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Digitalization: A Threat or an Opportunity in Replacement of Labor and Job Task

A generic perspective at developing economy, a case in Ghana's digitalization policy.

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Abstract

Persistent technology advancements and their impact on the labor force are producing a domino effect that will affect business culture, legislation, and workers in the next years. Artificial Intelligence's importance for businesses is also a major topic that could lead to conflicts between cities around the world. Seasonal workers, 24-hour contracts, and informal employment methods are limiting collective bargaining power and job satisfaction. As a result of the so-called "Information Society," labor modifications and role transformations have played a significant role and have progressed. Because of all the improvements in information technology and robotics, several vocations have been relegated to a significant change in various industries. This process will accelerate in the next decades as new sorts of occupations are created to support the changing economy. When this "macro" and "micro" vision intersect with those who have been laid off because of the automation process, a dispute ensues. We can confirm that digital changes and transformations will continue to grow because of the facts presented and current market trends. From technological practicality to other elements impacting on job automation, the substitution of labor and job task is examined. The Internet of the Future. The primary goal of this study is to investigate how the Internet and digitalization have influenced entrepreneurship and innovation in Ghana's digitization drive. This research looks at how technology and the Internet can affect labor market dynamics, with a special focus on Ghana's version of digitalization.

***Keywords* – Digitalization, Digitization, Artificial Intelligence, Automation, Robotics, Machine Learning.**

I. INTRODUCTION

To provide a strong understanding of the ideas, this paper begins with a brief explanation of digitalization and automation, as well as the three key technologies enabling work automation: artificial intelligence (AI), machine learning (ML) - a subset of AI, and robotics. The study then goes on to analyze the many human capabilities that are required in the workplace, as well as the extent to which the three key technologies can currently replace for these qualities. The paper then moves on to a classification of job duties based on a widely used framework of routine vs. non-routine and cognitive vs. manual jobs and maps the preceding section's human capacities in the workplace onto this matrix. This study then goes on to analyze the automation possibilities of tasks, jobs, and sectors in the next section. The report then moves on to a collection of characteristics that influence the pace and extent of job automation that are not related to technological feasibility. The report finishes with a brief overview of the findings, which support labor's long-term prospects.

- **A Quick Look at Digitalization and Automation**

It is necessary to first gain a comprehensive grasp of the processes and technology that underpin this substitution before making a good judgment on the substitution potential of certain tasks, or even entire jobs. This section seeks to establish the foundation for this understanding by delving into the definitions and histories of each of the technologies and processes involved.

First, it will discuss the digitalization process, which is technology-driven and has had, and will continue to have, a substantial impact on labor. The focus of this research will then shift to automation, which is an umbrella term for the replacement of human work by robots. Following that, artificial intelligence, and its subsection of machine learning, as well as robotics, will be presented as the three most prevalent technology domains within Automation.

- **Digitalization**

The term "digitalization" is defined as:

Digitalization, of all the subjects covered in this paper, is likely the widest notion with the most varied definition. Digitalization encompasses a wide range of concepts, including the Internet of Things (IoT), big data, mobile applications, augmented reality, social media, and many others. Digitalization is a term used in the business world to describe the process of upgrading or modifying business models and processes by leveraging digital technologies and digitized resources to generate new sources of value.

Digitalization also refers to the broader worldwide trend of people adopting digital technologies and the consequences of that adoption in all aspects of society [1]. The terms "digitalization" and "digital transformation" are commonly used interchangeably. It is, nonetheless, beneficial to distinguish between the three. Digitization shall be used only in this study to refer to the process of converting analogue data (such as pictures, sounds, and so on) into a digital format, i.e., binary code [2].

This study will refer to the business process outlined above while discussing digitalization. Finally, the term "digital transformation" is used to characterize both a corporation's journey to become a digital company and the broader effects of digitalization on society. Mechanization, automation, industrialization, and robotization are all terms that are sometimes used interchangeably when talking about digitalization. These phrases, on the other hand, usually refer to improving current processes, such as workflows, whereas digitalization refers to the creation of new sources of value creation [3].

II. A QUICK OVERVIEW OF DIGITALIZATION

The creation of the current binary system by Gottfried Wilhelm Leibniz in 1703 marked the beginning of the digitalization era. However, digitalization as we know it now began in the 1940s with the introduction of the first digital computers and intensified in the second half of the century with the widespread use of the personal computer [4]. With the creation and development of the World Wide Web in the 1990s, digitalization exploded, revolutionizing global access to and dissemination of information. This shift is occurring at an unprecedented rate today, because to the rapid growth of digital technologies such as the Internet of Things, big data, and AI. Even though digitization has piqued the interest of both the public and private sectors, IBM claims that most businesses are still unprepared for a digital future [5].

- **Automation**

Automation is defined as the process of automating tasks.

The process of adding technologies to automatically execute a task formerly performed by a human or impossible to accomplish by a human is referred to as automation [6]. The field is closely related to mechanization, which refers to the use of machines to replace human work [7]. This is distinct from autonomous systems, which refer to the achievement of a goal without the use of specified execution rules provided by people. As a result, the term automation implies that the system follows a set of predetermined rules to achieve its aim [8]. [9] Automated systems are often made up of three components:

- Feedback control systems: These systems keep track of whether the specified action is being carried out appropriately. A thermostat, for example, monitors the temperature in a room to see if it matches a target temperature and adjusts the heating element's output if it doesn't.
- Power sources, such as electricity, are required to carry out the desired action. In general, power sources are utilized to carry out two types of actions: processing, which is concerned with an entity's mutation or transformation, and transfer and positioning, which is concerned with an entity's mobility.
- Machine programming refers to the programs and directives that specify the system's desired output as well as the processes required to achieve it. Paper/steel cards, tapes, and computer software are all common ways for machine programming. Computerization is another term for automation by computer-controlled equipment [10].

Manufacturing is one of the most common applications for automation. Industrial Automation is another name for automation in this industry. According to Groover (2017), there are three forms of industrial automation:

- The automation has been fixed. The equipment arrangement is set in stone and cannot be changed to accommodate a different process. As a result, the processing steps are always performed in the same order.
- Automation that can be programmed. Although the equipment can be modified to perform a different function, this takes time and requires human intervention.
- Automation that is adaptable. A central computer controls the system, which may be reconfigured automatically and instantaneously. As a result, the system can run multiple processes at the same time.

Several technologies are used in modern, complicated automated systems (Robinson, 2014). As a result, advancements in these technological sub-fields are intimately linked to advancements in the field of automation. Artificial intelligence, neural networks, and robots are among examples [11]. These will be covered in more detail later in the report.

- ## An Overview of Automation

The term "automation" was first used in 1946, however it has a long history dating back to the dawn of time. As previously said, automated systems are usually made up of three components. The evolution of these three blocks can be used to illustrate the history of automation [9].

The invention of instruments that used a power source other than human muscle was the first major advancement in automation. The development of technologies that multiplied human muscle force, such as the cartwheel and the lever, began in the early phases of humanity. Following that, gadgets that could operate entirely without human power were developed by harvesting the energy of wind, water, and steam. Stronger power sources, such as electricity, were put into machines in the 19th and 20th centuries, considerably increasing their power. The increasing machine power necessitated the development of control methods to manage production. Initially, human operators were required to control the machine's energy input. The advent of the first negative feedback system, on the other hand, eliminated the need for humans to participate in the process. These systems check to see if the machine's output matches the intended level, and if it doesn't, the machine can self-correct its input. From the 17th century onwards, advancements in this sector gave rise to current feedback control systems.

The introduction of programmable machines was the third major step in the history of automation. The first was invented in 1801, by Joseph-Marie Jacquard, who employed steel cards with various hole patterns to control the output of his mechanical loom. Machines were later programmed using paper cards with complete patterns and, later, computers. Automation arose because of the convergence of these three processes. At the turn of the century, the introduction of electrical power enabled a spike in automation. Following various technical developments in the second half of the twentieth century and the beginning of the twenty-first, the capabilities of automated systems considerably improved throughout the second half of the twentieth century and the beginning of the twenty-first century.

To begin with, after the development and integration of the digital computer, automated systems became far more sophisticated and speedier. Following advancements in computer science, programming languages, and storage technologies, this rise in power intensified. In the meantime, the cost of these technologies has plummeted. Second, advances in mathematical control theory and sensor technology have increased the variety and power of feedback control systems, allowing them to operate autonomously in unstructured situations.

III. ARTIFICIAL INTELLIGENCE (AI).

Artificial Intelligence (AI) is a term used to describe a computer program that:

Artificial intelligence (AI) is a technological field that, in many ways, has a bright future ahead of it. It's difficult to pin down exactly what it is because it's such a big field. "Artificial intelligence is that work committed to making machines intelligent, and intelligence is that property that permits an entity to function effectively and with foresight in its environment," writes [12].

To put it another way, AI refers to computers accomplishing tasks that would ordinarily necessitate human intelligence [2]. "Intelligence," on the other hand, is a complicated phenomenon that has been investigated in a variety of academic subjects, including psychology, economics, biology, engineering, statistics, and neuroscience. Advancements in each of these domains have benefited AI tremendously over time. Artificial neural networks, for example, were motivated by findings in biology and neuroscience [13]. Over the last few decades, AI research has advanced tremendously, and it has been applied to a wide range of applications, from defeating pros in board games like chess and go to self-driving car navigation (Marr, 2016a). Big data, machine learning, robots, and deep learning are all terms that refer to AI, indicating the technology's breadth.

There are a variety of ways to organize and categorize AI's various methodologies, subsets, and applications. One method is to distinguish between generic and applied artificial intelligence. The term "applied AI," sometimes known as "weak" or "narrow AI," refers to algorithms that solve specific issues and systems that complete certain jobs [14]. For example, a computer may excel at one single board game with strict rules, but it is useless in other situations. General AI, also known as strong AI, aims to create machines that can reason and do practically any task without having to be coded particularly for it (Copeland, 2017). This indicates the computer has its own thinking and can make decisions, whereas weak AI only allows the machine to mimic human behavior and appear clever [15].

Another way to categorize AI is by current "hot" research areas. This is a good division since AI is prone to the "AI effect," or "strange paradox," which means that once humans become accustomed to a technology, it is no longer recognized as AI. Large-scale machine learning, deep learning, reinforcement learning, neural networks, robotics, computer vision, natural language processing (NLP), collaborative systems, crowdsourcing and human computation, algorithmic game theory and computational social choice, Internet of things (IoT), and neuromorphic computing are just a few of the "hot" research areas today [13].

Robotics, deep learning, and machine learning are all explored in further depth later in this study; however, natural language processing (NLP) is a subset that has made significant progress in recent years. NLP software tries to decipher natural human communication, whether written or spoken, and respond in natural language [16]. The focus of this field's research is changing away from reactiveness and styled demands and toward constructing systems that can converse with people [13]. The remaining sub-fields will not be discussed separately.

- **A Brief History of AI**

John McCarthy coined the phrase artificial intelligence in 1956 at the Dartmouth Conference, the world's first artificial intelligence conference. The conference's purpose was to figure out how machines could be programmed to mimic features human intelligence. Although this was the inaugural AI conference, the technical concepts that define AI have been around for a long time. The study of probability of events was born in the eighteenth century; in the nineteenth century, logical reasoning could be done systematically, which is similar to solving a system of equations; and by the twentieth century, the field of statistics had emerged, allowing rigorous inferences to be drawn from data [17].

Despite its extensive history, AI has just lately begun to gain traction in terms of research. Many fields of AI arose between the 1950s and 1970s, including natural language processing, machine learning, computer vision, mobile robots, and expert systems. By the 1980s, however, no meaningful practical success had been achieved, and the "AI winter" had arrived, with interest in AI dwindling and money drying up. The Internet and improvements in storage devices facilitated the collecting and storage of vast volumes of data a decade later. Furthermore, the adoption of industrial robots was aided by the availability of inexpensive and reliable hardware, as well as developments in software that allowed systems to function on real-world data. As a result of these occurrences, AI was resurrected and once again became a "hot" research field [18].

- **Machine Learning (ML)**

There are numerous articles that cover machine learning (ML), but none of them fully explain what it is or what sub-disciplines exist. As a result, the term "machine learning" is sometimes misinterpreted as "artificial intelligence." ML is a subset of artificial intelligence, according to the Oxford Dictionary, and is described as "the capacity of a computer to learn from experience, i.e., to adjust its processing on the basis of newly acquired knowledge" [19]. This definition defines machine learning; however, it does not go into detail on what the field entails. The paragraphs that follow attempt to describe what machine learning entails.

Machine learning has evolved into a core study area, with a variety of methodologies and algorithms to choose from depending on the challenge. The field can be divided into supervised and unsupervised learning. The answer is known in supervised learning (discovered in previous or completed data), but not in unsupervised learning. Supervised learning makes predictions for future datasets using a known dataset (a training dataset, which is a set of labeled objects). Unsupervised learning, on the other hand, uses datasets with no labelled responses to make inferences [20].

Unsupervised learning enables computers to reason and prepare for the future, even in situations they have not yet encountered or for which they have not been programmed. Both types of ML, for example, can be used to classify objects based on their shape and color, which is a popular machine learning task. The computer has already been taught how to detect and cluster the items if supervised learning is utilized. It will recognize that an octagon has eight sides and will so group all objects with eight sides as octagons. The system does not follow a predefined set of clusters or object properties in unsupervised learning. The system must generate these clusters by recognizing logical patterns between the objects; for example, if numerous objects have eight sides, the system will cluster them if the qualities are common [21].

Algorithms for supervised learning fall into two categories: 2) Regression - used for continuous response values, and 1) classification - used to split data into distinct classifications [22].

Unsupervised learning can be further separated into two categories:

i. Cluster Analysis is a technique for detecting hidden patterns or groupings in data based on similarities or distances between them [23].

ii. Dimensionality Reduction - the process of producing smaller subsets of original data by deleting duplicates or irrelevant variables [24].

Because the output is known, supervised learning is the less sophisticated of the two. As a result, it is more widely utilized. Unsupervised learning, on the other hand, is currently one of AI's main focus areas [25]. Deep learning is one of the machine learning techniques that has received a lot of attention in recent years. Deep learning, which is used in both supervised and unsupervised learning, trains computers to learn by example, which is something that humans do naturally. Deep learning recognizes incredibly complex patterns by first recognizing and merging smaller, simpler patterns using deep neural networks, which are networks made up of several layers of neurons loosely modeled after the brain [21].

Pattern recognition in sound, pictures, and other data is possible with this technique. Deep learning is used to predict the outcome of judicial processes, precision medicine (medication genetically tailored to an individual's genome) and transcribe language into English text with as little as a 7% mistake rate, among other applications [26].

- **A Quick Overview of Machine Learning**

Machine learning was coined by Arthur Samuel in 1959, three years after AI, but the technological ideas behind it had been created far earlier. The insight that computers might be able to teach themselves, made by Arthur Samuel in 1989, and the emergence of the Internet, which expanded the amount of digital data generated, saved, and made available for analysis, were the two primary factors that enabled the breakthrough of machine learning [27].

Machine learning's focal point has shifted over time. During the 1980s, knowledge engineering with basic decision logic was the most popular theory. Between the 1990s and 2000s, research focused on probability theory and categorization, before shifting to neurology and probability in the early to mid-2010s. It was made easier by the development of more precise picture and voice recognition systems. The most popular study topics right now include memory neural networks, large-scale integration, and reasoning over knowledge. Recent breakthroughs in these disciplines are responsible for the widespread adoption of services like Amazon Echo and Google Home, especially in the United States [26].

IV. ROBOTICS

Robotics is a term used to describe the study of robots.

Robotics is the science and technology of robotics, with the goal of developing, operating, and maintaining robots through studying the relationship between sensing and acting [28]. Robotics is a hybrid of multiple academic disciplines, including computer science, mechanical engineering, and electrical engineering, and is one of the most widely utilized automation technologies [9]. The area is closely linked to artificial intelligence, particularly machine learning, computer vision, and natural language processing [9].

It's tough to come up with a general definition for robots because they vary so much in terms of function, intellect, and design. "A machine capable of carrying out a complex set of tasks automatically, especially one programmable by a computer," according to the Oxford Dictionary [2]. There are two sorts of robots, according to the International Federation of Robotics (IFR): industrial robots and service robots. Industrial robots are "automatically operated, reprogrammable, multipurpose manipulators programmable in three or more axes, which may be either fixed in place or transportable for use in industrial automation applications," according to the IFR.

A robot arm employed in the manufacturing process of a vehicle manufacturer is an example of an industrial robot. Robots that "perform beneficial tasks for humans or equipment outside industrial automation applications" are referred to as service robots. Personal service robots and professional service robots are further separated by the IFR. Service robots that are not used for business reasons, such as a domestic vacuum cleaner robot, are classified as the first, while service robots that are used for commercial purposes, such as delivery robots in hospitals and offices, are classified as the second [29].

Wilson [30] defines robots as "artificially generated systems conceived, manufactured, and implemented to perform jobs or services for people" by combining the previous criteria. Furthermore, he broadens the definition of robots to include cognitive computing, which refers to computer programs that are automated. To put it another way, physicality isn't a necessary, and many robots are made entirely of software [31]. Twitterbots and IPSoft's virtual assistant, Amelia, are two examples. The term "robot" shall be used in this report to refer to all artificially constructed systems that perform jobs and services for people, whether they are physically present. We'll also stick to the distinction between industrial and service robots. Furthermore, while some authors distinguish between robots and automated vehicles, for the purposes of this paper, both are considered robotics.

- **A Quick Overview of Robotics**

Mankind has always fantasized about building competent and intelligent robots, from Greek mythology to da Vinci's machine designs, yet the term "robot" was only coined in 1920 by Karl Capek, a Czech playwright [32]. In the 1950s, the first electrical autonomous robots were built, followed by the first industrial robot in 1959. Despite this, it took another two years for the first industrial robot to be purchased and placed in a manufacturing process. Since then, robotics has become widely used in industrial, warehouse, and military applications [32].

The field of robotics has advanced tremendously in the last decade, thanks to advancements in programming, sensors, AI, and robotic systems that have considerably boosted the intelligence, senses, and dexterity of robots [33], [34]. As a result, robots have become more versatile, smaller, and better connected to one another (Decker et al., 2017). As a result, it is safer for robots and people to collaborate closely, and the spectrum of robot applications has grown dramatically. Technological advancements, for example, have allowed robots to enter the world of services, which was previously thought to be impossible. Technological advancements are predicted to boost the capabilities of robots in the future, while prices are expected to decrease. As a result, robotics is predicted to grow rapidly [35].

V. METHODOLOGY

Three Technologies: Where We are Now (WWN)

The analysis of the technologies' current capabilities is the second phase in examining the technical viability of technologies posed to take over work activities. To put it another way, what can today's technologies do? To do so, this study's uses a framework developed by [36], which identifies five broad categories of capabilities: sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities, and physical capabilities, all of which enable humans to perform 18 workplace tasks. These classifications were created based on an examination of 2000 separate job activities from 800 different occupations as shown in Figure 1.

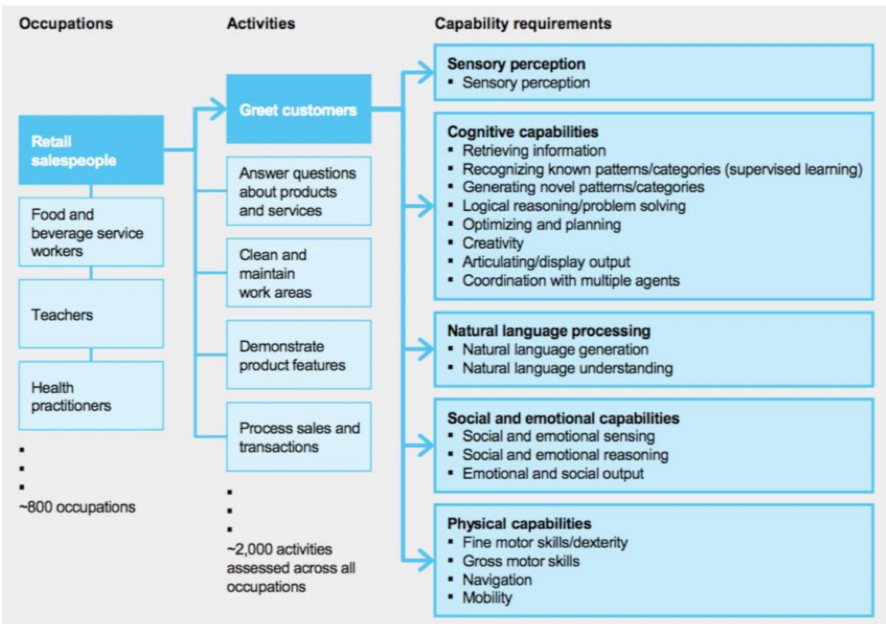

Figure 1: depicts the skills needed in the workplace [36]

This segment examines the current state of technology for each of these five broad categories of capabilities. The three technologies will be discussed concurrently because they are closely related and are frequently used in tandem to perform a single task. It is important to note that many of these capabilities are still being tested in laboratories and are not yet commercially available.

- **Perception of the Senses (PS)**

Sensory perception, also known as machine perception, encompasses the sensing and processing of external information from sensors and includes the three subfields of visual, tactile, and auditory perception [37]. Sensory perception encompasses both the capabilities of the sensors and the underlying software that processes and integrates the data. Sensory perception is required for a wide range of applications, including automated system feedback control systems and robot physical capabilities. Sensors and the underlying machine learning algorithms have become increasingly sophisticated over the years and in some fields, machines have even reached a capability level comparable to humans, according to McKinsey [37]. Computer vision has advanced significantly over the last decade, thanks to advances in sensors, deep learning, and the Internet's abundance of data. Computer vision systems can outperform humans in some narrow-classification tasks. Meanwhile, advances in 3D object recognition sensors and algorithms, such as LIDAR (Laser- Imaging Detection and Ranging), enable more precise distance measurement than ever before. Nonetheless, complex tasks, such as dealing with cluttered vision and fields, continue to pose a challenge to current technology [21], [38], [39].

One of the major enablers of autonomous vehicles is computer vision, which is required for machines to perceive and adapt to their environments. Advances in vision technology also allow for advancement in other applications, such as industrial and software robots. For example, it allows robots to manage patients at a pharmacy's front desk and assemble customized orders in pharmaceutical settings [40], [41].

Machine Touch" refers to the processing of tactile/haptic information, which is required for a robot to grasp and manipulate objects. Despite advances in the development of sophisticated haptic sensors that mimic human capabilities, robots continue to struggle to obtain accurate local information. For example, it is difficult to estimate how much force to apply when grabbing an object or to accurately estimate an object's position once it is in the gripper of the robot and out of sight of its camera. One recent development is Georgia Tech's robot skin, which gives robots the ability to feel textures [36].

The term "machine hearing" refers to how computers process sound. The ability to separate and group acoustic data streams is critical for natural language processing and auditory scene analysis. Machine hearing seeks to enable machines to distinguish between different sounds, organize and comprehend what they hear, and respond in real time [42]. A serving robot in a restaurant, for example, should be able to distinguish and group the voices of the various customers at a table and accurately take their orders. In comparison to machine vision, machine hearing is still in its infancy today. Math, engineering, physics, and signal processing are required for the design, analysis, and comprehension of machine hearing models. Although some subfields of sensory perception have advanced rapidly, it remains a significant challenge to integrate multiple sensor streams into a single system, and it will take several years for technology to completely surpass the human level [43].

- **Cognitive Capabilities (CC)**

Making tacit judgments, retrieving information, logical thinking, optimizing, and planning, creativity, coordination with multiple agents, and recognizing and generating known and novel patterns/categories are all covered in this domain. Significant progress has been made in this area, but it also contains the most technical challenges [36], [44]. There are cognitive systems that currently outperform humans in a variety of activities.

IBM's Watson computer, for example, has a 90% success rate in diagnosing lung cancer, compared to 50% for humans [45]. Watson also defeated the reigning chess champion in 1997 and the Jeopardy! champions in 2011. [46]. Each individual capability will be briefly discussed. A computer can now optimize and plan for objective outcomes across multiple constraints with the same precision as the most skilled humans in this field [36]. It includes real-time optimization of operations and logistics, such as optimizing power plants based on energy prices, weather, and other real-time data, or automating machinery to reduce errors and increase efficiency.

The ability to search for and retrieve information from a wide range of sources is part of retrieving information. Based on this information, a computer should be able to write research reports as well. Because computers are much faster than humans and can search through millions of sources in the blink of an eye, technologies are far more skilled at retrieving information than humans. For example, IBM Watson searched through 20 million cancer research papers and diagnosed a patient with a rare form of leukemia in only 10 minutes, whereas doctors at the University of Tokyo had missed this for months [47]. Recognizing known patterns/categories is the same as supervised learning. As previously stated, supervised learning employs known patterns to categorize and predict future datasets. The use and power of supervised learning have grown significantly because of the Internet's increased availability of large data sets and advances in sensor technology. Computers already outperform humans in the ability to recognize patterns. A deep-learning-based lip-reading system developed by Google's DeepMind and the University of Oxford, for example, easily outperformed a professional human lip-reader after being trained by watching over 5,000 hours of BBC programming [36].

Technology has not progressed as far in generating novel patterns/categories as it has in recognizing them; the field of unsupervised learning, which addresses this issue, is still in its early stages, and computer capability levels are lower than the median human performance [36]. One of the challenges is that creating something new necessitates creative intelligence, which is extremely difficult to codify, as will be discussed later. Mathematicians, for example, are responsible for "developing new principles and new relationships between existing mathematical principles to advance mathematical science" [48].

This task necessitates a great deal of creativity and is thus difficult to automate. One of the most difficult abilities to automate is creativity. To be creative, one must be able to create new combinations of familiar concepts, which necessitates a broad knowledge base. Because computers lack common knowledge, the challenge for them is to create combinations that "make sense." For this to happen, the study’s must be able to precisely specify the creative values so that they can be codified. Another barrier is that these creative values differ across cultures and change over time. Despite the challenges, AI has already been used for some creative tasks, such as music composition and performance staging [13].

Logical reasoning and problem solving can be performed at various levels of complexity, ranging from limited knowledge domains with simple output combinations to many contextual domains with multifaceted, potentially conflicting inputs. Ability to recognize individual parts of an argument and their relationships, as well as draw well-supported conclusions, is an example of such a task [49]. This capability is also one of the most difficult for machines to perform, and performance remains low when compared to humans. However, technology is improving. Some activities requiring judgment may even benefit from computerization because AI algorithms make unbiased decisions while humans frequently do not. It has been demonstrated, for example, that experienced judges are significantly more generous in their rulings after a lunch break. An algorithm would produce the same results regardless of time of day [36].

Collaboration with multiple agents demonstrates a machine's ability to collaborate with both other machines and humans. This capability, particularly human-machine collaboration, is still in its early stages. Although early stages of robot collaboration have been demonstrated, they are largely based on laboratory research. For example, researchers at Carnegie Mellon University collaborated two different types of robots by allowing a mobile robot to deliver work to a static robot arm controlled by the latter robot [50].

As previously stated, the general emphasis has shifted from substitution to human-machine collaboration. However, machines' ability to collaborate with humans is currently at a low level, hampered, for example, by AI systems' inability to explain their decisions and actions to humans, as well as to understand and produce natural language. Advanced Step in Innovative Mobility

(ASIMO), a humanoid robot with limited ability to respond to voice commands and human gestures, is an early example [51].

- **Natural Language Processing (NLP)**

Natural language processing includes both natural language comprehension and natural language generation. This field's research has shifted from responding to clearly specified requests with a limited set of answers to developing refined and sophisticated systems capable of having actual conversations with people. Natural language generation is defined as "the ability to deliver spoken messages with nuanced gestures and human interaction". The definition of natural language understanding is the comprehension of language and nuanced linguistic communication in all its rich complexity. While computers' current level of natural language generation is comparable to humans', their understanding of natural language remains below. One of the key factors influencing the pace and extent of automation is progress in this area [52], [53].

Natural language processing necessitates a thorough understanding of lexical, grammatical, semantic, and pragmatic concepts. Even though computers now have some of this knowledge, they are still less capable than humans. Computers struggle to understand multi-sentence language as well as fragments of language, while in society, incomplete and erroneous language is the norm. Furthermore, teaching computer systems and robots to detect sarcasm (Maynard, 2016), both in written and verbal conversations, as well as the distinction between polite and offensive speech is currently proving difficult [45].

A machine must know what to say and how to say it to generate natural language. To know what to say, the machine must have data and be able to determine what information to include from that data. The latter process, to put it another way, necessitates that a machine understands the language rules to produce a text (verbal or written) that makes sense. Currently, software is still struggling to produce grammatically correct and well-formed texts with natural flows that fit into an individual's context and needs [54]. Recent advancements in the field have occurred, and companies such as Google, Amazon, and Apple use NLP in their products. When you ask Alexa, Siri, or Google Home about the weather in your area or where to find a Japanese restaurant, NLP allows the program to understand your speech and respond in verbal language [55].

- **Social and Emotional Skills (SeS)**

This field is concerned with human social intelligence, which encompasses a machine's ability to sense and reason about social and emotional states, as well as the ability to provide emotionally appropriate output. These are necessary skills for everyday (human) interaction as well as tasks such as negotiating, persuasion, and care. Social and emotional capacities are now the least evolved of the five main capacity areas and are unlikely to surpass human level for at least another two decades [56].

Machine learning and sensing advancements have provided machines with a limited ability to understand human emotions. However, these software programs' current skills are still far below human levels, and they confront substantial obstacles in terms of quick and precise emotion recognition. The social and emotional states of people are considerably more challenging for machines to comprehend and reason about. To detect human emotions, existing algorithms evaluate facial expressions, physiological parameters (e.g., heart rate or blood pressure), text, and spoken dialogues. These techniques have a bright future in a variety of applications, including automated call centers (Picard, n.d.) and emotion-based targeted advertising [57].

Several software applications for emotion recognition are already in use. For example, Affectiva uses facial expression analysis to adapt mobile applications to the user's emotional state. Even the most complex algorithms have never been able to communicate indistinguishably from humans, and no machine has ever passed the Turing Test. The existence of "common sense," which is tacit or implicit knowledge owned by individuals and engrained in human interaction and emotions, complicates the development of emotionally appropriate output [58]. Because this knowledge is difficult to describe and articulate, it is nearly impossible to include into algorithms. In the absence of common sense, communicating results in awkwardness or unnatural sensations. Some robots on the market can exhibit basic human emotions, such as the humanoid Pepper, which can express joy, surprise, rage, doubt, and melancholy, but emotion production is still a long way off [59].

- **Physical Skills**

Fine and gross motor abilities, navigation, and movement are all included in this category. It is linked to the domain of sensory perception, which offers information for physical actions. In terms of gross motor abilities, machines have already exceeded humans, and robots are widely used in industrial and warehousing contexts, such as for picking and placing, welding, packaging, and palletizing. Amazon has even used robots to entirely automate parts of its warehouses [60].

However, when it comes to fine motor abilities and dexterity, technology is substantially behind. The human cognitive system is strongly interwoven with manual skills. As a result, grabbing and manipulating tiny, deformable items remains a significant sensory problem for present technology. The strength of tiny actuators as well as optical and tactile sensors, which now perform considerably below human capabilities, limit robot dexterity [61].

Furthermore, robots do not yet have the same degrees of flexibility as human hands, and present control systems cannot handle the complex and unstructured nature of manual activities. Nonetheless, there are some anthropomorphic robot hands on the market with human-like characteristics. The Shadow Dexterous Hand is the most advanced of them, capable of performing delicate tasks like opening a bottle cap and collecting strawberries without crushing them [61]. Navigation has already surpassed human capabilities, thanks to breakthroughs in machine vision and machine learning. Advanced GPS systems, aided by large volumes of spatial data, allow for the precise pinpointing of exact locations and navigation to practically any destination. These skills are already commonly employed in (partially) self-driving automobiles and navigation apps such as Google Maps. Despite breakthroughs in computer vision, robot mobility, particularly autonomous mobility, remains poor. Although autonomous movement in static environments, such as specially constructed warehouses, has been largely solved, adapting mobility to new and dynamic contexts remains a significant difficulty [62].

Technical obstacles, such as balance and control, as well as insufficiently developed algorithms, are some of the causes for this. Furthermore, progress in the field of indoor mobile robots has been limited by a paucity of study on robot mobility in indoor settings [63]. However, work on algorithms is being made, as evidenced by the DeepMind computer, which has learned itself to navigate new, complicated situations in a computer simulation. Atlas, a humanoid robot that can navigate to many unknown terrains on two legs, and ASIMO, a humanoid robot capable of running, walking, kicking a ball, and reacting to human directions, are two real-life examples of advanced mobile robots [51], [64].

- **The State of Current Technologies in General**

Though significant progress is being made in each of the five capability areas, certain capabilities are still beyond the reach of existing technologies. Most notably, technology for processing and generating natural language and social/emotional output, autonomous movement, fine motor skills, and a variety of cognitive capabilities is underdeveloped. Technology, on the other hand, excels in areas like as pattern recognition, gross motor skills, and navigation, and is nearly on par with humans in the field of sensory perception. Furthermore, greater advancements are projected in all domains, with machines potentially reaching or exceeding human levels of capability in the next one to two decades [65].

Current technical advancement, on the other hand, is mostly focused on restricted, individual skills. Another key issue that must be addressed is the integration of numerous capabilities into well-functioning holistic solutions, which will most likely take considerably longer than the individual capabilities. Environmental control, on the other hand, can help robots overcome their current limitations. This notion refers to changing an environment or a task to make it easier and more structured, such as by breaking it down into smaller tasks or converting an unstructured setting to a structured one. Advanced flexibility, mobility, physical dexterity, and cognitive ability are not required when environmental control is used. Amazon, for example, placed bar-code stickers on the floor of its warehouses to help the robots navigate the space. They modified the surroundings to make it more structured

[66]. Even though environmental control is used in warehouses and other local settings, countries and towns are still lagging in terms of adjusting their infrastructures to accommodate new technology [67].

- **Are Work Activities now being Replaced?**

Following on from the preceding section's discussion of present technical capabilities, the following section seeks to connect these capabilities to their potential for replacing labor, concentrating on the specific functions that make up occupations rather than jobs. The reason for this is that employment contain a variety of responsibilities, each of which has a varied relationship to present technological capabilities. As a result, although some tasks can already be automated, others cannot. As a result, before examining the impact on jobs and labor in general, it is critical to first identify whether individual tasks can be replaced. Following the Task Model of [68], the many types of tasks are described below, with the substitution potential of each task category examined in connection to the competencies listed above. The study's use the findings in the next part, The Impact on Labor, to make a judgment on the overall impact of automation on a variety of jobs and industries.

- **The Four Different Job-Tasks**

[68] conceived work as a succession of tasks rather than whole jobs to estimate the job substitution potential of computers. The paper distinguishes between routine and non-routine tasks, as well as physical and cognitive tasks. Figure 2 shows the result of this classification, which is a 2x2 matrix. Routine tasks are tasks that are defined by specific rules that may be exhaustively specified and so converted into code. These rules are not widely known for non-routine processes, making codification much more difficult. Routine tasks are automatically classed as tasks that can be easily replaced by technology as a corollary of this description, but non-routine tasks are not. Cognitive tasks are mental processes, whereas manual tasks are physical activities that involve motor skills and movement.

	Cognitive	Manual
Routine	Explicit rules Mental processes	Explicit rules Motor skills
Non-routine	Rules difficult to codify Mental processes	Rules difficult to codify Motor skills

Figure 2. Four Different kinds of Job Tasks [68]

There are various task classifications in addition to the one listed above. [36], for example, have created seven main activity categories:

i. Physical predictability
ii. Data processing
iii. Data collection
iv. Unpredictable physical conditions
v. Communication with stakeholders
vi. Professionalism
vii. Supervising and mentoring others.

The two-by-two matrix proposed by Autor et al. fits these seven groups well (2003). The routine manual and non-routine manual work classifications of Autor et al. are associated with predictable and unpredictable physical activities (2003). Routine cognitive tasks include data collection and processing, but non-routine cognitive tasks include interacting with stakeholders, using expertise, and managing and developing people.

Each of the four categories is addressed in depth further below.

- **Manual Tasks That are Done Frequently**

Physical activities that need systematic repetition of a consistent technique, i.e., structured physical tasks that take place in predictable contexts, fall into the routine manual task category. Gross and fine motor skills, sensory perception, and, to some extent, movement are the primary qualities necessary to conduct these types of activities. Assembling, choosing, and sorting, welding, and cooking are examples of activities. These tasks are easily translated into computer programs, and the technology required to complete them is mature, particularly in gross motor skills, where robots have long outperformed humans.

As a result, this task category has the most technological potential for machine replacement [36], [68] . Manyika et al. (2017) estimate that in the United States, up to 81 percent of this category's tasks can be replaced. Routine manual chores have been replaced for a long time, dating back to the advent of the first devices that could work automatically. Since then, robots have continued to force humans out, and in the twentieth century, a large proportion of manual tasks were automated (Finnigan, 2016). Many processes in the agriculture and automobile manufacturing industries, for example, are currently carried out by machines. As a result, Autor et al. (2003) discovered that between 1960 and 1998, the percentage of persons working in jobs with a high share of routine manual activities decreased.

Recent advancements in sensory perception and physical dexterity have allowed robots to be assigned to activities that demand greater precision, such as slicing meat, assembling customized orders, and manufacturing electronic components. Robots have also gotten considerably safer and more adaptable to utilize, allowing them to transition between duties rapidly and safely alongside humans. Furthermore, developments in mobility and navigation enable robots to roam around in static areas such as warehouses autonomously [69], [70]. Furthermore, robots are becoming more prevalent in the service industry. Simple service jobs, such as cleaning, have been handled by robots for over a decade, with the robot vacuum cleaner being the most known example. Robots, on the other hand, are increasingly equipped to take on difficult routine manual jobs in the service industry, thanks to their enhanced dexterity and mobility. The food industry is an excellent example, as robots may be used to prepare and serve food and beverages [56], [66].

Most repetitive and routine operations can and will most likely be undertaken by robots in the future, reducing the proportion of repetitive, rule-based activity in professions. More high-precision operations, such as manufacturing tasks in the electronics industry, will become candidates for automation as sensor technology improves and robot dexterity improves. As robots become safer, they will occupy more positions alongside human coworkers. More engineering breakthroughs are needed to increase the flexibility of robotic systems by reducing the time it takes to reconfigure them [71].

- **Manual Tasks that aren't part of the Normal Routine**

Non-routine manual jobs are unstructured physical work that occur in unpredictable contexts and frequently need situational flexibility and face-to-face interaction. Sensory perception, fine and gross motor skills, social and emotional abilities, natural language processing, navigation, and movement are all required. Most of these talents have yet to attain human-like levels of performance, and including flexibility remains a significant difficulty [68], [72]. As a result, according to Manyika et al., the automation potential of this category is limited, at only 26%. (2017). Operating a crane, aiding with surgery, janitorial duties, and making hotel beds are examples of tasks.

Machine learning and recent advancements in sensory perception and physical capabilities have enabled machines to take over an increasing number of manual non-routine chores. Robots can now undertake high-precision, non-standardized jobs like manipulating delicate products like fruit and vegetables, thanks to advancements in sensor technology and hand dexterity. Computer programs can also take over condition monitoring activities like assessing the state of an aircraft engine or examining the moisture level in a field of crops by incorporating modern sensors. Human operators can execute the required maintenance when the program alerts them. Some maintenance activities are also being replaced. General Electric, for example, has created robots that can climb and service wind turbines [66].

The autonomous vehicle is another well-known new application of machines for non-routine manual chores. Autonomous driving was once thought to be impossible because it necessitated actions such as parking, lane change, and adjusting to traffic lights, other vehicles, and pedestrians. Today, Google's self-driving car, aided by machine learning and smart sensors, can navigate the streets entirely on its own, and is even considered safer than human-driven vehicles by some. The warehousing business has also used autonomous mobility. Many warehouses, such as Amazon's, have become largely automated because of environmental control [17], [73].

However, for the time being and in the foreseeable future, machines will be unable to perform most of the non-routine manual work. Despite advancements in the realm of autonomous vehicles, autonomous mobility remains a serious difficulty in general. Similarly, major advancements in perception and dexterity technologies are required before autonomous manipulation in unstructured and delicate environments is feasible. Furthermore, tasks requiring human interaction necessitate significant improvements in language recognition, social and emotional capabilities, and user interfaces. Walking a patient down a hospital (or nursery) hallway is one example [74].

- **Cognitive tasks humans should do everyday**

All mental (non-physical) tasks that repeat a specific method in a predictable setting are considered routine cognitive tasks. This refers to the various components of processing structured information, such as data gathering, organization, and storage, to a considerable extent. Retrieving information, identifying recognized patterns, optimizing, and planning, logical reasoning/problem solving, and natural language processing are all essential competencies for these activities. Data processing operations such as calculating and bookkeeping, as well as ordinary customer service activities performed by employees like cashiers, telephone operators, and bank tellers, are examples of tasks. According to Manyika et al., these tasks have a significant potential for machine substitution due to their routine nature, with 64 percent for data gathering tasks and 69 percent for data processing tasks in the US (2017) [68].

The emergence of the computer [68], which permitted the digitization and automatic processing of information, ushered in the automation of cognitive tasks. As a result, many operations have already been automated, including administrative activities, bookkeeping, invoicing, resource optimization, and a variety of others. The automation of ordinary cognitive work has reached unprecedented scale and speed thanks to technology advancements and the present focus on digitalization. Many businesses have begun "digital transformations," which entail the streamlining, standardization, and digitization of the entire organization.

This means that huge portions of consumer interaction interfaces can be automated on the front end. For mortgage brokers, examples range from the automation of customer data gathering to the hiring of full-fledged, AI-based virtual staff who can handle all elements of customer engagement. The reorganization of the organization's IT landscape eliminates many processes and operations on the back end [28].

Furthermore, robotic process automation, which uses software robots to automate well-defined transactions/user activities traditionally handled by people, can be used for some organized processes that stay in place. These software robots can be thought of as virtual employees who interact with existing applications in a human-like manner. The rate of digitalization will determine how quickly automated data collection and processing operations spread. As businesses complete their digital transformations, more data and processes will be digitized and, as a result, automated. Furthermore, greater automation of customer support operations will be contingent on machines' ability to connect with clients, which will be contingent on advancements in natural language processing and emotional capacities [75].

- **Non-routine cognitive job-tasks**

Non-routine cognitive activities are mental (non-physical/abstract) tasks that do not follow a set procedure and/or occur in unanticipated settings. These tasks necessitate a variety of cognitive skills, including creativity, logical reasoning, pattern generation, and coordination among several agents. Furthermore, natural language processing as well as social and emotional talents are frequently important. Interfacing with stakeholders, using expertise, and managing and developing people are examples of these types of tasks. Legal writing, bargaining, education, and disease diagnosis are all examples of activities [65].

These tasks have traditionally been the most difficult to automate. However, large data and recent advancements in machine learning (in particular, pattern recognition) have allowed machines to penetrate the domain of unstructured work. In an unstructured situation, a computer can generate its own structure through unsupervised learning. Furthermore, advances in user interfaces, such as language recognition, enable computers to respond directly to speech and gesture commands [76].

Fraud detection is one of the duties that can now be automated, and it requires the ability to spot trends in data as well as the ability to make conclusions. The system can employ pattern recognition to discover abnormalities, exceptions, and outliers by applying machine learning to develop models based on previous transactions, social network information, and other external sources. This means that fraudulent conduct can be detected, and transactions can be avoided in the banking industry. Court computerization in Ghana is another area where machines are making inroads; nowadays, computers can quickly analyze and order thousands of legal papers and communicate their findings visually to attorneys and paralegals [14].

However, for the time being, most of the capabilities involved are still well below human levels. The substitution potential of tasks that demand creativity, problem solving, and complex communication (a combination of natural language processing and social and emotional capacities) is extremely low (Manyika et al., 2017; Autor et al., 2003).

Even in sectors where robots can beat humans on certain tasks, such as route planning, humans are frequently necessary to set the goal, analyze the results, and undertake commonsense checks. Machine learning and artificial intelligence, it is arguable, will require significant advancements before they become mature technologies. There are various examples of AI systems that have failed, such as Microsoft's Tay Chatbot, which was forced to be shut down barely 16 hours after its launch due to very contentious statements it tweeted. Interfacing with stakeholders, using expertise, and managing people, the three categories defined by Manyika et al. (2017), all have a substitution potential of less than 20%. A substantial amount of task-specific knowledge is required for the automation of cognitive non-routine tasks, in addition to other requisite breakthroughs in cognitive, social, and emotional capacities. Pattern recognition cannot be used without this information. Environmental control, or work simplification, can also be used to alleviate engineering bottlenecks, as it can with other sorts of tasks. Self-checkout stations in supermarkets, for example, eliminate the need for advanced consumer interaction (Autor et al., 2003).

- **Job-task substitution in perspective**

As the preceding section has shown, technology has the potential to take over an expanding number of tasks. Routine tasks, both manual and cognitive, have been automated for some time, but machines have only recently gained the potential to replace human labor in some non-routine tasks. The potential for everyday work to be replaced is high, and it will only grow as technology progresses. Non-routine task substitution, on the other hand, is still primarily limited to niche applications that require human intervention. Figure 3 shows a summary of the discussion for each of the work task categories. Significant breakthroughs in all five capacity areas are required to take non-routine job automation to the next level, with natural language processing capabilities being the most crucial, according to Manyika et al (2017).

	Cognitive	Manual
Routine	***Primary Required Capabilities*** Retrieving information Recognizing known patterns Optimizing and planning Logical reasoning/problem solving Natural language processing ***Sample Tasks*** Data processing tasks, e.g., calculating and bookkeeping Customer service tasks by e.g., cashiers, telephone operators, bank tellers **Predicted Substitution Rate: 64-69%***	***Primary Required Capabilities*** Gross and fine motor skills Sensory perception Mobility to some extent ***Sample Tasks*** Assembling Picking and sorting Welding Cooking **Predicted Substitution Rate: 81%***
Non-routine	***Primary Required Capabilities*** Creativity Logical reasoning/problem solving Generating novel patterns Coordinating with multiple agents Natural language processing Social and emotional capabilities ***Sample Tasks*** Legal writing Negotiating Teaching Diagnosing diseases **Predicted Substitution Rate: <20%***	***Primary Required Capabilities*** Fine and gross motor skills Sensory perception Social and emotional capabilities Natural language processing Navigation Mobility ***Sample Tasks*** Operating a crane Assisting with surgery Janitorial work Making hotel beds **Predicted Substitution Rate: 26%***

Figure 3: Summary of required competencies, sample job-tasks, and predicted substitution rate for each job-task category.

- ## The Net impact of Automation on the Labour Market

Even though various books and studies predict that technology will take over many jobs, resulting in mass unemployment, this scenario is unlikely to occur at this time (Manyika et al., 2017). Many activities cannot currently be replaced by machines, and machines are unable to execute multiple sorts of activities in a coordinated manner (Autor, 2015). As a result, they are typically incapable of substituting labor for full occupations, which typically consist of several bundled operations. It is preferable to focus on the substitution potential of individual activities within a job when determining the employment's substitution potential. A huge amount of research supports this viewpoint, predicting that technology will take over significant portions of all jobs in all industries and at all levels of society (Manyika et al., 2017).

The following part will look at the possibility for automation in individual vocations and large occupational categories, as well as the nature of work and the impact of technology on industries.

- ## Job Automation's Promising Future

The possibility for job automation is estimated differently in different studies. According to Frey and Osborne (2013), up to 46% of all employment in the United States contain more than 70% activities that can be automated, making them highly automatable. [77] show that just 9% of jobs in the US have a 70% automation potential when utilizing the same methodology but with a task approach rather than an occupation approach.

While Manyika et al. (2017) do not use 70% as a criterion for significant automation potential, one might infer from their analysis that about 25% of all professions in the US are more than 70% automatable. Clearly, estimating the potential for automation is challenging and heavily reliant on subjective assessments of technological capabilities and the work structure of vocations. Despite the differences, there are a few high-level observations that may be made. To begin with, jobs that can be completely automated are likely to be made up solely of routine manual and cognitive tasks that do not require human interaction or manual dexterity.

Sewing machine operators and order clerks are two examples of these types of jobs. Secondly, positions with a high risk of automation are likely to entail some degree of human interaction or unpredictable/high precision physical activity. Manufacturing and production industries, for example, are highly automatable due to their strong reliance on manual regular operations, as are sales, office, and administrative support positions (World Economic Forum, 2016). Transportation (Frey et al., 2016), material movement, and food and lodging services are other career groups with a lot of routine manual operations. Manyika et al. (2017) claim that the latter has the most automation potential of all the categories.

Finally, the lesser the job's automation potential, the bigger the share of non-routine tasks. When skills like human contact (which necessitates natural language processing as well as emotional and social talents), creativity, logical reasoning/problem solving, high-level dexterity, or mobility are required, the effect is amplified. Jobs that need all or a major portion of these competencies are not at all vulnerable to automation. A choreographer's profession, for example, focuses on the creative task of developing a choreography as well as human contact in dealing with stakeholders and training dancers to bring it to life. To communicate with their clients, a dentist, on the other hand, demands high levels of dexterity and sensory perception, as well as emotional and social qualities. As a result, essentially no actions in both jobs can be automated [79].

Nonetheless, most job categories are somewhere in the middle, encompassing both routine and non-routine work. As a result, they may be partially automated. For investment bankers, for example, cognitive tasks are the main value drivers, but a substantial percentage of their job entails acquiring and interpreting data, which could be automated. Many legal professions are in the same boat. These types of employment are unlikely to vanish; rather, they will use technology to improve human efficiency and the quality of output (Frey et al., 2013). It's vital to keep in mind that this is a broad perspective. Significant percentages of the employment in the occupation categories have limited automation potential, and the substitution potential of a job varies greatly among industries. While both supermarket cashiers and specialized software sales agents are classified as sales occupations, the former has a high substitution potential while the latter has a low one due to the technical competence and emotional intelligence necessary (World Economic Forum, 2016).

However, due to changes in the structure of employment, industries, and education, as well as earlier expenditures in technology, the substitution potential of similar jobs varies among countries. For example, because Ghana is at the forefront of technological investment, in the sub-Saharan Africa its automation potential may be lower than average. As a result, many procedures will have already been automated, making huge portions of the remaining tasks impossible to automate [79].

- **Work in the Future**

Individual task replacement on a big scale will most certainly alter the nature of work and all occupations (Frey et al., 2013). Human employees will be able to spend more time on complementary tasks where humans have a comparative advantage, such as activities involving creativity and human connection, as machines begin to take over regular manual and routine cognitive duties (Autor, 2015; Arntz et al., 2016a).

Furthermore, humans will be assisted by machines for many of these jobs, and a closer collaboration between technology and humans is expected. While a doctor will most likely remain accountable for a patient's final diagnosis in the next decades, they will be able to make decisions based in part on AI-assisted diagnosis guidance [80]. As a result, jobs will necessitate additional training and technological knowledge. Furthermore, when technological integration improves efficiency, human employees may spend less time on work, resulting in shorter workweeks.

- **The Consequences for the Job Market**

Over the last few decades, automation has created a well-documented shift in the job market. Scholars have seen a polarization of the job market in both the United States and Europe because of this transition. A steep fall in the number of middle-skilled jobs was matched by increases in the share of low-skilled service jobs and high-skilled jobs because of this polarization. Because they mostly consisted of routine manual and cognitive duties, such as collecting and processing data, these middle-skilled positions may be automated. Non-routine manual and cognitive work were among the tasks that could not be mechanized. The former is typically found on the low-skill end of the spectrum, whereas the latter is typically found on the high-skill end. As a result, the increase in general labor demand because of increased productivity from automation disproportionately affects low-skilled positions, such as hairdressers and janitors, and high-skilled jobs, such as computer scientists, resulting in a polarization effect (Autor, 2015).

This polarization, however, is projected to fade because of current and future technological breakthroughs. There are three reasons for this. To begin with, many surviving mid-level professions involve a combination of non-routine duties and characteristics that machines cannot currently accomplish, including as emotional skills, problem solving, and adaptability. Second, the development of new technology has resulted in the creation of various new types of middle-skilled employment, such as healthcare technicians, as well as increased demand for others, such as restaurant managers. Finally, as this paper discusses, computers are more capable of taking over low-skilled service professions as well as high-skilled cognitive jobs (Autor, 2015; World Economic Forum, 2016a).

A global discussion has also raged about the impact of technology on offshore and reshoring projects, particularly in the US manufacturing industry. Many say that because robotics eliminates the need for low-cost labor, it will lead to a trend of reshoring manufacturing activity to the Western world, while the offshore trend will slow. However, alternative viewpoints have lately emerged, saying that technology is facilitating the offshore of numerous services and simplifying the management of complicated global supply chains, resulting in a surge in manufacturing outsourcing. The later consequences appear to be stronger, and the reshoring trend, as advised by BCG, appears to have come to a halt. Offshoring, on the other hand, is on the rise. It's nearly impossible to accurately assess the entire effect of the change drivers on the labor market, and estimates range from mass unemployment to increased labor demand. Because huge portions of tasks can be automated, fewer workers will be required to provide the same amount of production (Finnigan, 2016).

As a result, automation may result in job losses in the short term (OECD, 2016), before overall productivity improvements raise labor demand again. In the past, technical advancement has not resulted in major increases in long-term unemployment, but it is unclear whether this will be the case this time (Autor, 2015). What is known is that technological advancements will result in significant workforce displacements, particularly in high-routine occupations. To stay up with the rising rate of change, organizations and employees will need to expand their attention on education and training.

- **Industry Automation Possibilities**

Because different industries have different job constellations and comparable positions in other industries may have different sets of tasks, the automation potential of work varies between industries. Furthermore, there are considerable variances between countries in terms of the job composition of respective industries. Daily, an attorney in the US may conduct substantially different tasks than an attorney in Ghana.

As previously stated, the accommodation and food industry have the largest share of automatable tasks in the world, according to Manyika et al. (2017). These findings are backed up by a study on the relationship between innovation and employment conducted by Osborne and Frey and Citi Bank in the United States in 2015. Because food preparation comprises of relatively predictable manual operations, the sector has a significant automation potential. Order taking and serving, for example, do not necessitate high levels of emotional intelligence, leaving them both open to automation. KFC, for example, has used digital screens to automate its ordering and payment operations, and many casual dining operators are integrating tabletop tablet systems in their locations.

Transportation and warehousing, retail commerce, wholesale trade, and manufacturing are other businesses with substantial shares of automatable jobs identified by both studies. Amazon, for example, has already demonstrated that robots can run entire warehouses, and autonomous vehicle technology is nearly complete, allowing for the automation of truck transportation. Industries like educational services, revenue agencies, company and business management are at the bottom end of the automation spectrum. Emotional intelligence and complicated communications are important and crucial aspects of daily operations for many occupations in these areas, reducing the potential for automation.

The studies also vary on the possibilities for automation in several industries. For example, Manyika et al. (2017) estimate average automation potential for some mining, real estate rental, administrative and support services, and construction businesses, while Osborne and Frey (2015) estimate high automation potential for others. According to Osborne and Frey, the agriculture and information sectors are rarely automatable, however Manyika et al(2017). believe they are moderately automatable.

Research on the Swedish economy was also conducted by Manyika et al. (2017). Three industries, according to the report, have the largest shares of automatable tasks. Manufacturing, mining, transportation, and warehousing are among them. Educational services, the information industry, and the arts, leisure, and recreational sector have the lowest automation potential. The manufacturing sector has by far the biggest share of personnel who could be replaced in terms of absolute numbers. According to the report, up to 420,000 people's jobs might potentially be automated. Healthcare and social aid, administrative support and government, and retail trade are other industries with big populations. Manyika et al. (2017) estimate that 46 percent of operations in Rwanda might be automated, resulting in the redundancy of 2.1 million workers.

- **Other Automation Considerations**

Though it is technically possible to replace human labor with machines in many vocations and tasks, there are several other factors that influence the rate and scope of automation. Commercial availability, cost of implementation, economic benefits, labor market dynamics, and social, legal, and ethical acceptance are five of these aspects mentioned below. These parameters are based on the five factors identified by Manyika et al (2017). as determining the pace and degree of automation. To avoid any confusion with our usage of the word technological feasibility in this study, we renamed their first factor of technical feasibility as commercial availability.

Availability in the marketplace

Even though the technologies listed above have been validated in laboratories, the majority have yet to be commercialized. Many technologies are still in the early or medium stages of development; they have not yet matured to their full potential and require additional scientific research. Artificial General Intelligence is an example of this (AGI). Despite the large quantity of study into this technology and the demonstration of some applications, much more scientific research is required, and experts anticipate that broad adoption of viable AGI platforms will not occur before the year 2050 [81], [82].

There is also a distinction to be made between technological viability and commercial adoption. Applied research focuses on establishing engineering solutions for individual use cases, whereas basic (scientific) research focuses on large generalizable cases. It takes time and effort to turn novel technology concepts into commercial products. Predictive engineering for aviation engines, for example, and predictive healthcare, for example, could be considered equivalent scientific challenges because both forecast system failure. Both uses, however, would require separate software, models, and hardware to function, and each would take years to build (Manyika et al., 2017). Furthermore, computers can already identify diseases to some extent, but due to technical difficulties, computers diagnosing all types of diseases soon is improbable [81].

Implementation Costs

A credible business case must exist for a company to use automation and digitalization technology, aside from the availability of commercially ready solutions. As a result, the expenses of developing and implementing new technologies are a key factor in determining how quickly and broadly they are adopted. When comparing these costs, it's clear that the cost size and structure of hardware and software solutions are vastly different.

- **Hardware**

Hardware refers to all the physical parts of a technological solution, and it frequently necessitates sensory perception, fine motor abilities, gross motor skills, and/or mobility. These components have high capital expenditures and demand significant upfront investments. This complicates the business case and emphasizes the necessity for available funding. Because they face high labor costs and have easily available cash, large corporations in sophisticated nations, such as Rwanda, are projected to embrace these solutions at the fastest rate. Furthermore, sectors with a high capital intensity are prone to have longer adoption periods [83].

An industrial robot is a good example of a hardware solution. The cost of advanced robotics has been falling for decades and is predicted to continue to fall in the future. [84]. Significant cost reductions in modern sensors and actuators have enabled this price reduction. Furthermore, economies of scale may result in further cost savings as robot manufacturing quantities increase. Despite the price reductions, the cost of reliable mechanical devices remains high, and most industrial robots remain expensive, ranging from many tens of thousands to hundreds of thousands of dollars. Furthermore, considerable investments are required for engineering the robot's work cell, in addition to the costs of the robot itself. An industrial robot, for example, may require enhanced safety equipment to perform properly, and a tool-changing system may be required if a robot arm is to work with multiple tools. This type of technology is quite expensive, and it can easily quadruple the cost of implementing a robot [85].

Nevertheless, with the emergence of simpler general-purpose robots, the cost of automating simple jobs could be greatly reduced. These robots are more adaptable and do not require large work cells, in addition to being cheaper. They are also safer to work with for people, eliminating the need for costly safety equipment. The emergence of these types of robots could have a substantial impact on robot adoption. Service robots are generally less expensive than their industrial counterparts and do not require any additional equipment [86].

- **Software**

The capital requirements for software solutions are substantially reduced, especially for cloud-based systems. Increased performance and lower costs of computing power, data storage, and cloud computing enable these cheap costs. The marginal cost of an additional software unit is frequently insignificant (Autor, 2015).

However, software deployment can come with significant implementation expenses, particularly if existing software systems are in place. These implementation methods can be more expensive than the program itself, and they include things like software customization, staff training, and new process design. Furthermore, the talent required to design, customize, and integrate innovative solutions is in short supply and thus exceedingly costly [87]–[89]. Robotic process automation is a less expensive and faster alternative to implementing costly new software solutions. Without large investments, this technology can automate workflows and replace human labor. However, as compared to a total system redesign, the overall benefits are modest [31].

- **Benefits to the Economy**

The generated economic gains from implementation are another factor to consider when building a good business case for new technology adoption. Only if the advantages outweigh the costs will businesses be willing to embrace new technologies into their operations. The first and most evident economic benefit of implementing automation technology is a reduction in labor expenses because of human work being replaced. As previously said, it is doubtful that many professions would be entirely replaced, but because to greater productivity, fewer personnel will be required to accomplish the same output. The economic benefits of automation, on the other hand, are manifested not only in terms of reduced labor expenses, but also in terms of new value creation. Benefits such as greater throughput and productivity, improved safety, decreased waste, and superior quality are examples of benefits that can all help to increase profit in some way. These additional benefits can occasionally outweigh the labor substitution benefits.

Implementing autonomous trucks, for example, would not only save labor costs but also increase safety, fuel efficiency, and productivity because no driver is required to make stops. As a result of these enhancements, profit increases. Another example is Google DeepMind, where the use of AI from DeepMind machine learning in Google's data centers has resulted in a 40% reduction in energy usage and a 40% rise in profit (Manyika et al., 2017). Robots have also become more economically viable solutions for tasks that were previously considered too expensive or delicate to automate, such as robotic surgery support, thanks to improvements in robotics.

Digitalization, as defined in the Definition of Digitalization section, is a method of creating and capturing new value within an organization. It enables businesses to open new digital customer channels and produce new consumer insights, goods, and services, for example, resulting in the development of new value for both customers and businesses. Furthermore, the automation of mundane operations allows staff to devote more time to high-value projects. For example, in the financial sector, using a computer to observe existing processes and learn to recognize different scenarios (e.g., matching a payment with an order number) frees up finance personnel to focus on more important activities. As a result, organizations and industries that have gone digital to a greater extent, such as media, finance, and technology, often have stronger productivity and wage growth than those that have gone digital to a lesser extent, such as education, retail, and healthcare [48], [90], [91].

Technology deployment can provide significant benefits to society, in addition to higher profitability for businesses. A good example is transportation. As previously said, truck transportation automation will result in increased production, increased safety, and reduced fuel usage. Higher productivity means fewer vehicles are required, resulting in greater fuel savings and fewer congested roadways. As a result, there will be less pollution, fewer traffic bottlenecks, fewer accidents, and lower road maintenance costs for the general population. The advantages described above propel automation forward.

However, it's worth noting that most businesses are still in the early phases of adopting technology like AI, machine learning, and robotics. Due to the small number of extant implementations, estimating the total benefits of these technologies is difficult. Furthermore, the indirect economic gains can take years to manifest. In capital-intensive businesses, where hardware investments are required, the delay between investment and benefit is unusually long. As a result, understanding the cost-benefit tradeoffs of integrating new technology is difficult for businesses and regulators [26], [57]. An AI-based system is an example. Most corporate leaders, according to Bughin et al. (2017), have no idea what AI can do for them, where to utilize it, how to integrate it, or what the advantages and costs will be.

- **Trends in the Labour Market**

Because labor expenses are such an important part of a company's business case, the labor market's characteristics have a big impact on how quickly these technologies are adopted. These dynamics include the supply and demand for human labor, as well as the cost of human labor, and are strongly linked to a country's demographics and citizens' skill levels.

The cost of labor and, as a result, the economic gains received from labor substitution are heavily influenced by labor supply and demand. Wages fall because of a high supply of labor combined with low demand. As a result, low wages reduce the economic benefits of labor replacement, reducing the incentive for businesses to automate. For example, based on existing technologies, the food industry has been classified as one of Ghana's industries with the highest automation potential. However, due to an abundance of workers, wages have historically been low in comparison to most other industries. As a result, there has been little motivation for this business to automate, and the current level of automation is minimal.

The labor supply is determined by the demographics of a country and the skill level of its workforce (Manyika et al., 2017). The first has an impact on the number of individuals employed. In many industries, there will be an oversupply of labor in countries with a big working population, and the motivation to automate will be low. On the contrary, countries with dwindling labor markets, such as Rwanda and many other Western countries, have a stronger incentive to automate.

Which industries have labor surpluses and deficits is determined by the skill level of the working population. If many people have pursued an education to become English teachers, for example, the market for English teachers will become saturated, and earnings would fall. Meanwhile, there is a possibility that the supply of French teachers will be insufficient, causing wages to rise. If technology replaces tasks, it allows for a better degree of human productivity, which increases labor supply. If there is a demand for activities within their skill set, these personnel can be redeployed.

However, there is frequently a mismatch between in-demand abilities and oversupplied skills. People must reskill themselves through education and training before they may be redeployed in such a situation. This necessitates the investment of time, money, and effort. As a result, the adoption of labor-substituting technology frequently results in short-term unemployment and, as a result, a period during which people must re-educate. However, as the rate of technology change and acceptance accelerates, it is unclear whether educational and training systems will be able to keep up. This is especially tough for persons who are at the bottom of the competence scale.

When low-skill employees and high-skill workers make up the bulk of the workforce, a labor market polarization occurs. Technology has transformed the job market in Rwanda, as it has in other similar nations, over the last 10-20 years. Some say that the Swedish labor market is undergoing a labor substitution, and that the Swedish regulatory and social security systems are unprepared to deal with the changes. This will intensify polarization, and Rwanda will have a tough time redeploying staff if training plans are not implemented in a timely manner [73], [92].

Finally, the future of the job market is impossible to foretell. It can be stable with low unemployment one year and instable the next with high unemployment and a high degree of polarization the following. Unfortunately, when automation technologies are used, the job market is unlikely to benefit everyone evenly. Some people will be negatively impacted by job loss or wage pressure, while others will benefit from salary increases and new work opportunities. Government regulations, how businesses choose to work, and how individuals seek out new skills and professions can all help to narrow the gap in benefits delivered across the labor spectrum [69], [93].

- **Acceptance in terms of social, legal, and ethical norms**

Applications of new technology must be socially and legally acceptable before they can truly replace human work. This is likely the most important element impacting the speed of automation, second only to technological feasibility. The concepts of social acceptance and legal acceptance are intertwined, and both rely heavily on the concept of ethical acceptability. As a result, these three topics will be discussed together. Both the legal and social approval of new technologies are lengthy procedures. It will take time for a patient to accept a robot as a nurse or for a government to establish self-driving buses, for example. As a result, it is unavoidable that new technologies will take years to fully embrace and integrate into society. Decision makers must see the potential and benefits of AI, and employees and workers must adapt to the technologies once they are implemented, to name a few criteria.

Privacy problems are one of the primary roadblocks to automation. A vast amount of data is required for new technologies and solutions to evolve in the best interests of society. Data is difficult to access or anonymize due to privacy concerns and legislation. Furthermore, people are hesitant to share personal information because they are unsure who will have access to it, how it will be used, or for what reason. When an employer, for example, gets access to a person's medical records, it becomes an ethical issue. An employer may be hesitant to hire someone who is unwell or overweight for whatever reason [81].

When technologies are utilized for predictive policies, for example, the ethical question comes into play. It's a technical difficulty to avoid feeding biased information into the systems – such as racial, sexist, or religious discrimination – to prevent innocent people from being unjustifiably monitored and discriminated when the real world is biased. There is a probability that AI algorithms will make less biased judgements than humans if predictive hiring processes are carried out with prudence and through thorough design, testing, and implementation [20].

As previously said, the scope and speed of automation are determined by society acceptance and trust in technology and AI. Many of the tasks that a nurse performs, for example, might theoretically be automated, but coworkers and patients will likely find it difficult to accept at first. When their meal is served, most patients expect to be greeted by humans and to have human interaction. Patients and coworkers must accept and trust the machines for the activity to be truly substituted. This can only be possible if hospitals fully incorporate automation technology and ensure that the connection between intelligent computers and humans is seamless (Manyika et al., 2017).

This level of confidence and acceptability is also required for security systems to incorporate cutting-edge technologies. Cities across North America have already implemented AI technology in border administration and law enforcement and will continue to rely extensively on them in the future. Surveillance will include driverless cars, drones, and cameras, as well as algorithms to detect financial crime and generate predictive rules. This is only conceivable, though, if there is widespread social acceptability. Furthermore, full-scale implementation necessitates governmental approval. While autonomous vehicles are completely functional, they will only be adopted after regulators approve them (Manyika et al., 2017).

Additionally, concerns have been expressed about accountability when the technologies are implemented. Issues such as who is responsible for robots' and AI's actions and conclusions have never been addressed before, making them difficult to address. For example, who is accountable for a traffic collision involving and maybe caused by an autonomous vehicle? Is it the car's owner, the automaker, the city, one of the numerous software or hardware providers, or one of the numerous programmers that wrote some of the software code lines? [81].

There may be implications if the technologies are utilized. There's no way of knowing, for example, if AI will optimize the job market without considering subtle social preferences or sell sensitive documents about people's skills to private corporations or political parties. Although it is improbable that AI will want to hurt people on its own, there is still a significant possibility that it could be misused by humans for negative purposes.

To summarize, social, legal, and ethical acceptability of automation technologies are major elements that influence their adoption. Because many individuals fear losing their jobs, it's understandable that social adoption of new technologies is tough. However, as previously stated in this report, activities within jobs, rather than complete jobs, would be substituted. To promote social acceptance, regulators must clearly disclose this fact and that only certain people would have access to personal information.

VI. Conclusion

The goal of this paper was to look at the labor substitution potential of a variety of technologies in a developing economy. We initially addressed whether artificial intelligence, machine learning, and robotics could be used to replace labor in the future. The study discovered that technology can now undertake a wider range of occupational functions than ever before, and that automation is no longer limited to mundane operations. However, the automation potential for non-routine work is still limited, particularly for tasks requiring autonomous mobility, creativity, problem solving, and complicated communication.

In terms of occupations, the study found that most jobs will be impacted by individual activity automation, but only a handful have the potential to be entirely replaced. Jobs that are primarily routine in nature and do not require mobility or human interaction are the ones most at risk. Though few jobs may be totally replaced, automation may result in short-term unemployment, prompting retraining and further education. Furthermore, we concluded that the nature of jobs would alter as routine tasks are replaced and people and machines collaborate more closely. Food and lodging services, transportation and warehousing, retail trade, wholesale trade, and manufacturing are the industries with the most potential for activity substitution.

Commercial availability, cost of implementation, economic benefits, labor market dynamics, and social and legal acceptance are the five primary aspects that come into play before automation potential becomes actual automation, according to the study's conclusion. Each of these five elements has a substantial impact on the rate and extent of technology adoption. The use of technology is hampered by a lack of applied research, poor incomes, high costs, and legal and ethical limits. Overall, technology is progressing at a breakneck speed, and the rate of change is quickening. As a result, machines will be able to do an expanding number of tasks previously handled by people. Even though various obstacles have slowed the pace and extent of adoption, it is unavoidable that technology will become more prevalent in the workplace. Long-term unemployment is improbable, but reskilling will be required in the short term to allow displaced workers to reenter the workforce. To keep up with the rate of automation, individuals, businesses, regions, and countries will need to put more emphasis on education and training.

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