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Artificial Intelligence and Machine Learning for Job Automation:
A Review and Integration

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ABSTRACT

Job automation is a critical decision that has brought about profound changes in the workplace. However, the question of what drives job automation remains unclear. This study conducts an interdisciplinary review of five theoretical frameworks on job automation, paying particular attention to the role played by artificial intelligence and machine learning. It highlights the concepts and mechanisms underlying each of the frameworks, compares and contrasts their similarities and differences, and highlights challenges and suggests opportunities of job automation. It also proposes an integrated framework on job automation by addressing the research gaps in extant frameworks and thereby contributes to the research and practice on this important topic.

KEYWORDS

Artificial Intelligence, Data-Centric AI, Integrated Framework, Job Automatability, Job Automation, Machine Learning, Model-Centric AI, Nonroutine Tasks, Routine Tasks

INTRODUCTION

The wide use of computers has brought about profound changes to the world of business. Earlier studies of the impact of computers tend to focus on how computers have improved productivity, streamlined business processes, expediated information exchange, and facilitated distributed collaborations. In recent years, increasing attention has been paid to how computers, and information technologies (IT) in general, have affected individual employees, such as skill transformation and worker displacement. This trend is further accelerated by the rapid development of artificial intelligence and machine learning, which have pushed job automation to a level that could only be imagined a few years ago. A question that is of great interest to employees, business managers, researchers, as well as policy makers is: what jobs get automated and how this decision is made at the workplace?

Research on this topic is huge, and it is scattered across many academic disciplines such as philosophy, mathematics, economics, neuroscience, psychology, computer engineering, linguistics,

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and information systems. At the heart of this question is to what extent computers can mimic the cognitive capability of human beings.

This article conducts an interdisciplinary review on job automation, with particular interest on the impact of artificial intelligence and machine learning. It brings together five major research frameworks that shed light on this important topic. It also identifies research gaps in extant frameworks and suggests an integrated framework by addressing the research gaps. There are excellent reviews on artificial intelligence and machine learning in general (Haenlein & Kaplan, 2019; Janssen et al., 2019; Wang & Siau, 2019), as well as their impact on specific business areas such as organization (Benbya et al., 2021; Raisch & Krakowski, 2021), marketing (Davenport et al., 2020; Grewal et al., 2020; Huang & Rust, 2018), human resource management (Tambe et al., 2019; Vrontis et al., 2021), and operations management (Grover et al., 2022). Interested readers may refer to these reviews for more details.

AUTOMATION

The term automation comes from *automatos*, a Greek word meaning acting by itself, or by its own will, or spontaneously. Automation has been defined as the performance of tasks by machines (usually computers) rather than human operators (Parasuraman et al., 2000), or a technology that actively selects data, transforms information, makes decisions, or controls processes, as well as exhibits potential to extend human performance and improve safety (Lee & See, 2004). Although automation has been defined in many different ways, the common theme is that automation is about the autonomy of a system or process from human involvement and intervention, and, quite often, it frees humans from time-consuming and repetitive tasks, whether the tasks involve physical activities or simple cognitive activities.

Automation dates back to ancient times when tools were first invented by humans. Early examples of automation include windmills, water clocks, sundials, and self-moving artifacts. During the first *Industrial Revolution*, automated systems were designed for temperature control, operation of mills, and regulation of steam engines (Bissell, 2009). Many tasks performed by artisans were also automated, such as spinning and weaving in manufacturing (Acemoglu & Restrepo, 2019). Modern automation started during the early 20th century when Henry Ford introduced the assembly lines for mass production. Ever since then, automation has been widely used for various control systems for operating equipment, factory processes, boilers and heat treating ovens, telephone network switches, steering and stabilization of ships, aircraft and vehicles with the purpose to reduce human cost and intervention and improve efficiency and quality (Rifkin, 1995). Automation has been achieved by various technologies including mechanical, hydraulic, pneumatic, electric, and electronics, or in combination (Parasuraman & Wickens, 2008; Williams, 2009). Although automation may not involve computers, it is the computers that have revolutionized automation and made it so widely adopted in every industry today (Janssen et al., 2019).

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Artificial intelligence (AI) as an academic discipline was founded in the 1950s (Hyder et al., 2019). It is a fast-growing field which includes a huge variety of sub-fields (Haenlein & Kaplan, 2019; Russell & Norvig, 2020). There are many different definitions of AI (Davenport et al., 2020), but in a broad sense, AI refers to the ability of computers to mimic human intelligence so that they can "think" and act as intelligently as humans.

Debate on whether computers can really "think" as humans has existed ever since the early years of AI. Opponents claimed that computers acting intelligently would not actually be able to think; rather they are merely a simulation of thinking (Dreyfus, 1992; Pettersen, 2019; Searle, 1980). The human mind and its thought processes are simultaneous, non-sequential, and emergent, rather than a linear, sequential, and reductionist program of symbolic manipulations (Braga & Logan, 2017). Thus, they believe computers are only a form of technology and a medium that extends human intelligence, not a form of real human intelligence, and computers lack the capability to possess such human characteristics as emotion, passion, joy, intuition, humor, and judgement. Therefore, it is impossible for computers to "think" as humans (Dreyfus, 1992; Searle, 1980). Correspondingly, opponents of AI introduced the distinction between weak AI—the idea that computers can do certain tasks more vigorously and precisely—and strong AI—the idea that computers can have a mind of a human and can literally understand and have other cognitive states as humans (Searle, 1980; Wang & Siau, 2019). They had no objection to computers being able to achieve weak AI but opposed the idea of strong AI.

However, most AI researchers are not concerned with whether computers can really "think" as humans. As commented by computer scientist Edsger Dijkstra that "the question of whether machines can think is about as relevant as the question of whether submarines can swim" (Dijkstra, 1984). AI researchers consider the human mind as a computational entity that can be implemented through a variety of physical devices such as computers and sensors (Laird et al., 2017). As suggested by Alan Turing that instead of asking whether machines can think, one should ask whether they can pass a behavioral test, or the *Turing Test*, in which an individual is asked to tell the difference between a human and a computer through interacting with them individually using text-only conversation (Turing, 1950).[1]

AI makes use of a variety of algorithms, such as logistical regression, K-nearest neighbors, Bayesian models, decision trees, and neural networks, to name a few. Depending on whether rules for actions can be predefined or not, AI can be broadly categorized into expert systems and machine learning (Arrieta et al., 2020; Ben-David & Frank, 2009).[2] *Expert systems* are collections of rules which assume that human intelligence can be formalized and reconstructed in a top-down approach as a series of "if-then" program statements, or a database of deductive rules by which, given a set of known facts, certain consequences can be inferred (Grote & Berens, 2020). Expert systems are designed primarily to solve rule-based problems or to process data according to pre-determined procedures. In these systems, the course of action may be conditional upon results obtained during the program implementation, but all the contingencies must be foreseen in advance. If an unforeseen contingency arises, the whole program comes to a halt and awaits necessary extension of the program (Grote & Berens, 2020; Licklider, 1960).

One of the key limitations of expert systems is that they depend on rules and procedures derived by humans, and they do not adapt easily. Machine learning has gained increasing popularity in recent years because it can potentially overcome this limitation. *Machine learning* (ML) is an application of AI that provides systems with the ability to learn and improve from experience or external data. ML at its most basic is the practice of using algorithms to parse data, learn from the data, develop its own rules and then use them to make future predictions. Because of this, ML can possibly automate tasks without even considering the rules and procedures followed by humans, i.e., ML can ignore and bypass these rules and procedures. Based on how computers derive their rules, ML can be categorized into supervised learning, reinforcement learning, and unsupervised learning (Brynjolfsson & Mitchell, 2017; Jordan & Mitchell, 2015; Kotsiantis et al., 2006). A key advantage of ML is that it can be used even in cases where it is impossible or difficult for humans to derive rules. ML has been applied in many scenarios such as drilling and mining, fraud detection, self-driving, image recognition, natural language processing, and robotics, and it has developed literally thousands of different algorithms over time (Hyder et al., 2019; Kotsiantis et al., 2006; Sze et al., 2017).

Many ML algorithms already existed back in the 1960s, but it is the increased processing capacity of computers and the availability of large amounts of data of today that have made ML a reality (Jordan & Mitchell, 2015). Rather than preselecting a model or a rule first and then feeding data into it as the expert systems do, in ML it is the data that determine which models should be selected to best perform the task at hand—ML analyzes the data to which it is exposed, chooses the best course of action or the model, and then acts accordingly. Because models are the main focus of this process, the current approach to AI is called *model-centric* AI. However, there has been a movement to *data-centric* AI where it is proposed that data should take the center stage. The backdrop of this movement is that when developing AI applications, particularly for ML, efforts for improving the models can be better paid off if diverted toward improving the quality of data (Press, 2021). In essence, data-centric AI advocates the importance of data in AI, and it tries to balance the role played by models as well as the data in improving performance of AI.

Although quite often the terms of automation and AI are used interchangeably, strictly speaking, they are different: First, automation can be realized without using AI algorithms or even without using computers. Second, automation is the process of using machines to do work that mostly requires physical movements common in manufacturing and agriculture, while AI focuses mainly on cognitive-intensive activities, often in the service industry (Davenport et al., 2020). Third, automation has existed for a long time, probably ever since humans learnt how to use tools. But AI as an academic field only came into existence in the 1950s.

JOB AUTOMATION AND EXTANT RESEARCH FRAMEWORKS

Jobs can be considered as a collection of tasks that need to be performed at workplace (Bystrom & Jarvelin, 1995; Huang & Rust, 2018). Tasks are the activities carried out in turning inputs into outputs. Complicated tasks consist of progressively smaller subtasks. Job automation refers to the extent through which the constituent tasks of a job can be automated. Therefore, examining job automation requires first an understanding of the constituent tasks of a job, such as which tasks are better to be performed by humans and which are better to leave for computers.

Recognizing that computers and humans have their own strengths and weaknesses, Nobel Laureate Herbert Simon, one of the co-founders of the field of AI, argued that a human's greatest comparative advantage lies in: (1) the use of the brain as a flexible general-purpose problem-solving device, (2) the flexible use of sensory organs and hands, and (3) the use of legs, on rough terrain as well as smooth, to move the body wherever needed. He then proposed that a human's job will mainly involve tasks requiring flexible eye-brain-hand coordination, system preventive and remedial maintenance, product and process design, and interpersonal relationships (Simon, 1960).

Over time, some jobs have been completely automated and eliminated, such as operators for telephone switches and lifts in buildings. However, for most other jobs, computers only automate some tasks within the jobs, and concurrently the content of these jobs have undergone significant changes. For example, as bookkeeping and online tax return software are taking care of administrative chores, accountants today no longer have to do the daily bookkeeping and number-crunching work, and their role has changed to that of a business advisor, engaging with clients and focusing on business strategies. Similarly, adoption of ATM machines in banks has not eliminated the job of bank tellers; instead, the number of bank tellers actually has increased, and their job responsibility is now shifted towards customer service which requires more marketing and interpersonal skills (Bessen, 2015). As computers continue to become smaller, faster, more capable and cheaper, the distinction between human and machine tasks are becoming increasingly blurry; thus the proper automation or allocation of tasks between human and machine is a moving target (Sheridan, 2000).

In literature, the scope of automation is also reflected to as the levels of automation (LOA). For example, prior studies (Sheridan & Verplank, 1978) have proposed ten LOA involving decision making and actions, from the lowest level where humans must take all decisions and actions to the highest level where computers decide everything and act autonomously. As systems in general have distinct stages such as information input and output, some researchers further extended LOA to staged models (Parasuraman et al., 2000; Parasuraman & Wickens, 2008).

However, this stream of research focuses on the functions of jobs, not the automatability of tasks. *Automatability* of a task represents the ease with which the task can potentially be programmed and relegated to computers or robots. While it is certainly important to know what functions need to be automated, whether a job can be automated or not eventually depends on the automatability of its tasks. Therefore, recent research on job automation has been focusing on the automatability of job tasks or simply job automatability.

One of the most cited frameworks that have been used to analyze job automatability is the ALM framework (Autor et al., 2003). In this framework, a job consists of a series of routine and nonroutine tasks. Routine tasks basically follow rule-based logic and can be fully described as a series of if-then-do logic designating what actions to perform and in what sequences and for what contingencies. Therefore, routine tasks are easier to be automated and performed by computers. Nonroutine tasks, on the other hand, cannot be easily expressed into if-then-do logic since these tasks involve dealing with semi- or unstructured problems which require human intuition and creativity. For these tasks, there are many contingencies that are hard or impossible to enumerate and anticipate and will eventually result in dead ends. For these reasons, nonroutine tasks are not ready to be carried out by computers or automated (Autor et al., 2003).

The concepts of routine and nonroutine tasks are essential to the ALM framework, and they can be traced back to the early work of the pioneers of AI. When discussing rational choice, March and Simon (1958) regarded a set of activities as routinized to the degree that choice has been simplified by development of fixed response to stimuli, and activities as unroutinized to the extent that response has to be preceded by problem-solving activities. Simon (1960) further argued that cut-and-dry, structured, and routine decisions can be highly programmable by computers and those ill-unstructured, strategic, and nonroutine decisions are unprogrammable. The ALM framework has received a wide range of support and achieved great success in explaining a variety of phenomena such as job automation, wage structure, and employment polarization.

The framework of task complexity has also been applied to job automatability (Sintchenko & Coiera, 2003). According to this framework, task complexity can be defined as the aggregation of any intrinsic task characteristics that influence the performance of a task (Liu & Li, 2012). Wood (1986) argued that task complexity can be expressed as a linear combination of three sub-complexities: component complexity, coordinative complexity, and dynamic complexity. Each of the sub-complexities can be characterized as the sum of the cognitive efforts needed to accomplish the task. Component complexity represents the number of cognitive acts that need to be executed to accomplish the task and the number of information cues that must be processed in this process. Coordinative complexity refers to the nature of relationship between task inputs and outputs, and it recognizes that interdependence between steps can increase complexity. Dynamic complexity reflects the dynamic nature or the speed of changes in component and coordination complexity—changes in either one increase task complexity and shift the knowledge or skills required for a task. Overall, more complex tasks lead to more information cues, frequent interactions, and speedy change of their status, and thus are more difficult to automate.

The third framework is organizational technology, which is defined as the actions that an individual performs upon an object, with or without the aid of tools or mechanical devices, in order to make some change in that object (Perrow, 1967). In this framework, tasks can be examined from two perspectives: (1) task variety, and (2) task analyzability. Task variety refers to the frequency of exceptions or unexpected events that occur when performing a task. Task variety is low if few exceptions are encountered in carrying out the task and high if there are many variations and possibilities that can occur. With low task variety, the rules for performing the tasks can be clearly articulated and further translated into computer programs. On the other hand, when task variety is high, many contingencies cannot be predicted, making the task difficult to be translated into logical instructions. In contrast, task analyzability refers to the ease with which solutions can be searched and found when exceptions or unexpected events do arise. The higher the extent of search, the lower the analyzability. High task analyzability suggests the existence of predetermined responses or well-defined procedures to perform the task; low task analyzability, on the other hand, suggests that solutions are often ill-defined, and human intuitions and judgment become necessary in performing the task (Perrow, 1967; Rice, 1992). In literature, researchers have applied this framework to examine work design and job automation (Crowston & Bolici, 2019).

Early automation and AI primarily focus on mechanical or cognitive tasks, and those involving emotions or affect are largely ignored. For one, emotions are believed to be inherently non-scientific, and two, it is difficult for computers to understand, represent, and act emotionally (Braga & Logan, 2017; Dreyfus, 1992). However, the role of emotions becomes increasingly important as AI continues to develop. Emotions such as happiness, sadness, anger, surprise, disgust, and fear aid in many situations such as decision-making, learning, communication, empathetic understanding, and social interactions (Breazeal, 2003). Understanding emotions can help improve the accuracy and effectiveness of AI systems in scenarios interacting with humans. In addition, if computers should act like a human, as in strong AI, understanding and possessing emotions and acting emotionally should be an inherent part of the systems.

The field to study and develop AI systems that have emotional intelligence is known as affective computing (Picard, 1997), and it has made much progress in recent years. However, affective computing still faces many challenges in such areas as sensing, modeling, understanding, and expressing emotions (Barrett et al., 2019; Calvo & D'Mello, 2010; Chen & Hao, 2020; Hudlicka, 2003; Tao & Tan, 2005). Different from the traditional AI devices such as industrial robots that are designed to focus on mechanical and cognitive tasks and rarely interact with humans, affective computing devices need to address the additional issue of emotional intelligence.

Consistent with the above argument, Huang and Rust (2018) categorized human intelligence into four levels—mechanical, analytical, intuitive, and empathetic—in the order of difficulty with which AI masters them to perform tasks that demand them. Each level of intelligence requires additional abilities to perform the tasks. Potential automation of human intelligence starts at lower levels and progresses to higher levels. This also implies that AI possibly displaces workers first for mechanical tasks, and then for analytical tasks, followed by intuitive and empathetic tasks. Huang et al. (2019) named analytical and intuitive intelligence as thinking intelligence and empathetic intelligence as feeling intelligence. They further termed the past economy where mechanical intelligence dominates as mechanical economy, the current economy where thinking intelligence dominates as the thinking economy, and the emerging economy where the feeling intelligence plays a key role as the feeling economy. They believed that achieving real feeling intelligence by computers still takes time. Indeed, as discussed earlier, whether or not computers can possess cognitive intelligence and experience emotions as humans do still remains a controversial issue.

Related to the human intelligence framework, Deming (2017) examined the increasing importance of social skills in the workplace. He argued that as computers become increasingly capable of performing tasks requiring cognitive skills, many tasks have been turned from nonroutine to routine. On the other hand, social skills are hard to be substituted by computers since human interaction requires the ability to attribute mental states to others based on their behavior, or to "put oneself into another's shoes". Thus, there is an increasing demand for occupations that require significant social skills. He also argued that all current occupations are becoming less routine over time, and, in general, computers and automation have shifted jobs away from rigid categorization toward increased flexibility, adaptive responses, team production, personal touch, and customer-oriented occupations where social skills play a key role. Similarly, Borghans et al. (2014) emphasized the importance of people skills that are required to effectively interact with or handle interactions with people. They recognized the difficulty for computers to perform tasks requiring people skills, but also realized that as computers get more powerful, it is increasingly possible for computers to automate these tasks.

AN INTEGRATED FRAMEWORK

The above section reviewed five theoretical frameworks for job automation: ALM, task complexity, organizational technology, human intelligence, and social and people skills.[3] Among the five, the

ALM framework (Autor et al., 2003) has been the most widely used in prior studies. This framework is based on the comparative advantages of humans and computers (Simon, 1960). To the extent that automation follows explicit rules that humans use to perform jobs, the ALM framework remains valid and effective. The organizational technology framework (Perrow, 1967; Rice, 1992) focuses on two key characteristics of tasks, variety and analyzability. It can be inferred that tasks of high variety and low analyzability also tend to be nonroutine, and thus this framework corresponds well to the ALM framework. The task complexity framework delineates the dimensions of task complexity, with explicit consideration of the cognitive efforts, timing, frequency, intensity, location, and speed of change of task inputs and outputs (Campbell, 1988; Wood, 1986). The human intelligence (Huang & Rust, 2018) and the social and people skills frameworks (Borghans et al., 2014; Deming, 2017) emphasize the importance of feeling intelligence, which computers have difficulty with but are increasingly capable of performing. These frameworks have greatly helped researchers understand the mechanisms and dynamics of job automation from different perspectives.

However, there are also challenges and research gaps, which present opportunities for further exploration. First, the above five frameworks share one commonality: they all highlight the comparative advantages of humans and computers, and the ensuing allocation of work between them. The fundamental reasoning beneath the frameworks is that automation can occur only to the extent where human cognition can reach. In other words, these frameworks assume that automation happens through making use of rules built in the expert systems; if no explicit rules can be derived through human cognition, then automation would not happen. This shared commonality also suggests a common challenge for these frameworks: they have not sufficiently considered the impact of ML on job automatability.

As discussed earlier, ML has the capability to learn and improve from experience and environment through algorithms behind it (Carabantes, 2020). Simple algorithms are easy to interpret by humans. But complicated algorithms can be very difficult to interpret and explain. For example, deep neural networks, one of the most successful and promising algorithms, consists of hundreds of layers and millions of parameters, and it is virtually impossible for human to understand and explain their reasoning processes and to justify the results in the forms of prediction, classification, or recommendations (Arrieta et al., 2020; Burrell, 2016; Sze et al., 2017). Added to this complexity is the fact that, quite often, ML is based on correlational rather than causal relationship. The consequence is that, with ML, the distinction between routine and nonroutine tasks, or the routineness of a task, does not matter anymore (Brynjolfsson & Mitchell, 2017; Brynjolfsson et al., 2018; Levy, 2018), and tasks that are difficult to automate under the extant frameworks—tasks that are nonroutine, complex, of high variety and low analyzability, involving feeling intelligence, and applying social and people skills—can be automated through ML in the same way as those tasks otherwise.

Second, all the five frameworks reviewed above focus on the automatability of jobs, and none of them consider the actual decision for job automation at workplace. Strictly speaking, automatability and automation are not the same—the former is an intrinsic characteristic representing the ease with which a task can be programmed and relegated to computers or robots, while the latter symbolizes a state in which computers perform the task rather than humans. Job automatability is the intrinsic driver for job automation, but in addition to it, there are other practical considerations that facilitate or constrain the actual decision for job automation at workplace (Fleming, 2019; Hancock, 2014).

One prominent practical consideration that has received increasing attention is ethical and moral issues related to AI (Grote & Berens, 2020). Without AI, human operators of tasks are typically held responsible for the consequence of operations. However, with AI, and ML in particular, humans are not in control, and naturally it is arguable to hold humans responsible for the consequence (Matthias, 2004; Siau & Wang, 2020). Ethical and moral issues are also glaring in healthcare. For example, when a clinician's independent diagnosis disagrees with that of a device powered by ML, should the clinician insist on her own diagnosis or defer to that of the device? In fact, there is a high likelihood the clinician defers to the device even if they have the same confidence level of diagnosis, leading to the practice of "defensive medicine" (Grote & Berens, 2020).

Another practical consideration is the economic benefit of automation. Firm decisions are typically motivated by profit maximization, and automation is largely driven by efficiency and quality gain compared to manual work. Therefore, how firms incorporate the cost and benefit analysis into their decision of job automation is another important consideration.

Additionally, there is huge concern for trust in job automation where ML may be running in the background. ML models are data driven and are based on correlations. For complicated ML, the reasoning processes beneath the recommendations can be hard to understand or are intentionally hidden from users (Arrieta et al., 2020). Such "black-box" models impair trust toward them and further delay job automation. Related to trust are the biases that may exist in AI models. Unrepresentative data may be used in training AI models and thus lead to the selection of models that exhibit systematic biases (Wang & Siau, 2019). Indeed, this is one of the problems that have motivated the current movement of data-centric AI.

Last, but not least, there has always been a concern for potential technological unemployment caused by job automation and thus resistance to job automation. There is no doubt that some employees will lose jobs due to job automation. But at the same time, technologies can also create new jobs (Acemoglu & Restrepo, 2019; Autor, 2015). Therefore, the relevant issue is not to avoid worker displacement from automation but to redesign existing jobs or train employees for emerging new jobs.

Taking into account of the above, we propose an integrated framework for the decision of job automation. The proposed framework incorporates two groups of factors: (1) impact of task routineness and ML, and (2) practical considerations. The first group focuses on the intrinsic characteristics or the automatability of a job, and the second group includes a variety of extrinsic factors such as economic, organizational, ethical, social, and psychological. The factors we have studied here are not exhaustive. It is possible other intrinsic and extrinsic factors can be identified and thus can be incorporated into the two groups.

CONCLUSION

This study bears important practical implications. While job automatability is the intrinsic and ultimate driver for job automation, many practical considerations may come into play for the actual decision to automate a job, and therefore firms need to balance both groups of factors. In addition, advancement of technologies, particular ML, has created a very different mechanism for job automation from what are delineated in extant frameworks. The proposed integrated framework provides a possible guideline for job automation at the workplace. In light of the potential that job automation may displace workers, firms should take appropriate actions so that employees can take on a new role in the automated work environment (Raisch & Krakowski, 2021). It has been proposed that future work requires employees to possess more analytical skills to carry out information-intensive tasks (Peng et al., 2018). In addition, interpersonal skills may become increasingly valuable in the upcoming feeling economy (Kaplan & Haenlein, 2020). Concurrently, colleges and universities may need to adapt their curriculum design to reflect this shift of demand in workforce skills (Huang et al., 2019; Ma & Siau, 2018).

The impact of job automation through AI and ML can be enormous, and it is hoped that this study helps better understand the theoretical frameworks, the underlying mechanisms, and the rapidly changing dynamics of job automation.

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ENDNOTES

[1] Some researchers argue that the Turing test might be a necessary condition for a computer possessing human-like intelligence, but not a sufficient condition (Braga & Logan, 2017).

[2] Some researchers consider ML the same as AI or they are parallel to each other. But most researchers hold the view that ML is a sub-field of AI (Jordan & Mitchell, 2015; Russell & Norvig, 2020).

[3] There are other streams of research such as job design and human-in-the-loop, but they are very closely related to the five frameworks reviewed here.

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