Eurasian Academy of Sciences
Eurasian Business & Economics Journal
2020 Volume: 22 S: 64-76
Published Online April 2020 (http://busecon.eurasianacademy.org)
http://dx.doi.org/10.17740/eas.econ.2020.V22-05

TECHNOLOGICAL UNEMPLOYMENT ANXIETY SCALE DEVELOPMENT

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Received Date:26.03.2020, Revised Date:18.04.2020, Accepted Date:21.04.2020

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ABSTRACT

In the post-digital ecosystem, production methods are changing radically. Thus, the need for humans dramatically decreases. Jobs in various sectors have become vulnerable due to accelerated automation. It is expected that advances in artificial intelligence technology, in particular, will cause unprecedented amount of job loss. Furthermore, unemployment would trigger other problems in economy. This can be regarded as the vicious circle of digital economy. This economical phenomenon causes anxiety in the mind of the employees, and this negative perception regarding technology may exert pernicious effect on the motivation, performance and commitment of the employees. Therefore, from the angle of management, need for measuring this perception has emerged. Within this context, the aim of this paper to develop a scale to measure the technology-induced unemployment perception of employees. As a result of the analyses, Technological Unemployment Anxiety scale was developed with the following sub-dimensions: (1) Lack of Technical Skill, (2) Incremental Technological Improvements and (3) Technological Disruption.

Keywords: Technological Unemployment Anxiety, Scale Development, Digitalization, Automation, Digital Economy
JEL-Classification: C02, E60, F23

1. INTRODUCTION

The development process of production technologies that started with the agricultural revolution and continued with the Industrial Revolution in human history is moving forward very rapidly today. The most distinctive feature of the Industrial Revolution compared to all the other revolutions is that it constantly develops and leads to new revolutions in the world. As a result of the Industry 1.0 to 4.0 improvement stages, the development of production technologies has shown great progress. Due to these changes, what the next developments will bring to human life is awaited by some people with curiosity, while others think about that future with anxiety. Although the observations show that these concerns of people are intense, this issue should be put forward in the light of concrete data. Therefore, the purpose of this research is to create a scale that will make the subject concrete and measurable in the light of personal perceptions and evaluations.

During the past half century, the technologies beginning with the use of personal computers and then followed by the internet have affected the nature of work and economy (Powell & Snellman, 2004). Nowadays, due to the inventions of modern technologies and with the effect of globalization, the distribution of information, data, and knowledge spreads very fast while all human activities are interconnected by a myriad of communication systems (Hadad, 2017; Zezulka, Marcon, Vesely, & Sajdl, 2016). Industry 4.0 has brought to life technologies that complicate the differences between the work of people and the work of machines (Ślusarczyk, 2018). As the major disruptive technology of the digital economy, the advent of the internet causes unprecedented changes in business processes. Relatedly, changing production methods trigger changes in social structure of the society. In digital economy, knowledge has emerged as the most important production factor. The importance of other production factors, especially labor, is gradually fading (Civelek M. E., 2009). Recently, advances in artificial intelligence technology are expected to cause unprecedented amount of job loss in several sectors (PwC, 2019). Also, especially in the recent years, pandemic problems affecting the social and work life of people further increase the level of unemployment anxiety of individuals.

As an economical concept, technology-induced unemployment was firstly defined by John Maynard Keynes in 1930 in his paper entitled Economic Possibilities for our Grandchildren. Keynes put forward original and farsighted ideas about technological unemployment and called the future as age leisure because there would be no need to work in the future. But he also defined technological unemployment as a disease infecting humanity (Keynes, 1931). Source of the technological unemployment concept depends upon Luddite movement. Luddism was originated at the end of the 18th century by British handweavers who aimed to destroy textile machines. Handweavers feared losing their jobs due to technology-related unemployment. This incident called as Luddite fallacy because machines created new jobs contrary to the estimated. Accordingly, Schumpeter argued that unemployment stems from innovation would recover over time (Schneider, 2017). However, this approach is not valid for the digital economy.

Especially advancing in artificial intelligence technology will inevitably lead to a significant loss of work (Ford, 2015).

2. THE POST-DIGITAL ECOSYSTEM AND UNEMPLOYMENT

In the post-digital ecosystem, all business processes undergo radical changes. The main economic goals of many governments are to increase the number of the employed person in labor supply. The labor supply consists of both employed and unemployed people. Looking at the 2020 January OECD Harmonised Unemployment Rate data in some countries, the following figures emerge: the United States 3.6%, Canada 5.5%, Portugal 6.9%, France 8.2%, Italy 9.8%, Spain 13.7%, Greece 16.3%. The averages of the OECD countries were 5.1% and the European Union including 28 countries were 6.2%. In the OECD countries 32.9 million people were unemployed (OECD, 2020). In Turkey, 2019 when this research was conducted, December unemployment rate was 13.7% (TUIK, 2020). Unemployment is still an unresolved problem in many countries, the unemployment rates of the countries fluctuate every year, and thus, it is hard to predict what will happen in the face of developing technologies.

With respect to the technological developments, automation and artificial intelligence lead to more efficient and effective production methods. Changing in production methods will inevitably cause considerable increase in unemployment. Rising unemployment will cause to demand uncertainty. This is the vicious cycle of the post-digital ecosystem. This vicious cycle would lead the current economic system to collapse. During the recent years, excess fiat money has been injected to revive the economy and personal debt ratio of the people has increased (Civelek, 2018). Increasing inequality is the most important feature of the post-digital ecosystem. In this new ecosystem, digital divide leads to economical divide. Digital divide is the inequality in access to technological communication facilities especially the internet. In digital economy, knowledge is a production factor and therefore digital divide causes economic inequality (Civelek M. E., 2009). Furthermore, advances in artificial intelligence technologies decrease labour force (Ford, 2009). Inequality and unemployment will lead to chaos because consumers who demand products are constantly losing their jobs.

Today, artificial intelligence and robot technologies are advancing at an accelerated pace. It is estimated that these technologies could boost productivity but at the same time, they will also cause unemployment rate to reach a very high level. It is estimated that job loss will take place in three consecutive waves until 2030s. The first wave is named as algorithm wave and it is currently happening. Algorithm wave refers to automation of simple computational tasks. The second wave is augmentation wave which refers to automation of repeatable tasks like autonomous aerial drones and robots in warehouses. This wave is currently underway, and expected to reach maturity until the end of 2020s. The third wave is autonomy wave. In this period, robots are expected to gain manual dexterity and problem-solving ability by the end of 2030s (PwC, 2019). Wright & Schultz (2018) point out that many countries see the next wave of automation as a strong potential disruption that will affect its citizens. According to OECD (2019) predictions, as a result of automation in the next 15-20 years, 14% of the existing jobs could disappear. Also, another 32% are likely to change radically as individual tasks are automated.

3. UNEMPLOYMENT ANXIETY AND NEED FOR INDICATOR

As an output of industrial revolution stages, newly invented machines and automation continue to take over jobs that used to be done by humans previously. Simultaneously with automation, digital technologies especially marketplaces on the internet also allow firms to scale upwards or downwards in trade very quickly. These rapid scale changes in businesses lead to organizational change very fast, and such developments can easily cause employees to lose their jobs. Technology is blurring the boundaries of the firm (the rise of platform marketplaces) and it is reshaping the skills needed for work while some human skills can be replaced by technology (The World Bank, 2019). As the labor market changes, educational and social changes jointly occur with it (Loren, 2014). Soon, artificial intelligence will be able to realize all the related processes and transactions in the most optimum way without needing human intervention. These technological developments create unemployment anxiety for many employees about their future. At this point, technology is a threat to the job status.

As a main management result of disruptive technological changes in the world, unemployment anxiety is the insecurity feeling of employees about their future. This feeling causes an increased level of stress on individuals, lowers self-motivation, decreases commitment to job and work performance, and leads to less participation of employees in the decision-making processes. Researchers mention that job-insecure employees are usually in an undesired zone between employment and unemployment (Niesen, et al., 2018) and the increasing level of challenge of the organizations and the management is to ensure that employees are assured of their jobs (Lucky, Minai, & Rahman, 2013). Therefore, in the managerial context of unemployment anxiety, managing the declining performance, commitment and motivation of employees are all great difficulties for the managers of today and tomorrow while achieving organizational goals.

Technological, economic, social and political changes in the last years have become the primary concern of employees and employers (Shoss, 2017; Barling & Cooper, 2008). Researches in the literature underline the positive relationship between perceived job insecurity and psychological distress (Kekesi & Agyemang, 2014; Richter, Tafvelin, & Sverke, 2018). Also job insecurity indirectly increases the adoption of negative decision-making strategies, lowers satisfaction of the job and supervisors, higher turnover intentions and work withdrawal behaviors (Probst, 2005). According to Dickerson & Green (2012), employment insecurity causes the following feelings in the employees: the risk of job loss, the chances of not finding another job, loss of income while unemployed, and uncertainty over job content.

Unemployment is a situation that can emotionally wear individuals out. It often involves loss of daily activities, social support and status. Many unemployed individuals feel a sense of aimlessness. The basic life requirements of people are met through employment. In the case of unemployment, individuals might feel increased levels of anxiety and depression, lower self-esteem, and adverse physical health consequences (Linn, Sandifer, & Stein, 1985). Therefore, unemployment anxiety affects both mental and physical health. Economically, when the job is lost, there might be a period of unemployment and lower income in the future (Green , 2015). All the feelings regarding the odds-of not finding another job, loss of income and uncertainty affect the concentration of the employee on his or her job.

The level of feeling unemployment anxiety might vary from employee to employee depending on their contract status and their occupational class. Usually, employees on temporary contracts are more worried than those on permanent contracts (Gallie et. al., 2017). Employees with temporary contracts are aware that they need to find another job or project after the end of the contract and that is not an easy thing to do. Their psychology is affected more compared to permanently contracted employees. The technological unemployment anxiety level of individuals may vary from occupation to occupation as well. Employees who think that they have professions that cannot be replaced by technology may feel this anxiety less than others. Unemployment anxiety is mostly felt by employees who lack technical skills. These people are commonly unable to improve their skills because of technical incompetency. A distinct reason for this situation is the generational difference between employees.

4. SCALE DEVELOPMENT METHODOLOGY

Scale development process consists of two phases. Initially, a qualitative study was conducted in order to identify and distinguish the anxieties of employees regarding digitalization and automation. In this phase, the items of the questionnaire were generated by means of interviews and group discussions. Face-to-face meetings were held with 21 employees in various hierarchical levels and sectors. In the second phase, a field survey was performed, and through this, the quantitative data were collected. The sample size consists of 520 valid questionnaires. Explanatory factor analysis was conducted on the data for purification and subsequently confirmatory factor analysis was conducted for the determination of the convergent validity. In addition to these, square roots of average variance extracted (AVE) values were calculated to determine the discriminant validity. After that, for the determination of reliability, Cronbach α and composite reliability were used. Consequently, the items in the scale were grouped under three dimensions. Sub-dimensions of Technological Unemployment Anxiety scale were denominated as (1) Lack of Technical Skill, (2) Incremental Technological Improvements and (3) Technological Disruption.

5. CONSTRUCT VALIDITY AND RELIABILITY

At the first stage, all the questions were entirely included in the principle component analysis. After this explanatory factor analysis, data purified and items listed in Table 1 were removed from the scale.

Table 1. Removed Statements after Explanatory Factor Analysis

Title of Sub-Dimension	Items	Statement
Lack of Technical Skill	LTS00101	I think that my current professional technical knowledge will not be sufficient after a while as a result of the technological developments.
	LTS0202	I think the education I have received will be insufficient to meet my future professional needs.

Incremental Technical Improvement	ITI0511	I think that the number of employees in the unit I work for will decrease as a result of the technological advancements.
Technological Disruption	TDS0112	I think that the advancement of technology will kill my profession.

After the explanatory factor analysis, 12 items remained. In the second step, the convergent validity of the scale was investigated. Therefore, confirmatory factor analysis was performed (Anderson & Gerbing, 1988). As the prominent indicator of the convergent validity, the fit indices values were evaluated. The satisfactory fit indices values obtained are as follows: $\chi 2/DF = 1.83$, CFI=0.95, IFI=0.95, RMSEA= 0.08.

CMIN/DF ratio yielded a result under the threshold level of 3 (Bagozzi & Yi, 1990). CMIN refers to the likelihood ratio chi-square test which is the most important indicator of the conformity of the initial model and acquired model. Other fit indices approached their recommended thresholds. Subsequently, factor loads that resulted from the confirmatory factor analysis were evaluated. The standardized factor loads are indicated in Table 2. Loads of each item were found ~~as~~ to be larger than 0.5 and significant. This result can also be considered as the power and validity of the scale.

Table 2. Confirmatory Factor Analysis Results

Variables	Items	Standardized Factor Loads	Unstandardized Factor Loads
Lack of Technical Skill	LTS00505	0.706	1
	LTS0404	0.752	0.635
	LTS0606	0.671	0.936
	LTS0303	0.937	1.187
Incremental Technical Improvement	ITI0309	0.804	1
	ITI0107	0.759	1.065
	ITI0410	0.880	1.246
	ITI0208	0.861	1.167
Technological Disruption	TDS0516	0.795	1
	TDS0415	0.697	0.837
	TDS0213	0.770	0.859
	TDS0314	0.885	0.938

$p<0.05$ for all items

Another indicator of the convergent validity is AVE (Average Variance Extracted) value of each construct. Results are obtained beyond the threshold level (i.e. 0.5) (Byrne, 2010). AVE values are shown in Table 3. Additionally, the discriminant validity of the scales was examined. In order to determine discriminant validity, square roots of AVE values were calculated and compared with the correlation coefficient (Civelek M. , Essentials of Structural Equation Modeling, 2018). The obtained results are greater than the correlation coefficient in the same column as shown in Table 3. These results indicated discriminant validity.

In order to determine the reliability of the new developed scale, composite reliability and Cronbach α were calculated for each construct separately. All the values are beyond the threshold level (i.e. 0.7), as shown in Table 3 (Fornell & Larcker, 1981).

Table 3. Construct Descriptives, Correlation and Reliability

Variables	1	2	3
1.Lack of Technical Skill	(.773)		
2.Incremental Technical Improvement	.464*	(.827)	
3.Technological Disruption	.594*	.633*	(.789)
Composite reliability	.854	.896	.868
Average variance ext.	.598	.685	.623
Cronbach α	.829	.898	.857

*$p < 0.05$
Note: Diagonals show the square root of AVEs.

In Table 3, Pearson correlation coefficients, AVE values, composite reliabilities and Cronbach α values are indicated.

Table 4. Statements of the Technological Unemployment Anxiety Scale

Title of Sub-Dimension	Items	Statement
Lack of Technical Skill	LTS00505	I think I will lag behind in terms of performance as technology advances.
	LTS0404	I do not feel comfortable using the technologies such as the internet and smartphones.
	LTS0606	I do not think I will be able to improve myself aptly so that I can adapt to technological advances.
	LTS0303	I find it difficult to adapt to the systems I use while doing my job.
Incremental Technical Improvement	ITI0309	I think that the change in the business processes due to the technological advancements will make me unhappy in the future.
	ITI0107	I think that the continuous improvement of the systems used in the workplace will reduce the need for me over time.
	ITI0410	I think my business life will become shorter as a result of the technological advancements.
	ITI0208	As a result of the continuous advancement of technology, I think my current job description will change in a way that will affect me negatively.
Technological Disruption	TDS0516	I am worried that I may spend the rest of my life as unemployed due to the new technologies.
	TDS0415	I think that the education I have received at school will be invalid due to technological advances.
	TDS0213	I think that technological advances may cause the organization I am working for to close down in the future.
	TDS0314	I think that technological advancements can completely eliminate the business line I have trained.

6. CONCLUSION

The researches in the literature show that individuals will face drastic changes and many of them will have to change not only their jobs but even their occupations. Due to projected technological changes in the future, most individuals will need to upgrade and modernize their skills, and thus reinvest to improve their competencies.

In this scale development research, the unemployment anxiety is gathered under three dimensions: (1) Lack of Technical Skill, (2) Incremental Technological Improvements and (3) Technological Disruption. Lack of Technical Skill, the first dimension, refers to the fact that individuals have the perception that they are unable to improve themselves due to technological advances and feel uncomfortable using the new technologies and systems while performing their jobs. The second dimension, namely, Incremental Technological Improvements, means that individuals have the perception that their business life will become shorter, hence, the changes in the business processes and job description will affect them negatively. Finally, Technological Disruption means that individuals have the perception that technological advancements will completely eliminate some of the business lines, many people will be unemployed in the rest of their lives, the school education that people have received will be invalid and many organizations will close down in the future.

All things considered, this is a new scale development research, which can be regarded one limitation of the study. Since this is a newly developed scale, there is the need of testing it in different samples and industries. The more the scale is tested and verified, the more it will contribute to the literature.

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