's technology choice is presented, where a more advanced technology is assumed to have a higher set up cost, but it is more productive.

(Hiilamo, 2022) conducted research entitled "Machine beats man - prospects of paid work". The main issue for technological unemployment is the expected labor market impact of technological change, which in the modern time, includes broad and vague concepts such as automation, robotization, increasing computing power, Big Data, the penetration of the Internet, the Internet-of-Things, online platforms and artificial as discussed by the authors.

(Kim, 2022) conducted research entitled " A Study on the Impact Factors of R&D Efficiency and

Efficiency by Technology Level: Focused on Equipment Investment in 30s Manufacturing Industries". a Data Envelopment Analysis (DEA) method was used to measure the R&D efficiency by technology level in the manufacturing industry, and the impact factors of RDR efficiency were derived using the Tobit regression analysis.

(Lydeka & Karaliute, 2021) conducted a research entitled " Assessment of the effect of technological innovations on unemployment in the European Union countries", the authors used data from 28 European Union countries for the period of 1992-2016 and pursued to research how technological innovations affect unemployment rate, using a dynamic two-step System Generalized Method of Moments (GMM-SYS).

The study's contributions lie in its comprehensive exploration of the impact of technology advancement on unemployment in Yemeni manufacturing companies. By examining the specific factors of technology advancement and unemployment, the study provides valuable insights into the challenges and opportunities faced by the industry. These insights can inform evidence-based decision-making, enabling the formulation of targeted policies, interventions, and strategies that promote inclusive growth, mitigate job losses, enhance job security, and foster a dynamic and resilient labor market in the Yemeni manufacturing sector.

Based on the information provided, the following hypotheses are formulated:

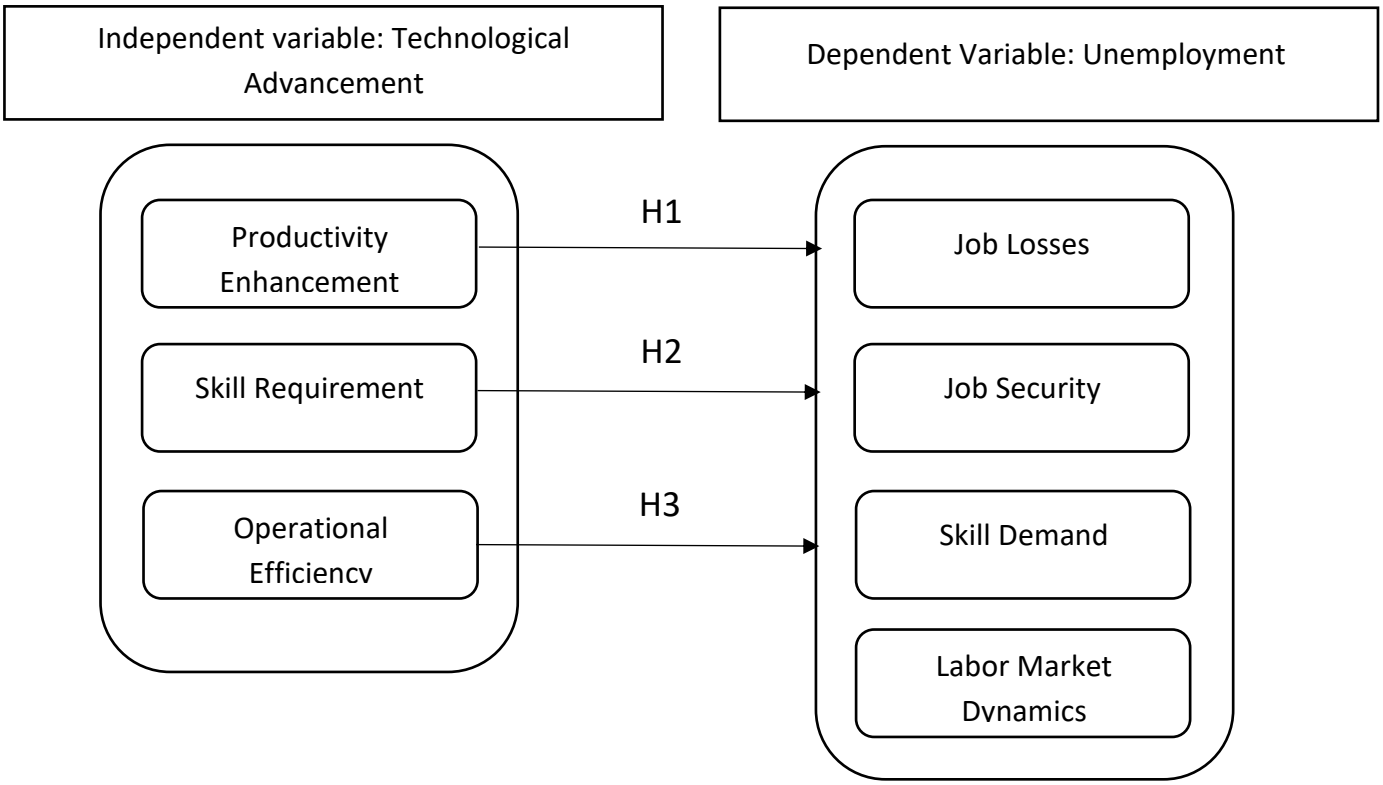
H1: Productivity Enhancement has a significant impact on Unemployment

H2: Skill Requirement has a significant impact on Unemployment

H3: Operational Efficiency has no a significant impact on Unemployment

Drawing upon the findings of prior research and the established hypotheses, a research model is formulated and represented in the figure 1.

Figure1 Framework (Source: Developed for this research (2025)



RESEARCH METHODS

Population refers to the entire group of individuals or elements that possess certain characteristics and are of interest to the researcher (Indrawati, 2015). In the context of the study on "The Impact of Technology Advancement on Unemployment in Yemeni Manufacturing Companies," the population under investigation comprises the employees of water manufacturing firms located in Yemen's capital city, Sana'a. The specific water manufacturing firms included in the population are Alnahdaieen Company (Haddah), Hawawea Water, Al-qema Group, and Haniya Company. These firms were selected based on their relevance to the research topic and their presence within the manufacturing sector in Yemen. The choice of these firms allows for a focused examination of the impact of technology advancement on unemployment within the specific context of the water manufacturing industry in Sana'a. By studying employees from these firms, the research can capture insights and experiences related to technology adoption, job losses, skill requirements, and other factors affecting unemployment in the sector.

Sample refers to a subset of the population that is selected for the purpose of conducting a study (Sekaran & Bougie, 2017). In the study a cross-sectional research design was employed. This design allows for data collection at a specific point in time, providing a snapshot of the relationships between technology advancement and unemployment within the selected sample. The sample for this study consisted of 151 valid respondents, who were employees of water manufacturing firms located in Yemen's capital city, Sana'a. These respondents were selected using a combination of purposive and convenience sampling techniques. Purposive sampling was utilized to ensure that the sample included individuals from the target population who possessed relevant knowledge and experience related to the research topic. Convenience sampling was employed to select respondents based on their accessibility and willingness to participate in the study. The criteria for inclusion in the sample were as follows: being an employee of a water manufacturing firm in Sana'a and having a direct experience or knowledge of the impact of technology advancement on employment within the company. The sample size of 151 was considered appropriate for the study, taking into account the available resources and the feasibility of data collection within the given timeframe.

Data collection was conducted through structured questionnaires administered to the selected respondents. The questionnaires were designed to gather information on variables such as technology adoption, job losses, job security, skill demand, and labor market dynamics. Measures were taken to ensure the validity and reliability of the questionnaire items, including pre-testing and piloting as shown in Table 1.

Table1 Reliability Statistics

Variable	N of Items	Cronbach's Alpha
Productivity Enhancement	3	**.722**
Operational Efficiency	3	**.568**
Skill Requirement	3	**. 695**
Job Losses	3	**.821**
Job Security	3	**.728**
Skill Demand	3	**.625**
Labor Market Dynamics	3	**.671**
Overall	21	**.854**

The reliability statistics presented in Table1 provide valuable information about the internal consistency and reliability of the measurement scales used in the study. Cronbach's Alpha is a commonly used measure of reliability, indicating the extent to which the items within a scale or construct are measuring the same underlying concept.

In this study, the Cronbach's Alpha values for various constructs are as follows:

- Productivity Enhancement: The Cronbach's Alpha value of 0.722 suggests a moderate level of internal consistency for the items measuring productivity enhancement. This indicates that the items within the scale are reasonably reliable in assessing the construct of productivity enhancement in the context of technology advancement and its impact on

unemployment.

- Operational Efficiency: The Cronbach's Alpha value of 0.6 suggests a moderate level of internal consistency for the items measuring operational efficiency. While this value is somewhat lower than desirable, it still indicates a reasonable level of reliability for the construct.
- Skill Requirement: The Cronbach's Alpha value of 0.695 reflects a moderate level of internal consistency for the items measuring skill requirement. This suggests that the items within this scale are reasonably reliable in assessing the construct of skill requirement in relation to technology advancement and its impact on unemployment.
- Job Losses: The Cronbach's Alpha value of 0.821 indicates a high level of internal consistency for the items measuring job losses. This suggests that the items within this scale are reliable in capturing the concept of job losses in the study, providing a solid measure of this important construct.
- Job Security: The Cronbach's Alpha value of 0.728 suggests a moderate level of internal consistency for the items measuring job security. This indicates that the items within the scale are reasonably reliable in assessing the construct of job security in the context of technology advancement and its impact on unemployment.
- Skill Demand: The Cronbach's Alpha value of 0.625 indicates a moderate level of internal consistency for the items measuring skill demand. This suggests that the items within this scale are reasonably reliable in capturing the concept of skill demand in relation to technology advancement and its impact on unemployment.
- Labor Market Dynamics: The Cronbach's Alpha value of 0.671 reflects a moderate level of internal consistency for the items measuring labor market dynamics. This suggests that the items within this scale are reasonably reliable in assessing the construct of labor market dynamics in the study.
- Overall Questionnaire: The Cronbach's Alpha value of 0.854 indicates a high level of internal consistency for the entire questionnaire. This suggests that the items collectively measure the intended constructs reliably, providing confidence in the overall reliability of the questionnaire used in the study.

RESULT AND DISCUSSION

1. Frequency Analysis

The frequency analysis was conducted on a sample of 151 respondents to examine the distribution of various demographic variables. The results are summarized as follows:

1- Gender: The majority of respondents were male, accounting for 123 individuals, representing 81.5% of the total respondents. Female respondents, on the other hand, were only 28 individuals, comprising 18.5% of the total respondents.

2- Age: Among the respondents, the largest group was under 30 years old, with 68 individuals, accounting for 45% of the total respondents. The age group of 30-40 years old followed, with 52 individuals, representing 34.4% of the total respondents. The age group of 41-50 years old consisted of 26 individuals, making up 17.2% of the total respondents. Only 5 respondents were over 50 years old, representing 3.3% of the total respondents.

3- Education: The majority of respondents held a Bachelor's degree, with 95 individuals, accounting for 62.9% of the total respondents. The next significant group had a Diploma degree, with 36 individuals, representing 23.8% of the total respondents. Respondents with a Master's degree comprised 19 individuals, making up 12.6% of the total respondents. Only 1 respondent held a PhD degree, representing 0.7% of the

total respondents.

4- Occupation: The distribution of respondents by occupation showed that the majority were employees, with 80 individuals, accounting for 53% of the total respondents. Supervisors constituted the second-largest group, with 49 individuals, representing 32.5% of the total respondents. Managers comprised the smallest group, with 22 individuals, making up 14.6% of the total respondents.

5- Experience: The frequency distribution of respondents based on their years of experience indicated that the largest group had 6-10 years of experience, with 49 individuals, representing 32.5% of the total respondents. The second most numerous groups had 2-5 years of experience, consisting of 48 individuals, accounting for 31.8% of the total respondents. Respondents with less than 2 years of experience comprised 37 individuals, making up 24.5% of the total respondents. Lastly, individuals with over 10 years of experience were the smallest group, with 17 persons, representing 11.3% of the total respondents.

2. Correlation Analysis

As shown in Table 2, The correlation coefficient of 0.499 suggests a moderate positive correlation between the variables of Unemployment and Technological Advancement. This indicates that as Technological Advancement increases, there tends to be a moderate increase in the Unemployment. However, it's important to note that correlation does not imply causation, and other factors could be influencing the relationship between these variables.

Table 2 Multiple Correlations Analysis

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.499a	.249	.234	.43607
a. Predictors: (Constant), Skill Requirement, Productivity Enhancement, Operational Efficiency				

3. Regression Analysis

Based on Table 3, the multiple regression analysis examined the effects of the independent sub-variables (Productivity Enhancement, Operational Efficiency, and Skill Requirement) on the dependent variable (Unemployment). The results showed that the adjusted R Square was 0.234, indicating that approximately 23.4% of the variability in the Unemployment could be explained by the independent sub-variables. The remaining 76.6% of the variability was unexplained by the model. The coefficient of determination (R Square) also indicated that around 24.9% of the variance in the Unemployment was accounted for by the independent sub-variables. Additionally, the standard error of the estimate was 0.43607, representing the average deviation between the observed and predicted values. These findings suggest that the independent sub-variables have a moderate influence on the Unemployment.

Table 3 Multiple regression analysis

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.499a	.249	.234	.43607
a. Predictors: (Constant), Skill Requirement, Productivity Enhancement, Operational Efficiency				

The ANOVA results, presented in Table 4, indicate that the F statistic has a value of 16.277 with a p-value of .000. This p-value is significantly smaller than the conventional threshold of $p \leq .05$, suggesting strong evidence to accept the hypothesis. The global test, using the Adjusted R Square and F statistic, demonstrates that the independent sub-variables (Productivity Enhancement, Operational

Efficiency, and Skill Requirement) have the capability to explain the variability observed in the Unemployment. Consequently, the regression model can be considered acceptable.

Table 4 ANOVA analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.286	3	3.095	16.277	.000b
	Residual	27.953	147	.190		
	Total	37.239	150			
a. Dependent Variable: Unemployment						
b. Predictors: (Constant), Skill Requirement, Productivity Enhancement, Operational Efficiency						

The findings presented in Table 5 reveal that the t-statistic for the slope was significant at the .05 critical alpha level for the independent sub-variables. Specifically, the t-values for Productivity Enhancement, Skill Requirement, and Operational Efficiency were 1.957, 1.093, and 3.106, respectively, with corresponding p-values of .050, .276, and .002. These results indicate that there is a significant positive relationship between Unemployment and Productivity Enhancement, as well as Skill Requirement. This suggests that both Productivity Enhancement and Skill Requirement have a positive and statistically significant impact on the Unemployment, with regression coefficients (B) of .129 and .229, respectively, and p-values below 0.05. These findings provide support for the first and second alternative sub-hypotheses.

On the other hand, the results also indicate that the independent sub-variable, Operational Efficiency, does not have a significant impact on Unemployment. The regression coefficient (B) for Operational Efficiency is .070, with a p-value greater than 0.276. This lack of statistical significance does not support the third alternative sub-hypothesis, suggesting that Operational Efficiency does not have a significant influence on the Unemployment.

Table 5 t-statistic

Coefficientsa						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.940	.246		7.894	.000
	Productivity Enhancement	.129	.066	.179	1.957	.050
	Operational Efficiency	.070	.064	.102	1.093	.276
	Skill Requirement	.229	.074	.298	3.106	.002
a. Dependent Variable: Unemployment						

4. Hypothesis Testing

Table 5 presents the results of the hypothesis testing using the t-test.

Table 6 Summary of Hypotheses Testing Results

Alternative Hypothesis	Statement	Result
Ha	Productivity Enhancement has a significant impact on Unemployment	Supported

Alternative Hypothesis	Statement	Result
Hb	Skill Requirement has a significant impact on Unemployment	Supported
Hc	Operational Efficiency has no a significant impact on Unemployment	Not Supported

CONCLUSION

In this study, we examined the relationship between Unemployment and three independent sub-variables: Productivity Enhancement, Operational Efficiency, and Skill Requirement. Through various statistical analyses, including correlation analysis, multiple regression analysis, ANOVA, and t-tests, we have gained insights into the factors influencing the Unemployment. The findings indicate that there is a moderate positive correlation between Technological Advancement and Unemployment. This suggests that as Technological Advancement increases, there tends to be a moderate increase in the Unemployment. However, it is important to note that correlation does not imply causation, and further investigation is needed to fully understand the nature of this relationship. The multiple regression analysis revealed that approximately 23.4% of the variability in the Unemployment can be explained by the independent sub-variables: Productivity Enhancement, Operational Efficiency, and Skill Requirement. This indicates that these factors have a significant influence on the Unemployment. Specifically, Productivity Enhancement and Skill Requirement were found to have a positive and significant impact on the Unemployment, while Operational Efficiency did not show a significant effect. Furthermore, the results of the hypothesis testing, as shown in Table 5, confirmed the significance of the relationships between the independent sub-variables and the Unemployment. This study provides evidence that Technological Advancement: Enhancement, and Skill Requirement are important factors contributing to changes in the Unemployment. However, it is crucial to consider that other factors may also influence the Unemployment, and further research is needed to explore these factors and improve the understanding of the complex dynamics at play. These findings have implications for policymakers and stakeholders in addressing unemployment challenges and promoting economic growth and workforce development.

References

Abualrejal, H. M., Abu Doleh, J. D., Salhieh, L. M., Udin, Z. M., & Mohtar, S. (2017). Barriers of supply chain management practices in manufacturing companies in republic of Yemen: pre-war perspective. International Journal of Supply Chain Management, 6(3), 246-251.

Aithal, P. (2023). How to Create Business Value Through Technological Innovations Using ICCT Underlying Technologies. International Journal of Applied Engineering and Management Letters (IJAEML), 7(2), 232-292.

Almaliki, O. M. (2023). Determinants of economic development amidst political instability: Yemen's case İstanbul Gelişim Üniversitesi Lisansüstü Eğitim Enstitüsü].

ALSHAMI, R. S. (2024). IMPACT OF WAR ON THE SMALL BUSINESS SECTOR IN YEMEN AND SYRIA.

Angyridis, C., & Zhou, H. (2022). Search, technology choice, and unemployment. International Studies of Economics, 17(3), 296-310.

Bargelis, A., & Mankute, R. (2010). Impact of manufacturing engineering efficiency to the industry advancement. Mechanics, 84(4), 38-44.

Beale, N., & Nethercott, S. (1985). Job-loss and family morbidity: a study of a factory closure. The Journal of the Royal College of General Practitioners, 35(280), 510-514.

Cahuc, P., & Zylberberg, A. (1999). Job protection, minimum wage and unemployment. Minimum Wage and Unemployment (December 1999).

Caliendo, L., Dvorkin, M., & Parro, F. (2019). Trade and labor market dynamics: General equilibrium analysis of the china trade shock. Econometrica, 87(3), 741-835.

Chandrashekar, A. C., Nagar, S. V., & Guruprasad, K. (2021). A Skill Enhancement Virtual Training Model for Additive Manufacturing Technologies. Cyber-physical Systems and Digital Twins: Proceedings of the 16th International Conference on Remote Engineering and Virtual Instrumentation 16,

DAĞLI, İ. (2022). The Rise of Technology for the Future Labor Force: The Nexus between Technology and Unemployment in OECD Countries. Çalışma ve Toplum, 5(75), 2775-2794.

Dahlgren, S. (2014). More than half of society: Southern Yemeni youth, unemployment and the quest for a state job. Why Yemen Matters: A society in transition, 10, 1.

Dina, A. (1994). Skill promotion or skill exploitation? New organizational approaches in manufacturing. Control Engineering Practice, 2(4), 667-675.

Ellonen, N., & Nätti, J. (2015). Job insecurity and the unemployment rate: Micro-and macro-level predictors of perceived job insecurity among Finnish employees 1984–2008. Economic and Industrial Democracy, 36(1), 51-71.

Fiaschi, D., & Tealdi, C. (2021). A general methodology to measure labour market dynamics. arXiv preprint arXiv:2104.01097.

Finamor, L., & Scott, D. (2021). Labor market trends and unemployment insurance generosity during the pandemic. Economics Letters, 199, 109722.

Gavin, W. T. (2013). The mechanics behind manufacturing job losses. Economic Synopses, 2013(2013-07-26).

Goldmann, S., & Knörzer, M. (2023). Technology advancement propels work productivity: Empirical efficiency potential determination in marketing and sales. Managerial and Decision Economics.

Hafizji, Z., Rajput, B., & Chaudhry, A. R. (2022). Impacts of Integrating High-Tech and IoT Developments for Workplace Performance. In Applications of Computational Methods in Manufacturing and Product Design: Select Proceedings of IPDIMS 2020 (pp. 377-394). Springer.

Handoyo, S., Suharman, H., Ghani, E. K., & Soedarsono, S. (2023). A business strategy, operational efficiency, ownership structure, and manufacturing performance: The moderating role of market uncertainty and competition intensity and its implication on open innovation. Journal of Open Innovation: Technology, Market, and Complexity, 9(2), 100039.

Hiilamo, H. (2022). Machine beats man-prospects of paid work. In Participation Income (pp. 17-26). Edward Elgar Publishing.

Illing, H., Schmieder, J., & Trenkle, S. (2024). The gender gap in earnings losses after job displacement. Journal of the European Economic Association, jvae019.

Indrawati, P. D. (2015). Metode Penelitian Manajemen dan Bisnis Konvergensi Teknologi Komunikasi dan Informasi. Bandung: PT Refika Aditama.

J. Johny, M. T. (2019). Productivity enhancement in A pressure vessel manufacturing industry using lean principles.

Janeček, V., & Hynek, J. (2015). Impact of advanced technologies utilization on manufacturing firms' efficiency in times of economic decline. 2015 IEEE International Conference on Industrial Technology (ICIT),

Jarosch, G. (2014). Falling off the Ladder-Earnings Losses from Job Loss. 2014 Meeting Papers,

Juhász, R., Squicciarini, M. P., & Voigtländer, N. (2024). Technology adoption and productivity growth: Evidence from industrialization in France. Journal of Political Economy, 132(10), 3215-3259.

Khanchanapong, T., Prajogo, D., Sohal, A. S., Cooper, B. K., Yeung, A. C., & Cheng, T. C. E. (2014). The unique and complementary effects of manufacturing technologies and lean practices on manufacturing operational performance. International journal of production economics, 153, 191-203.

Kim, K.-S. (2022). A Study on the Impact Factors of R&D Efficiency and Efficiency by Technology Level : Focused on Equipment Investment in 30s Manufacturing Industries. https://doi.org/10.35373/KMES.27.1.2

LINGAN, Y. (2018). Influence of technologies like BIM, SAP and other tools for enhancement of quality and productivity of the organization based on lean manufacturing techniques. International Journal of Advance Research, Ideas and Innovations in Technology, 4(4), 129-135.

Lydeka, Z., & Karaliute, A. (2021). Assessment of the effect of technological innovations on unemployment in the European Union Countries. Engineering Economics, 32(2), 130-139.

Malhotra, R., Massoudi, M., & Jindal, R. (2023). An alumni-based collaborative model to strengthen academia and industry partnership: The current challenges and strengths. Education and Information Technologies, 28(2), 2263-2289.

Maxwell, N. L. (1989). Labor market effects from involuntary job losses in layoffs, plant closings: The role of human capital in facilitating reemployment and reduced wage losses. American Journal of Economics and Sociology, 48(2), 129-141.

Mohammed, T. B. (2019). The Impact of Technological Advancement On Entrepreneurship in an Organization. International journal of scientific and research publications (International Journal of Scientific and Research Publications (IJSRP)), Vol. 9(Iss: 6), pp 90107. https://doi.org/ 10.29322/IJSRP.9.06.2019.p90107

Montenegro, C. E. (2007). Job security and the age-composition of employment: Evidence from Chile. Estudios de Economia, 34(2), 109-139.

Mukashov, A., Breisinger, C., Engelke, W., & Wiebelt, M. (2022). Modeling conflict impact and postconflict reconstruction: The case of Yemen. Economic Systems, 46(1), 100940.

Murtin, F., & Robin, J.-M. (2018). Labor market reforms and unemployment dynamics. Labour Economics, 50, 3-19.

Nugroho, R. A., & Kartono, D. T., Areeg Gamil Al-Aghbari. (2024). The Problems of Development and Economic Security in Yemen Proceedings of Sunan Ampel International Conference of Political and Social Sciences,

Nyori, G., & K'Obonyo, P. Advanced Manufacturing Technology Adoption And Organizational Structure.

Oeij, P. R., Hulsegge, G., & van der Torre, W. (2023). The impact of technology on work: enabling workplace innovation by technological and organisational choice. Chapters, 67-90.

Picchio, M., & Ubaldi, M. (2024). Unemployment and health: A meta-analysis. Journal of Economic Surveys, 38(4), 1437-1472.

Saleh, M. A. K., & Manjunath, K. (2020). Review of Historical and Temporary Challenges Facing Small and Medium Enterprises in Yemen. International Journal of Trend in Scientific Research and Development, 4(3), 752-764.

Schmitz, C. (2012). Building a Better Yemen (Vol. 3). JSTOR.

Schweitzer, M. (2017). Manufacturing employment losses and the economic performance of the Industrial Heartland.

Sekaran, U., & Bougie, R. (2017). Metode Penelitian untuk Bisnis: Pendekatan Pengembangan Keahlian Edisi 6 Buku 2.

Sordan, J. E. E., Oprime, P. C., Ferreira, J. L., Marinho, C. A., & Pata, A. (2024). Lean manufacturing for reducing lead time in foundry processes: a design science approach. International Journal of Lean Six Sigma.

Townsend, A. R. (2024). The Impact of Recession: On Industry, Employment and the Regions, 1976–1981. Taylor & Francis.

Tuttle, T. C. (1983). Organizational productivity: A challenge for psychologists. American Psychologist, 38(4), 479.

Weaver, A., & Osterman, P. (2013). Skill demands and mismatch in US manufacturing: evidence and implications. American Economic Association 2014 Annual Meeting, Philadelphia, January,

Weaver, A., & Osterman, P. (2017). Skill demands and mismatch in US manufacturing. ILR Review, 70(2), 275-307.

Yang, X. (2014). Labor market frictions, agglomeration, and regional unemployment disparities. The Annals of regional science, 52, 489-512.

Zeebaree, M., Ismael, G. Y., Nakshabandi, O. A., Saleh, S. S., & Aqel, M. (2020). Impact of innovation technology in enhancing organizational management. Studies of Applied Economics, 38(4).

Tables Index

Figures Index

Contents