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AUTOMATION AND ITS EFFECT ON STEM OCCUPATIONS. ECONOMIC AND ETHICAL IMPACT

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Abstract. The article discusses the effect of automation on occupations in general and more specifically on STEM jobs in the USA. The analysis considers characteristics of occupations and their classification into routine and non-routine tasks followed by the examination of occupations' susceptibility to transformations due to advancements in computer technologies and resulting automation. STEM occupations and their various vulnerability to automation are discussed. Future trends which will affect STEM workforce of various industries are addressed. The socio-economic and ethical ramifications of the technological changes in the USA and beyond are discussed as well.

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1. INTRODUCTION

With the introduction of the division of labor, Adam Smith's "The Wealth of Nations" laid the foundation of the capitalistic market system of mass production we have today. Ever since the dawn of industrial revolution manufacturing industries have been transforming and improving their processes to increase productivity. Modern and post-modern economies are expanding the use of automation employing computerization in areas beyond traditional, well established manufacturing industries to include service sectors. Recent developments in artificial intelligence (AI), machine learning (ML), big data (BD) and its algorithms, as well as mobile robotics (MR) made automating plausible even in cognitive non-routine based occupations. Automation and computerization are not synonymous. Traditionally, automation was understood as mechanization of a processes. Computerization refers to the use of computer-based technologies for variety of tasks including problem-solving. In recent decades, computer-based systems became a vital component of the control schemes of the automated mechanized processes. Computerization is an increasingly important component of automation.

2. CONCEPTS OF WORK AND AUTOMATION

Here concepts of work and automation are defined as applied to the analysis of susceptibility of various occupations including STEM area to technological advancements.

2.1. Concept of Work

Work was the subject of investigation by variety of disciplines such as philosophy, sociology, economics, and ethnographics. The concept itself underwent changes in understanding and interpretation as civilizations and nations advanced from agrarian to industrial, and in the last century from modern to postmodern societies (Segal, 2001). Here we assume the definition of work following Heyman (2005) who wrote that "only when effort – physical and mental – is turned into a commodity sold to an employer who then monitors and controls it can we discern an abstract concept of 'work'." This interpretation will be adopted here since the focus will be placed on tasks in the realm of "work" susceptible to automation. Other concepts of "a work" outside of that understanding as related to finished manufactured articles made by craftsman, artist, farmer, etc., will be out of scope of this article.

2.2. Concept of Automation

Here we will use the term of automation, after Merriam-Webster dictionary (Merriam-Webster, 2017), as “the method of making a machine, a process, or a system work without being directly controlled by a person.” Scenario of the past decades where one of the main determining factor of automation was an ability to replace routine manual activities with automated mechanization is being expanded to include a non-routine based tasks. Consequently, the previous era where manufacturing industries dominated processes of automation is being expanded to include automation of tasks and jobs in service sectors. Automation will increasingly include computerization of not only routine, but also non-routine tasks.

3. JOB TRENDS

Ever since the Industrial Revolution there was a fear among labor and society in general that automation will lead to mass unemployment. While it is true that automation eliminated the need for some occupations, the advancement of technology created demand for labor in different types of jobs. For example, the nineteenth century mechanization of manufacturing processes by simplifying tasks created demand for more numerous but less skilled workers (Segal, 2001). Accordingly, in the nineteenth century the unskilled workers “have been the greatest beneficiary of the Industrial Revolution” (Clark, 2008). However, in modern times this changed. Automation no longer just simplifies tasks, but also completes not only simple tasks but increasingly complex ones as well. Acemoglu (2002) wrote that “the idea that technological advances favor more skilled workers is a twentieth century phenomenon.” Frey and Osborne (2013) added “The conventional wisdom among economic historians… suggests a discontinuity between the nineteenth and twentieth century in the impact of capital deepening on the relative demand for skilled labour.” In short, in the nineteenth century, automation created increased demand for labor, specifically, less-skilled labor; however, in modern times, automation is reducing the demand for less-skilled labor but is increasing demand for high-skilled workers.

With increasing computerization and sluggish economic growth globally, it is not surprising that today’s society is once again concerned with possible mass unemployment. Frey and Osborne (2013) examined the probability of computerization for many occupations in the USA based on data from the U.S. Bureau of Labor Statistics (BLS) and found that 47% of workers are at “high risk of potential automation”. Subsequent reports place the equivalent number at 35% of the workforce for Great Britain and 49% for Japan, reflecting the different respective levels of creative occupations, which are based on creative attributes (designing, writing, creating) of job responsibilities versus total workforce in these countries (Frey and Osborne, 2013). Similarly, Chui, Mayika and Mireadi (2016) showed that present day technologies "could automate 45 percent of the activities people are paid to perform and that 60 percent of all occupations could see 30 percent or more automated." Chui et al. (2016) reported that irrespective of the occupations, one-third of the time spent on the job involves data collecting and processing, which have the "potential for automation exceeding 60 percent." Chui et al. (2016) listed five factors which influence the extent of an automation: technical feasibility, costs to automate, the relative scarcity of workers with skills, benefits, and regulatory and social considerations. Essentially, implementation of automation of tasks and occupations is and will be determined and influenced by a composition of factors.

There is no surprise then that the Pew Research Center (Smith, 2016) reported that "two-thirds of Americans expect that robots and computers will do much of the work currently done by humans within 50 years." Accordingly, 17 percent of workers who perform mostly routine manual or physical labor and 5 percent of workers whose activities do not encompass manual or routine tasks feel concern for the threat of automation (Smith, 2016).

Autor, Levy and Murname (2003) recognized the differences between non-routine and routine tasks, and between manual and cognitive occupations and their various susceptibility to automation. Frey and Osborne (2013) investigated 702 different occupations in the USA and their probabilities of automation. While routine manual and routine cognitive occupations were the most susceptible to automation, the non-routine manual and especially non-routine cognitive tasks were the least susceptible (Frey & Osborne, 2013). Chui et al. (2016) investigated the technical feasibility to automation of various activities resulting in the following categorization with descending probability of automation: predictable physical/manual work, data collection and processing, unpredictable physical work, stake-holders interactions, applying expertise, and managing others. Chui et al. (2016) found the most susceptible activities and their corresponding occupations in: food service and accommodation, operating machinery, predictable (Frey's "routine") physical work, retailing, and data collection and processing; less susceptible: unpredictable physical work (unpredictable environment/machinery); and the least susceptible activities in: managing others and expertise-based. Surprisingly, they found occupations with relatively high level of expertise to fall into a middle range of technical susceptibility such as financial services and insurance due to the fact that these occupations spend "50 percent of time" on data collection and processing which are highly prone to automation.

The susceptibility to automation is reflected in employment trends where jobs in the middle-skill set (manufacturing) are declining, while low-skill set (low paid) and high-skill sets (high paid) jobs are on the rise leading to the bifurcation of the available jobs with hollowing of the middle section of the wage scale (Morgenstern, 2016). In the USA, while employment in routine manual and routine cognitive jobs remained mostly flat with fluctuations between 27 and 36 million between the years of 1983 and 2014, employment in non-routine manual and especially non-routine cognitive jobs roughly doubled from 13 million to 26 million, and from

28 million to 57 million, respectively (Morgenstern, 2016). This is illustrated in Figure 1 with data from the Federal Reserve Bank of St. Louis (Morgenstern, 2016).

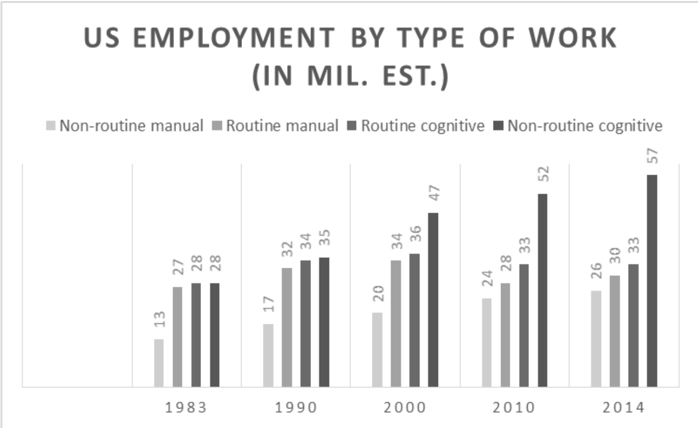

Fig. 1. Graph based on data from Federal Reserve Bank of St. Louis, U.S. Population Survey

4. STEM AND STEM EMPLOYEMENT

Here the concept of STEM is defined followed by an analysis of current U.S. STEM employement.

4.1. STEM

Although there is no uniform definition of STEM, there is a general agreement that the abbreviation stands for science, technology, engineering, and mathematics, areas that are used by theoreticians and practitioners alike to describe disciplines which explain how phenomena/devices work and solve specific scientific and engineering problems (Viloro, 2014). Viloro provided an overview of current, as of 2014, STEM occupations of the most currently employed, projected future employment, and growth in employment. Viloro's extensive list of circa one hundred different STEM occupations can be grouped into the following major categories: (1) management, (2) computer and mathematics, (3) architecture and engineering, (4) life, physical and social science, (5) healthcare, (6) education, training and library, (7) sales and related. Irrespective of occupation, due to the advancement and use of digital technologies in almost all areas of knowledge creation and goods and services production, workers utilize computers and associated digital tools in increased scale and numbers. This fact is particularly true for STEM occupations where use of computer technologies became ubiquitous.

4.2. STEM Employment

According to data from the USA Department of Labor, Bureau of Labor Statistics (BLS), U.S. STEM employment has experienced an increase across the nation between 2009–2016. Table 1 shows the U.S. states with the largest changes in STEM employment. During this period, the most populous states increased STEM jobs by 160,960 in California, 102 190 in Texas, and 42,990 in New York. By comparison Pennsylvania added 29 560 STEM jobs. Several states have experienced STEM employment growth of more than 20 percent including North Dakota 26.3%, Tennessee 24.9%, Oklahoma 24.4% to name a few, compared with the national average of 10.5%. Only few states experienced a decrease in STEM jobs: including Kansas with –5.7%, and New Hampshire with –3.8% among others.

Table 1. U.S. Employment change for STEM occupations, May 2009 to May 2015. U.S. selected states with the biggest change of employment with either an increase or decrease. Source: U.S. Dept. of Labor. Bureau of Labor Statistics (BLS) (https://www.bls.gov)

US State	Percent STEM Employment Change Increase	Employment Change
North Dakota	26.3	3 920
Oklahoma	24.4	16 470
Tennessee	24.9	25 590
Oregon	22.2	21 940
Nebraska	18.8	7 850
Georgia	18.9	38 400
Arizona	18.6	27 340
Utah	17.1	12 780
Michigan	16.1	41 110
California	15.8	160 960
Texas	15.6	102 190
New York	10.1	42 990
Pennsylvania	9.7	29 560
	Decrease	
Kansas	–5.7	–4 370
New Hampshire	–3.8	–1 650
New Jersey	–3.0	–8 100

As of 2015, seven out of the top ten STEM professions are computer related totaling 3 285 350. See Table 2 for details. Of the non-computer related professions, sales representatives of manufacturing, technical, and scientific products totaled 334 010, mechanical engineers totaled 278 340, and civil engineers totaled 275 210.

Table 2. Employment for the largest STEM occupations, May 2015. Source: U.S. Dept. of Labor. Bureau of Labor Statistics (https://www.bls.gov)

Largest USA STEM Occupations	Employment (jobs)
Software developers, applications	747 730
Computer user support specialists	585 060
Computer systems analysts	556 660
Software developers, systems software	390 750
Network and computer systems administrators	374 480
Computer and information systems managers	341 250
Sales representatives, wholesale and manufacturing, technical and scientific products	334 010
Computer programmers	289 420
Mechanical engineers	278 340
Civil engineers	275 210

The smallest STEM employment occupations are in the mathematical and agriculture sciences to name a couple categories (Tab. 3). These categories provide employment that amounts to a few ten of thousand nationwide.

Table 3. Employment for the smallest STEM occupations, May 2015. Source: U.S. Dept. of Labor. Bureau of Labor Statistics (https://www.bls.gov)

Smallest USA STEM Occupations	Employment
Nuclear science teachers, postsecondary	6 500
Environmental science teachers, postsecondary	5 540
Epidemiologists	5 460
Mathematicians	3 170
Animal scientists	2 430
Agricultural engineers	2 330
Mathematical science occupations, all other	1 880
Astronomers	1 760
Forestry, conservation science teachers	1 660
Mathematical technicians	820

The BLS classification and data are used in the following sections to assess an impact of automation on various occupations.

5. MANUFACTURING AND STEM OCCUPATIONS: GLOBAL AND LOCAL TRENDS

It is hard not to overstate the importance of STEM occupations in manufacturing as the major contributing factor to economic development and the increasing living standards world-wide. Karlgaard (2017) states that "manufacturing has the best wealth- and job-multiplier effect." According to a POSCO (South Korean steel industry global company/conglomerate) presentation (WEEF, 2016), manufacturing "has been the major economic and industrial growth engine, not only in Korea but also globally." Manufacturing contributes 16 percent to GDP globally, provides 62 million jobs, and provides 2/3 of global exports (WEEF, 2016). However, manufacturing sector jobs as "a percentage of the labor force has steadily fallen from
a peak of 22% in 1977 to about 8% today" (Karlgaard, 2017). Despite of the declining contributions in workforce, manufacturing still employs 20% of Germany's workforce and 17% of Japan's workforce. Manufacturing plays a substantial role in the economic growth of major economic powerhouses: contributing 23% to the GDP of Germany, 18% in Japan, 13% in the UK, 10% in the USA, and 30% in South Korea (WEEF, 2016). South Korea is quite an outlier. This is due to its long term, national economic policies promoting technology and manufacturing. As mentioned above, in South Korea manufacturing contributes 30% to GDP, 3 million jobs in a population of circa 30 million and accounting for 90% of national exports (WEEF, 2016). Currently, South Korea is preparing for the next generation of current information era, an era what POSCO and Samsung Corp. (WEEF, 2016) envision to be a "smart era" with "smart industry", where Information and Computer Technology (ICT) with Internet of Things (IoT), BD, and AI will lead technological progress. STEM occupations will play an even bigger role in the future due to the increased requirements of high-tech knowledge and skills.

The effects of automation in manufacturing and robotics on the workforce have been the subject of numerous publications that include journal papers and newspaper articles (Ford, 2015; Gapinski & Czajkiewicz, 2009; Manjoo, 2017; Lohr, 2017; Aupperle, 2017).

Manual, routine jobs such as machine operators and professional truck drivers are particularly vulnerable due to developments in automation of routine tasks including autonomous, driverless technologies pursued nowadays by numerous companies (Isaac, 2017a; Manjoo, 2017; Lohr, 2017). Automation has expanded into sectors such as the energy sector eliminating many blue-collar jobs in gas exploration while creating demand for high-tech workers (Krauss, 2017; Gapinski, 2014). Computers now control multiple drilling sites replacing manual control and wireless technologies allow for remote monitoring either onshore or miles out to sea. Modern technology with automated controls, instrumentation, and sensory environments create demand for STEM college graduates and workers (Krauss, 2017).

South-Western Pennsylvania underwent quite a dramatic and successful transformation from an almost exclusively heavy industry based economy to a high-tech region with companies in sectors such as material engineering, robotics, bio-medical sciences, healthcare, industrial equipment, advanced manufacturing, energy, and automated steel and coal production (Gapinski & Czajkiewicz, 2009; Gapinski, 2014; Aupperle, 2017). STEM occupations are a significant contributor to the local workforce. The expected retirement of skilled workers in the region and nationwide will exasperate the shortage of skilled employees across many sectors including STEM in IT, business and finance, health care and life sciences, energy and advanced manufacturing (Oliver & Denova, 2016). There are multiple initiatives nationwide and locally such as the Appalachia Partnership Initiative with Chevron Appalachia, the Claude Worthington Benedum Foundation, and RAND Corporation that address the “gaps in skills and the talent pipeline to prepare for long term vitality” across the tristate area of Pennsylvania, West Virginia and Ohio (Oliver & Denova, 2016).

Various initiatives are being implemented at the K-12 education level. Although Pennsylvania initially brought the introduction of computer based instructions, “digital world,” more than three decades ago to the public schools (Balser, 2017), it was done not on a wide, compulsory basis. Recently, in 2016 Pennsylvania “allotted computer science a place in schools, ruling that high school computer science can be counted as a credit toward graduation in science or math” (Balser, 2017). Currently, in Pennsylvania “about 50 percent of high schools offer computer science in some form” including electives, but this does not compare favorably with English speaking educational systems elsewhere, beyond the U.S.A., where computer science is often one of the curriculum requirements (Balser, 2017). Some school districts in Pennsylvania have placed a renewed emphasis on STEM education by adding an art component (STEAM) and “breaking barriers among subject areas” by “integrating STEM into all of the classes” and by bringing “real-life problems” to the classroom (Erdley, 2017). With early introduction to robotics and writing programming code, educators intend to instill life-long abilities in “critical thinking, problem solving, working with others, and a different way of thinking (outside the box)” (Erdley, 2017). Industry recognizes its role in encouraging STEM education by sponsoring various initiatives such as robotics competitions in Pennsylvania and elsewhere nationwide (Robotics, 2016).

6. STEM OCCUPATIONS AND THEIR SUSCEPTIBILITY TO AUTOMATION

The invention and wide application of the digital computer led to the third industrial revolution at the end of the twentieth century. With this revolution came an “increasingly polarized labor market, with growing employment in high-income cognitive jobs and low-income manual occupations, accompanied by hollowing-out of middle-income routine jobs" (Frey & Osborne, 2013). The nature of various occupations: routine manual, non-routine manual, routine cognitive, and non-routine cognitive makes their vulnerability to computerization an inconstant quantity. Past automation of routine manual jobs is being expanded to include routine cognitive jobs and tasks beyond traditional occupations prone to computer-based automation. Frey and Osborne (Frey & Osborne, 2013) categorized hundreds of occupations based on susceptibility to automation using a probability risk value (p): high ($p > 0.7$), medium ($0.3 < p < 0.7$), and low ($p < 0.3$). Frey and Osborne (Frey & Osborne, 2013) identified the factors related to job characteristics such as perception and manipulation (manual dexterity), creative intelligence, and social intelligence affecting the susceptibility of various occupations to computerization processes. The same factors may also define "engineering bottlenecks" that could prevent computerization (Frey & Osborne, 2013) and thus automation of tasks. As expected, non-routine cognitive tasks and occupations including STEM tasks and jobs have the lowest probability of being automated. Based on cited studies (Frey & Osborne, 2013; Chui et al., 2016) one can claim that since STEM occupations tend to require rather high cognitive and knowledge skill set, these jobs would be the least susceptible to automation. However, within the STEM group there are occupations in each of the above mentioned groups (routine manual, routine cognitive, non-routine manual, and non-routine cognitive), which exposes many STEM jobs to possible automation.

Table 4 lists STEM professions grouped together based on low, medium, and high probability of automation with thresholds of 0.3 and 0.7 based on data from Frey and Osborne (Frey & Osborne, 2013). STEM occupations that are relatively high in knowledge, cognitive character, and non-routine in nature have the lowest probability (below 0.3) of automation, these include: sales engineers, physicians and surgeons, computer systems analysts, chemical engineers, civil engineers, electrical power-line installers and repairers, electrical engineers, information security analysts, web developers, etc. On the other end the spectrum with respect to susceptibility to automation are the following STEM occupations or professions: mathematical technicians, surveying technicians, electrical/electronic assemblers, accountants and auditors, electro-mechanical technicians, avionics technicians, statistical analysts, computer support specialists, geoscientists, chemical technicians, mining machine operators, electrical/electronic/industrial equipment repairers, etc. (Tab. 4).

As noted in Table 4, occupations with higher knowledge prerequisites and non-routine cognitive characteristics have lower probability numbers and consequently are less prone to be automated. Consequently, STEM occupations which represent opposite characteristics, i.e., that of being either routine manual, routine cognitive, or non-routine manual are the most vulnerable and may experience increasing pressure of automation in the coming decades if not sooner.

Table 4. Ranking of STEM occupations according to susceptibility to computerization. Based on C.B. Frey & M.A. Osborne (2013)

Ranking of selected STEM occupations according to probability of computrization from low to high	Probability of computerization
Sales engineers	0.0041
Physicians and surgeons	0.0042
Computer systems analysts	0.0065
Chemical engineers	0.0170
Civil engineers	0.0190
Electrical power-line installers and repairers	0.0970
Electrical engineers	0.1000
Information security analysts, web developers	0.2100
Engineering technicians	0.2400
Electrical/electronics repairers, industrial equipment	0.4100
Mining machine operators	0.5400
Chemical technicians	0.5700
Geoscientists	0.6300
Computer support specialists	0.6500
Statistical analysts	0.6600
Avionics technicians	0.7000
Electro-mechanical technicians	0.8100
Accountants and auditors	0.9400
Electrical/electronic assemblers	0.9500
Surveying technicians	0.9600
Mathematical technicians	0.9900

7. FUTURE TRENDS IN STEM OCCUPATIONS

With a time horizon of “perhaps a decade or two” Frey and Osborne (2013) estimated that almost 50 percent of total U.S. employment is in the high-risk category of being automated. The list of occupations covered by the study is quite extensive and it covers STEM specialties as well. In their analysis (Frey & Osborne, 2013) the distribution of occupational employment for BLS 2010 data shows the “hollowing out” of employment in occupations with the middle range of susceptibility to automation. That is, while 19 percent of employment has occupations with middle range of vulnerability, 33 percent of jobs are in the lower range of vulnerability to automation, and already 47 percent of employment shows a high susceptibility level. The holders of occupations in the high susceptibility range, consequently, should be cognizant of the high susceptibility to automation and should proactively initiate acquiring new skills and even change careers. Automation has already led to a bifurcation of salary levels with high-end, non-routine cognitive and knowledge-based occupations on one end of the spectrum and routine, low-skilled occupations on the other end. The same trends are observed within STEM occupations.

Table 5 and Table 6 show the projected growth rates for various types of STEM occupations from 2014 to 2024, according to the U.S. Bureau of Labor Statistics. Considering the susceptibility to automation coefficients as indicated by data in the added columns in Tables 5 and 6, the accuracy of the BLS data have to be questioned. For example, while BLS predicts an increase of 28.2 percent in mathematical science occupations, the very high susceptibility to automation factor for mathematical technicians, may significantly tamper future employment in this field, if not eliminate it all together.

Table 5. Projected growth rates for various type of STEM occupations, 2014 to 2024. Based on data from U.S. Dept. of Labor. Bureau of Labor Statistics (https://www.bls.gov) and C.B. Frey & M.A. Osborne (2013)

STEM occupation group	Percent Change	Probability of Computerization
Mathematical science occupations **Mathematical Technicians**	28.2	0.047 0.990
STEM-related postsecondary teachers	13.4	0.008
Computer occupations **Computer programmers**	12.5	0.220 0.480
STEM-related management	10.1	0.250
STEM-related sales **Sales engineers**	6.9	0.004
Physical scientists **Biological scientists**	6.7	0.015
Life scientists **Biological scientists**	6.1	0.015
Architects, surveyors, and cartographers **Surveyors**	6.1	0.380
Life and physical science technicians	5.3	0.610
Engineers **Electrical engineers** **Industrial engineers**	4.0	0.100 0.029
Drafters, engineering technicians, and mapping technicians **Nuclear, electrical technicians and repairers** **Electricians**	–1.4	0.810 0.360–0.850 0.150

Interestingly, the U.S. BLS shows the projected growth for employment in various STEM disciplines that do require and do not require a B.S. degree. The occupations vary from computer and computer technology related to engineering

& science to technicians in various disciplines from nuclear, electrical, surveying, to life and physical science areas. Table 6 shows the occupations that can be performed by academic degree holders of 2-year college degree programs or various technical certifications. The list contains: web developers, technicians in various fields such as agriculture, geological and petroleum, computer technologies, health, etc. According to forecasts in various studies including ones by Frey and Osborne (2013) and Chui et al (2016) the occupations listed in Table 6 that do not require a B.S. degree are more vulnerable to computerization. Thus, these occupations may experience a decrease in employment in the coming decades due to the lower cognitive and knowledge skill set prerequisites even if they are non-routine and unpredictable in nature.

Table 6. Ten fastest growing STEM occupations that do not require a B.S. degree, 2014 to 2024 (projected). Based on data from U.S. Dept. of Labor. Bureau of Labor Statistics (https://www.bls.gov) and C.B. Frey & M.A. Osborne (2013)*

STEM occupation group	Percent Change	Probability* of Computerization
Web developers	26.6	0.21
Computer user support specialists	12.8	0.22
Geological and petroleum technicians **Chemical equipment operators**	11.8	0.76
Environmental engineering technicians	10.0	0.25
Environmental science and protection technicians, including health	9.5	0.25
Computer network support specialists	7.5	0.21
Electrical and electronics drafters	5.4	0.81
Agricultural and food science technicians **Agriculture inspectors**	4.9	0.94
Civil engineering technicians	4.8	0.75
Aerospace engineering and operations technicians **Avionics technicians**	3.6	0.70

8. LEGAL FRAMEWORK, ECONOMICS, AND ETHICS

In light of the ever-increasing role played by computer technologies, robotics and artificial intelligence in the economy, society should introduce a proper legal environment conducive to promoting and not inhibiting the application of new technologies for positive socio-economic changes. The changes affecting education, legal systems, and economics should also include ethics (Gapinski, 2016; Isaac, 2017b). As an example of such initiative, although outside of the U.S.A., one should list the European Union Draft Report (EU, 2016) on Civil Law Rules on Robotics, which proposed a framework for civil law liability, intellectual property rights, ethical conduct in the field of robotics. This quite comprehensive proposal (EU, 2016) addressed other issues related to the new challenges faced by societies and nations of the European Union as well. The EU Committee proposed the draft framework based on the fact that "robotics and AI have become one of the most prominent technological trends of our century" and, consequently, the risks posed by these new interactions between robots, AI and humans require a proper legal environment in order to ensure "human safety, privacy, integrity, dignity and autonomy" (EU, 2016). Furthermore, the EU Committee suggested to create a dedicated European Agency for robotics and AI given their growing significance. The proposed Code of Ethical Conduct for Robotics Engineers/Scientists (EU, 2016) lists the "following principles:

- Beneficence – robots should act in the best interests of humans;
- Non-maleficence – the doctrine of 'first, do not harm,' whereby robots should not harm a human;
- Autonomy – the capacity to make an informed, un-coerced decision about the terms of interaction with robots;
- Justice – fair distribution of the benefits associated with robotics and affordability of homecare and healthcare robots in particular."

It is worthwhile to note that the EU committee in the proposed ethical code proposed a taxation of robots taking jobs from humans, which was also suggested by Mr. Gates (Forrest, 2017).

Due to the transformations in the economy and the bifurcation in employment it will be critically important to engage government, state agencies, and private institutions to devise new, more effective ways of "how workers are trained and find jobs" (Duhigg, 2017) including STEM disciplines. As Mr. Cass in an article by Duhigg (2017) suggests, new ways should devise or create a 'new category of employment that is somewhere between a full-time employee and an independent contractor,' which would introduce more flexibility for both employers and employees in employment relations and reduce anxiety in workers undergoing inevitable transitions in the new economy.

As societies embark on the post information era, organizations such as POSCO (WEEF, 2016) correctly stress the importance of critical thinking, creativity, collaboration, and communication as the underpinning of any worthwhile education including STEM programs.

Advancement in technologies (ML, AI, BD, etc.) already caused a noticeable bifurcation of jobs into: low paying "not-very-good jobs" and high paying jobs for the "conceptualizers" who can take advantage of the new technologies (McKinsey, 2014). The new economy creates jobs for which the U.S. Department of Labor has aggregated data into the "other" category, signifying the innovative character of these jobs. Cearley, Walker and Burker (2017) in their analysis of ten strategic digital technology trends for 2017 and beyond that will affect automation of processes, formulated recommendations for technology innovation leaders and decision makers as to how to prepare for inevitable changes. If the effects of automation lead to big job losses and the disruption of social order, then there will be a need for government intervention that may include new monetary and/or fiscal policies (McKinsey, 2014).

9. CONCLUSION

The article examines the effect of automation on occupations focusing on STEM jobs in the USA and beyond. The character of the performed activities within the occupations including STEM area determines their susceptibility to automation. The analysis considers current routine and non-routine labor transformations trends due to advancements in computer technologies and implementation of automation. STEM occupations and their various vulnerabilities to automation are discussed. The analysis shows that automation already has and will have a considerable impact on majority of professions including STEM area despite relatively high cognitive content of STEM occupations. The analysis shows that automation does not only affect the professions' landscape but has social, economic, and ethical ramifications.

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