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Replacing Humans with Machines: Threats and Opportunities

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ABSTRACT

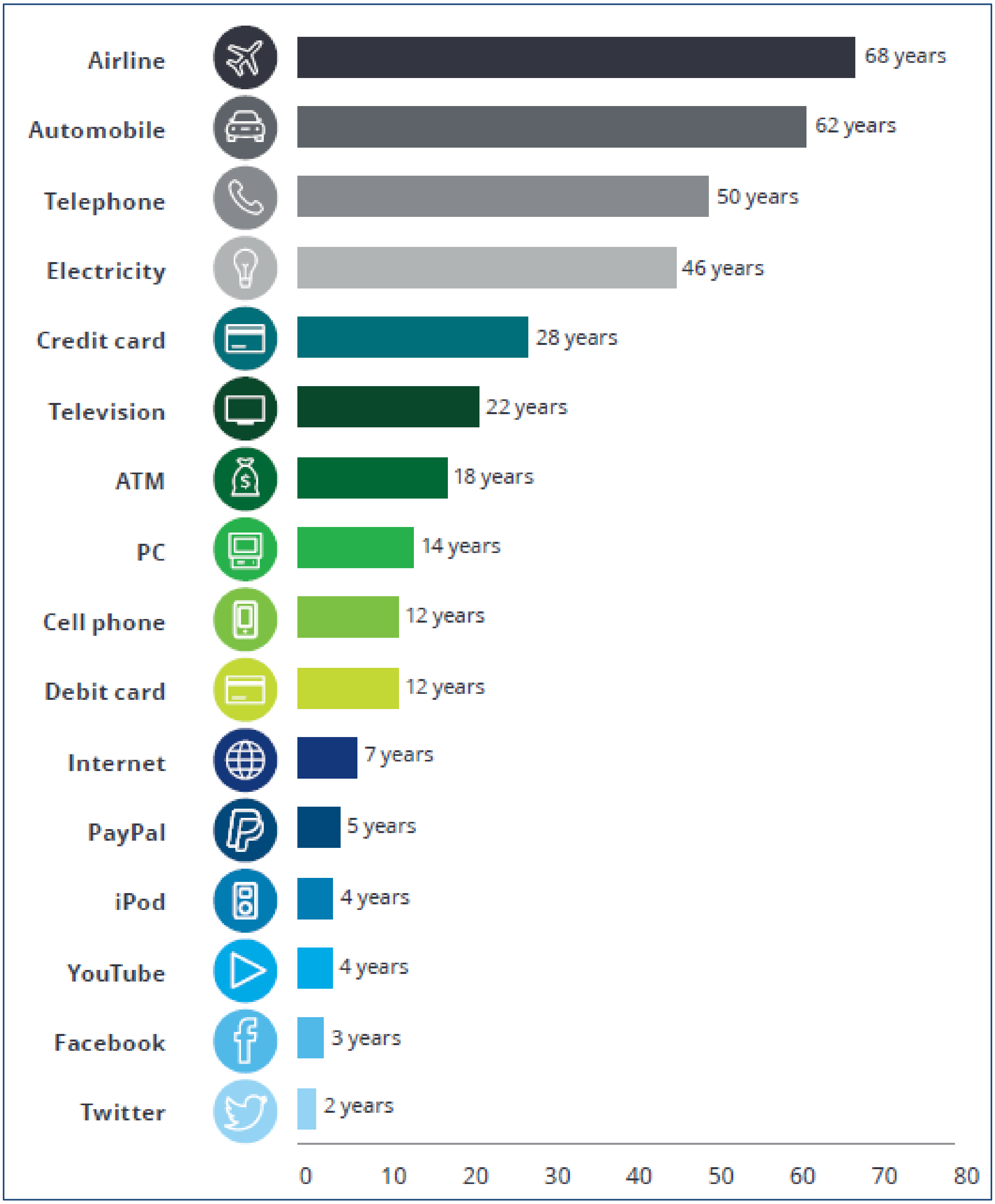
Many aspects of life stemming from professional to personal have been extremely changed and impacted by technological advancements. Traditionally, the labor market depended on routine manual labor offered by human capital; however with the technological advancements in computerization, the market behavior for routine human labor has extremely changed. Companies and people have been on the verge of ever trying to economize the use of labor and maximizing the available space while finding new uses and sources of labor, argued Frey and Osborne (2013). Jobs have become very susceptible to computerization, in that over the past three decades, computers and computerized mechanics have substituted a considerable number of jobs including functions of telephone operators and bookkeepers among others. A strong pattern is recorded over the years where tasks that were routine and repetitive are increasingly being replaced and performed by automated machines. Computerized and automated machined pose an overwhelming threat to the repetitive and routine manual labor traditional performed by human labor. Therefore, this paper provided a literature review about the extent of routine human labor susceptibility to computerization and automated machines.

INTRODUCTION

Frey and Osborne (2013) point out that the debates over the correlation between unemployment and technological revolutions are not a recent phenomenon but has a vast history. As man ventured and committed himself to find new ways of making work easier, new inventions were made that despite promoting the efficacy and productivity of work, they emanated significant undesired disruptions of labor systems. For instance, Frey and Osborne argue that Queen Elizabeth 1 raised considerable concerns about employment stability from the invention of the stocking frame knitting machine aimed at relieving works from hand knitting by William Lee in 1589. Lee's invention was a masterpiece and incredible manner of increasing production and work efficacy but a threat to the many workers who depend on hand-knitting as a source of income to support their livelihood. Technology and employment ensue a status quo as communities resent new technologies in fear of rendering their skills obsolete or rather reducing their earnings.

Frey and Osborne further indicate that the British Industrial Revolution manifests the status quo between technological advancements and employment rates. To protect and promote machinery innovation, in 1769, the British Parliament passed a punishable by death law for any destruction of machines for anyone who resented mechanization by destroying the machines. Between 1811 and 1816, the Parliament annulled over 1511 laws that prohibited the use of gig mills changing the state of wool-furnishing jobs. Riots further resented the decision but the adoption of technology and machinery innovation was inevitable. The increasing shift to mechanization is attributed to an increase of property owners among the political class and mechanization is attributed to benefit unskilled labor, consumers, and inventor. Despite the refute of technology, it is posited that unskilled workers significantly benefited from the inventions while others argue it helped capital owners to be accurate more share of national income. Nonetheless, it is postulated that technologies are likely to be embraced is the gains accruing from the inventions are distributed in an equitable manner even though the resentment due to susceptibility to increasing unemployment is unavoidable. The figure below shows the number of years different mechanized and computerized utilities took to reach at least 50 million users.

Figure 1: Number of Years Taken by Each Utility and Products to Gain At Least 50 Million Users



Source: (Harrington, Moir, & Allinson, 2018)

Consequently, Frey and Osborne (2013) allude that deskilling, where skills replaced by task simplification, was the primary characteristic of the nineteenth-century technological innovation of the manufacturing sector. Work traditional performed by artisans was mechanized such as steam powers. The principle of interchangeable parts was coined by Eli Whitney aimed at correctly and effectively substituting artisan skills with machinery operation whose acquisition is based on long-term experience and practice. The machines were to be operated by unskilled workers; the process was effected implemented by Ford Motor Company in manufacturing it T-Ford. The work of one person was performed by 29 operators using the machinery but reducing the work time by 34%. However, in the twentieth century, the phenomenon favored skilled workers due to the invention of machinery such as conveyors, haulers, and assemblers that replaced the unskilled manual working hence requiring skilled labor to operate some of the machines and equipment.

The assembly lines were characterized by increased labor division that required relatively skilled labor as most of the operations were automated. This did not only increase blue-collar jobs but as well as white-collar jobs the required higher educational skills. The office work was also revolutionized in the twentieth century with the invention of calculators, Dictaphones, address machines, mimeo machines and early computers reducing the information cost required educated personnel to operate them. The office work thus required skilled workers with set minimum educational and professional experience for certain clerical jobs. The era was characterized by Computer Revolution that began in the 1960s and progressed to e-commerce and internet in the 1990s and further sophisticated today. The Internet and computer made over 37% work of telephone operators redundant as the computers would effectively perform a significant portion of their work. The invention of cashier machines, barcode scanners and first personal computers installed with spreadsheets and word pressing functions in the 1980s rendered much work of repetitive calculation obsolete as they were automated. Computer generation jobs polarized the market increasing the demand for high income cognitive and low-income manual employments while eliminating a significant part of middle-income routine jobs changing the traditional occupational designs. For instance, it is pointed that over one and half decades ago, computerization has had over 800,000 low skill routine jobs in UK redundant but argued to have created over 3.5 million non-routine high skilled occupations (Sproul, Knowles-Cutter, & Lewis, 2015).

New Technology and Job Design

According to Gibbs (2017), the ever-advancing technological changes and revolution gas tremendously impacted on the labor markets and jobs. Many manual and routine tasks have been replaced by automated labor. Frey and Osborne (2013) point out that high rates of unemployment attributed to increasing reliance on automated labor have over the years, emanated significant debates by economists and political leaders many accusing the computer-controlled equipment being the primary influencer of the escalating growth of joblessness. Wisskirchen et al. (2017) recorded that in today's job market, tasks that consisted of well-defined procedures done by human labor can be easily performed using sophisticated algorithms, hence significantly changing the job design. It is postulated that the disappearance of manual jobs and the decline in manufacturing employability have substantially contributed to unemployment. Computers and robotics increasingly challenge the stability and stats of human labor.

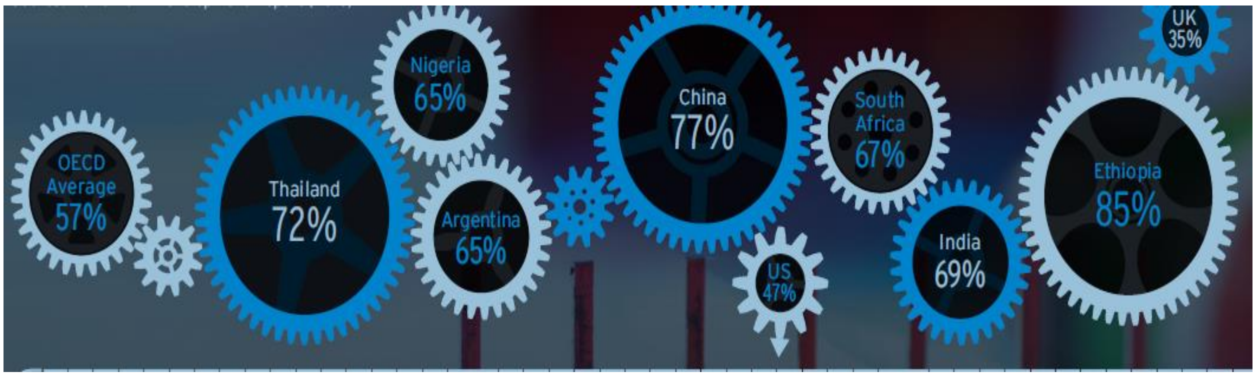
Frey and Osborne (2017) cite research by Autor and Dorn in 2013 that pointed out that structural paradigm shift in the job market to computerization is forcing many manufacturing workers to change the supply of their labor to low-income service occupations from middle-income manufacturing tasks. The low-income occupations require a high degree of physical adaptability and flexibility as opposed to middle-income tasks that are very susceptible to automation. For instance, West (2015) in the introduction of his paper, narrates a story of Amy, a “virtual assistant” that was artificial intelligence (AI) designed to schedule meetings. Amy performed the work of a human assistant to read emails, discerning content, and to come up with relevant responses; West notes that the way Amy performed its duties, nobody would doubt it was not human. West (2017) experience with Amy was a revelation that artificial intelligence was no more abstract or a futuristic vision, but a reality. Sproul, Knowles-Cutler, & Lewis (2015) shares West's experience indicating that due to automated and AI virtual assistants, many jobs have been lost in manual administrative and lower-skilled clerical occupations. According to Frey and Osborne, in the current century, jobs that require marginal and subtle judgment are highly prone to computerization, while the invention of artificial intelligence (AI) making even those that require exceptional judgment being computerized and mechanized.

The increasing pace of technological innovation characterized by the use of sophisticated software technologies is noted to progressively disrupting the labor market, making a significant number of manual labor redundant. Many jobs are ever being created that are technology dependent. Currently, secure and dependable routine manual human labor is being focused on designing or opting for tasks that require higher cognitive skills and exceptional degree of manual dexterity, for example, those that require human social interaction, nonetheless, the extent of security is stilled limited more so with the recent advancements in robotics. The job market is being presented with binary choices of either choosing robotics or human labor.

A study by Gibbs (2017) points out that artificial intelligence has accelerated the ability of machines to perform cognitive tasks increasing concerns about job security. Technology is complementary to many manual tasks where it increases quality, innovation, and productivity of work as compared to the routine and manual jobs.

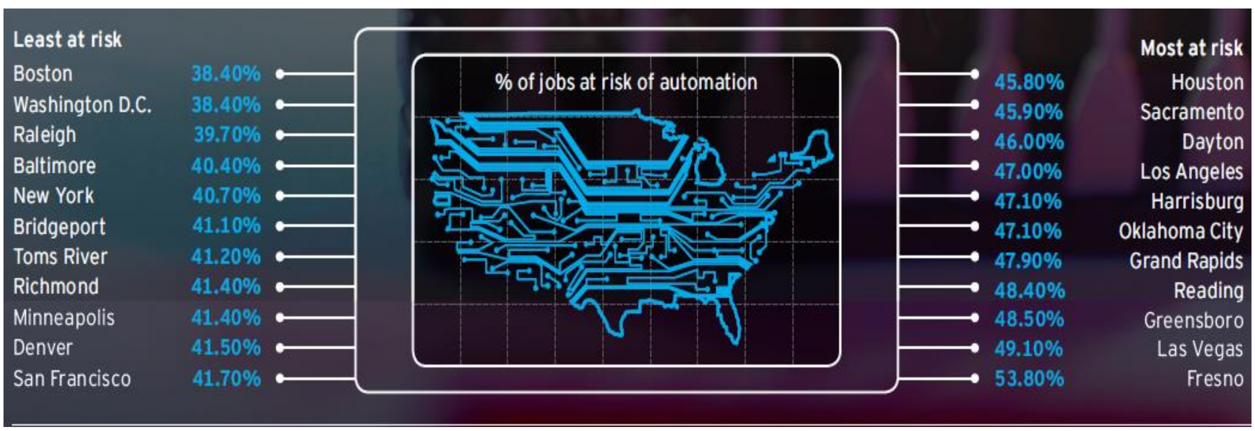
Nedelkoska and Quintini (2018) study on the stats of employment and labor market in the member states of Organization for Economic Co-operation and Development (OECD) found out that across the 32 countries, in every two jobs, one is prone to be substantially affected by automation depending on the risks involved. However, the risks of task redundancy vary with skills, but 14% of the jobs are jobs in the region are at least 70% vulnerable to automation, an estimate of 66 million job loss in 32 OECD member states. Besides, 32% of the jobs are 50-70% prone to be changed in the manner they are performed indicating alteration of the job description as a result of automation as the skills required shall vary. 6% and 33% of jobs in entire Norway and Slovakia respectively are prone to automation where the labor market in the Anglo-Saxon, Nordic countries are more probable to automation risks as to the Eastern and Sothern European countries, Japan, Chile, and Germany. *Figure 2* below shows that the risks of automation of occupations vary across countries and regions depending on their technological advancements, similarly as in cities as depicted by some of USA cites (*see Figure 3)*.

Figure 2: Occupations at Risks of Automation per Country



Source: (Citigroup, 2016)

Figure 3: Occupations at Risks of Automation per City, U.S.

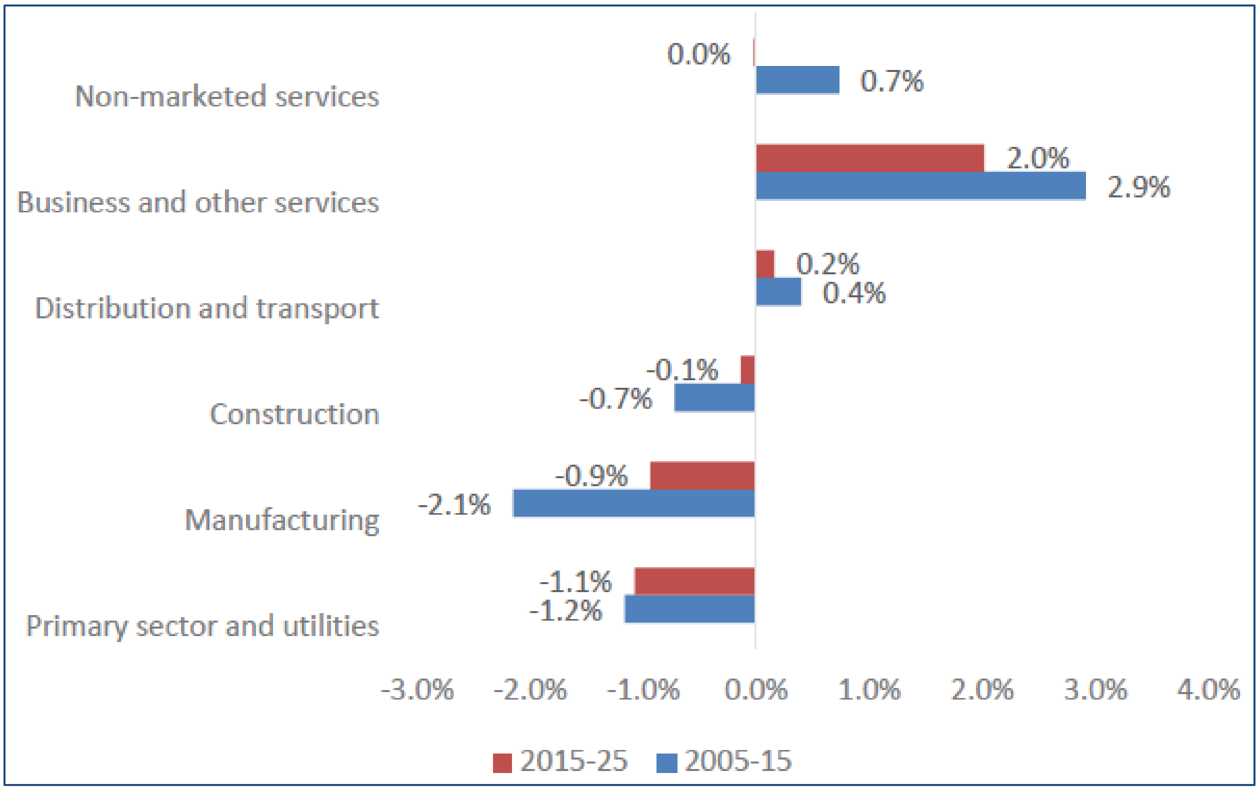


Source: (Citigroup, 2016)

Nedelkoska and Quintini (2018) indicate that the actual demand for skills and jobs resulting in variation of computerization and automation intelligence prove cumbersome to measure; however, the employment shares and levels are noted to be incredible proxies. Employment shares investigate the business in the creation and destruction of employment due to technological and organizational changes. It is estimated that most of the OECD member states registered a rise of employment share from the 1950s to 1970s but afterward recorded a drastic decline. In the 1950s, as the manufacturing jobs increased, the agricultural sector recorded a drop in the countries that were heavy manufacturers.

Conversely, managerial and clerical jobs grew in the 1980s and 1990s but started to decline in the 2000s due to increased automation. For instance, the European Union economy grew by 3% between 2005 and 2015 but the growth significantly differed across sectors. *Figure 4* below shows a decline in the construction, manufacturing and primary sector and utility sectors as compared to a highly skilled occupation such as non-marketed services. However, by 2025, all the sectors anticipate a further change in the employment shares due to automation and computerization of jobs.

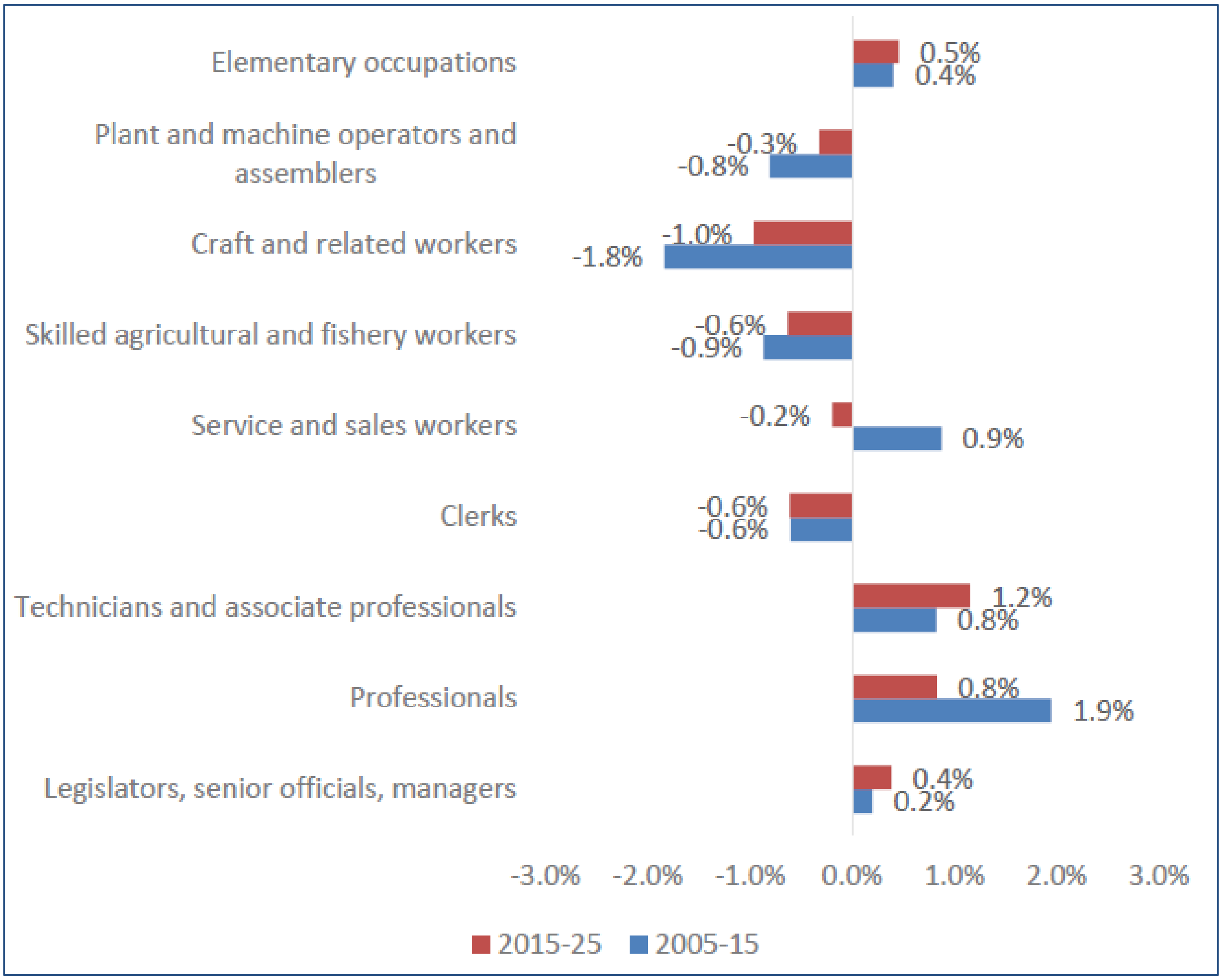
Figure 4: Employment Shares Changes in the EU Economy



Source: (Nedelkoska & Quintini, 2018, p. 25)

In reference occupations, the use of machines and computerized labor significantly affects different occupations but at varying levels. One occupation may be considerably rendered redundant due to the automation of the skills, while others remain relatively dependable due to the complexity is automating the skills required to perform the job. *Figure 5* below indicates that by 2015, the skills of service and sales sector were are anticipated to decline from 0.9% to 0.2% while skills of technical and associate professional expected to grow by 2025, indicating the ability to automate some jobs pose a dire channel to the security of some occupation than others.

Figure 5: Employment Share Change in the EU occupations



Source: (Nedelkoska & Quintini, 2018, p. 26)

Figure 6 below shows the probability of occupation liable to risks of automation. As alluded earlier, the data below shows that jobs that require minimal subtle judgment such as personal assistants, clerks, typists, and retail careers are more prone to automation as compared to the profession such as nursing and educational teaching, which requires utmost interaction between the facilitator and audience. Frey and Osborne (20130 postulated that occupation aligned with vocational and professional skills where the tasks were traditionally non-routine have a low probability of automation hence relative secure. They are relatively secure in that more sophisticated, flexible and adaptable software and machines are progressively being developed (Wisskirchen et al., 2017; West, 2015; Frey & Osborne, 2017; Nedelkoska & Quintini, 2018). According to Van der Zande, Teigland, Siri, and Teigland (2018), there are several technologies with the potential of replacing the routine and mal human labor whose application may converge or diverge at some point are dependable.

Figure 6: Occupational Risk to Automation

Occupations with largest fall in employment	Probability of automation (%)	Change in jobs by occupation ('000s)	Occupations with the greatest rise in employment	Probability of automation (%)	Change in jobs by occupation ('000s)
Personal assistants and other secretaries	85	-204	Care workers and home carers	50	271
Typists and related keyboard occupations	99	-108	Teaching assistants	56	235
Bank and post office clerks	98	-83	Nurses	1	186
Retail cashiers and check-out operators	97	-72	Secondary education teaching professionals	1	131
Shopkeepers and proprietors, wholesale and retail	16	-69	Sales accounts and business development managers	16	122
Postal workers, mail sorters, messengers and couriers	80	-65	Business and financial project management professionals	11	115
Assemblers (electrical and electronic products)	94	-60	Teaching and other educational professionals n.e.c.	1	113
Business sales executives	60	-58	Primary and nursery education teaching professionals	56	110
Metal machining setters and setter-operators	79	-51	Chefs	57	103
Sewing machinists	89	-47	Property, housing and estate managers	25	101

Source: (Sproul, Knowles-Cutter, & Lewis, 2015)

Automation and Machine Intelligence

Van Doorn, Bloem, Duivestein, and van Ommren (2017) notes that increasing sophistication of manual and cognitive tasks is available in a wide array of automation. Over the years, technology scientists and innovators have committed huge resources and time in developing new self-learning computers, cognitive systems, computers and software with a capacity to speak the human language and perform cognitive skills as efficient even more as humans. Van der Zande, Teigland, Siri, and Teigland's (2018) report highlighted the potential of three primary technologies namely machine learning (ML), artificial intelligence (AI) and robotics in replacing human labor through automation and digitization. It is through an understanding of the above technologies that people can their implication of occupational designs, unemployment, and job descriptions. Gibbs (2018) further allude that the manner in which computerization impacts job designs has meaningfully changed from the guided and well-defined task that humans would perform either through the use of traditional computer programs or expert systems designed to replicate and categorize human thinking to completely performing some of the tasks independently. The use of algorithms, mechanization and machine intelligence has shape job automation and designs. The subsequent topics evaluate the three categories of technology.

Artificial Intelligence (AI)

The concept of AI was coined by John McCarthy in 1955, who postulated that every concept of human learning, activities, behavior, and other intelligence domain could be precisely described and simulated by a machine. Van Der Zande, Teigland, Siri, and Teigland (2018) and Wisskirchen et al. (2017) note that the field of AI holds arguably varied potential in the present and future proven hard to define it precisely. Nonetheless, Van Der Zande, Teigland, Siri, and Teigland (2018, p. 11) quoted a definition by Nils J. Nilsson (200) that defined AI as a sequences of activities and processes that projected at making machines intelligent; the intelligence should be quality enough to enable an AI entity to functionally aptly, independently and with a foresight in its milieu. Whereas Wisskirchen et al. (2017) define equates an AI to a machine that has the relevant intelligence to perform some functions as humans; hence AI is an intelligent computer system. As per the definition, the use of AI has significantly advanced from video gaming to automated vehicles.

The scope of AI has expanded over the years to constitute deep learning, machine learning, big data, robotics, dematerialization, gig economy, and autonomous driving, among others. AI has been categorized primarily into two categories; the weak and strong AI. The weak AI are computer systems majorly used for the investigation of cognitive processes or simulation of intelligence. The algorithms designed in this AI are tailored to completing specific programs and solving specific problems bond by specific rules; thus, when taken outside of the rules, the AI becomes unless. On the other hand, the general or strong AI is aimed at developing computerized machines with a capacity of thinking and performing tasks without being specifically and precisely programmed for it. Machines with strong AI are expected to have a cognitive mind with an ability to make their own decisions contrary to weak AI, where the machine only simulates human behavior. Currently, the human labor is being advanced by research in natural language processing (NLP), deep learning, neuromorphic computing, reinforcement learning, collaborative systems, neural networks, crowdsourcing and human computation, robotics, Internet of things (IoT), computer vision, computational social choice, and algorithmic game theory (Van Der Zande, Teigland, Siri, & Teigland, 2018). An evaluation f robotics and machine learning will provide a better understanding of the impact of AI on the labor market.

Machine Learning (ML)

Machine learning is defined by Van der Zande, Teigland, Siri, and Teigland (2018) as a subset of AI where the computer can have a capacity to learn from experience hence capable of modifying its processes based on the sequenced of the newly acquired information. Brown and Camrass (2016, p. 7) describe ML as a computerized system with the ability to establish problems from evolving models using the collection and analysis of data. It is constituted by a set of algorithms designed to process the acquired data with the utmost accuracy while classifying and assessing the data. ML argues that machines can learn from the collected and analyzed data hence imparting it with the ability to gain new insights in real-time without the need for reprogramming. Using the insights and models developed by the ML systems, organizations can leverage their competitive advantage among other issues such as cyber threat analysis, fraud detection in financial services eliminating the need for may auditors, traffic congestion avoidance in transportation and medical diagnosis in healthcare. Different types of ML are invaluable in the labor market today (Van Der Zande, Teigland, Siri, & Teigland, 2018; Brown & Camrass, 2016).

Deep Learning

Deep learning (DL) is one of the widely covered ML systems where it uses supervised (programmed in a logical manner) and unsupervised learning (where machines decide on its own what to do) that enables computers to learn from example, a phenomenon that is naturally inherent to humanity. DL functionality is based on deep neural networks that constitute a network of multiple layers of loosely shaped neurons after the brain with a capacity to recognize dynamic patterns through primary detection and combination is smaller, simpler patterns. The technology has been applied in the detection of images and sounds and among other data. Rao and Verweij (2017) point out that deep learning substitutes work of marketing and sales analysts as through deep learning application wholesalers and retaliates can predict customer demand as the DL application collects and analyses data of customer consuming behavior in advance thus helping in making informed decisions.

The system is dependable and more accurate as compared to human workers, the system is connected at all time, and avoids recurrent mistakes as an error by one system is not likely to recur as the machine has a self-learning capacity. The University of Oxford in collaboration with Google's DeepMind developed a lip-reading system based on DL principles trained to view BBC programs for over 5,000 hours; the task is noted to be done a thousandfold better than a professional human lip-readers indicating an inevitable redundancy of lip-readers (Van Der Zande, Teigland, Siri, & Teigland, 2018, p. 22). Besides, Baidu, a Chinese company developed an ASkADoctor DL system focused on consumers where people can get doctor diagnosis and prescriptions at an accuracy of 75% as they further look forward to creating medical robots, this threats the job security of medical practitioner from a future perspective (Van Doorn, Bloem, Duivestein, & Van Ommren, 2017).

Data Mining and Big Data

Brown and Camrass (2016) point out that quality information has always been the backbone of decision making; hover has information is equivalent to having a gold mine, however having information is not sufficient, but how the information is used is critical. Over half a century ago, administrative systems recorded game-changing systems that such as Human Resource Management (HRM), Supply Chain Management (SCM), Customer Relationship Management (CRM), and Enterprise Resource Planning (ERP) in decision making. With technological advancements, data mining and big data increasingly become reckoning technologies in decision making.

Data mining is the use of exploratory algorithms to uncover data patterns; however, big data is increasingly used to refer to more advanced processes of data mining (Gibbs, 2017). Human and machines generate extensive volumes of data which is unstructured and anonymized. The data is stored; traditional analysts used the data through models to predict patterns but ever since the invention of the internet, the volume of data is anticipated to grow to at least 100 zettabytes by 2010. The huge volume of data is referred to as big data, while big data analytics refers to the system of collecting and analyzing the data into meaningful information desired by the organization. The data are sources of shared networks such as social media networking sites and can be collected from the organization's websites as well as cloud computing. The internet of things and big data creates a new disruptive purpose of artificial intelligence. The focus on big data is not merely on storage but analysis and usage of the gathers data (Wisskirchen et al., 2017; Van Der Zande, Teigland, Siri, & Teigland, 2018). For instance, Google Home boxes and Amazon Echo are big data tools used to collect necessary information on individual consumer's needs and other proffered data that would prove invaluable for marketing or whatsoever information.

Frey and Osborne (2013) point out that big data systems are increasingly being adopted in occupation and systems that rely on data storage and access to the information in decision making. It depicts a mandatory pattern for office and administrative tasks that depended on human capital such as market and financial analysts to succumb to computerization and automation of its operations hence susceptibility of middle-income skilled labor to be laid off. Big data is making a wide array of non-routine cognitive tasks to be automated due to scalability as opposed to human labor. Big data can detect patterns better than human making it more preferable. As technology advances, West (2015) notes that the need for specialized personnel in big data analysis, data mining, and management of data shared networks are increasingly being created. Bruckner, LaFleur, and Pitterle (2017) recorded that the rapid integration of AI, big data, and computational power makes even diagnosis of diseases, automated care navigation and legal writing among other less-routine aspects liable to automation. As noted by West, Wisskirchen et al. (2017) affirm that big data increase the employment demand for big data developers, data scientists, and data artists hence for the traditional data analysts to remain viable, they have to acquire training in big data analytics.

Figure 7: Employment Probability in the U.S. IT Sector

Title	Employment in 2012	Employment in 2022	Change % in 2012-2022
Information Security Analyst	75,100	102,000	37%
Computer System Analysts	520,600	648,400	25%
Software Developers	1,018,000	1,240,600	22%
Web Developers	141,400	169,900	20%
Computer Support Specialists	722,400	845,300	17%
Database Administrators	118,700	136,600	15%
Computer & Info Research Scientists	26,700	30,800	15%
Computer Network Architects	143,400	164,300	15%
Network Computer Systems Admin	366,400	409,400	12%
Computer Programmers	343,700	372,100	8%
Computer occupations (all other)	205,800	213,600	4%
Total	**3,682,200**	**4,333,000**	**18%**

Source: US Bureau of Labour Statistics, Citi Research

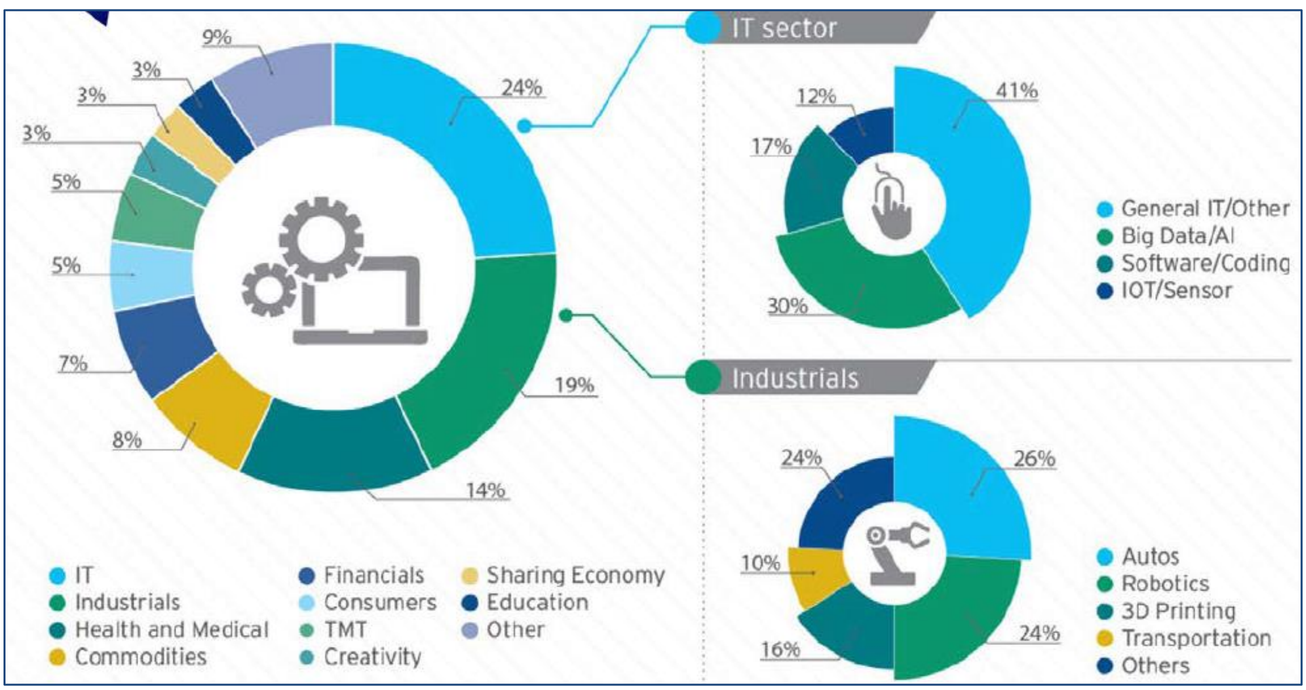
Source: (Citigroup, 2016)

Robotics

UNESCO and COMEST (2017) and Van der Zande, Teigland, Siri, and Teigland (2018) defined robots as robotics as an integration of multiple academic disciplines including electrical engineering, mechanical engineering, and computer science aimed at developing AI machines with mobility, communication, and intelligence capacity just like human beings.

Nevertheless, the definition of robots differs based on purpose but the principles are relatively the same aimed at replicated human intelligence, physical, cognitive, and emotional abilities to machines. Robots have been developed, capable of performing professional and personal services. Examples stem from domestic vacuum cleaners, delivery robots in offices and hospitals to drones and automated automobiles. Robotics has advanced to the point that Sophia, a robot, was awarded a citizen in Saudi Arabia, is the first robot to be considered equal to human beings (Retto, 2017). Robots have replaced and are replacing many booth routines and non-routine manual skills from industry levels, military, transportation (autonomous vehicles eliminating the need of a human driver), health care, to education (UNESCO & COMEST, 2017). Today nearly every job is prone to automation.

Figure 8: Most Promising Careers and Technologies in the U.S. Labor Market



Source: (Citigroup, 2016)

CONCLUSION

Computerization and automation of both routine and less-routine human skills are unequivocally prone automation due to the ever-increasing development of sophisticated software and machine capable of replicating human services and intelligence. High-income and middle-income are the most susceptible as compared to low-income that are majorly manual. Nonetheless, as much as job automation results in unemployment, it significantly creates many other jobs but required specialized skills and education to perform them. AI has its advantages as well as limitations.

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