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Faculty of Business Economics

Master of Management

Master's thesis

Challenges and best practices in AI adoption

Khayelihle Jacob Makhanya

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :

dr. Gert JANSSENSWILLEN

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MASTER THESIS

Challenges and best practices in AI adoption

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COVID-19 DISCLAIMER

This master thesis was written during the COVID-19 crisis in 2020-2021. This global health crisis might have had an impact on the (writing) process, the research activities and the research results that are at the basis of this thesis.

Abstract

The question of how to implement artificial intelligence (AI) has become a matter of life and death, as the development of the mRNA Covid-19 vaccine would not have been possible without the help of AI. As the world battles a pandemic and humans become more vulnerable, AI is proving to be more a friend than a foe. Organisations must continue to operate even though employees can no longer go to the office. Thus, the organisations that have invested in AI are reaping the benefits. Despite the promise of AI, many organisations' efforts with it are falling short. Most firms have run only ad hoc pilots or are applying AI in just a single business process. Why the slow progress? The aim of this paper is to examine the various factors that influence AI adoption in an organisation. This is done by exploring the technology-organization-environment (TOE) technology inhibitors model. TOE is a structured way of understanding the various barriers that are slowing the rate of AI adoption. Literature findings suggest that AI adoption is a step-by-step process and that being cognisant of the inhibitors is the first step towards reaping AI benefits.

Keywords: artificial intelligence, AI adoption, algorithms, organisation, TOE and machine learning.

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1 Introduction

As it continues to progress at a high pace, artificial intelligence (AI) does not intend to wait for humans to catch up (Klumpp & Zijm, 2019). While it has made many blue-collar jobs defunct, AI is now coming for white-collar jobs due to the advent of machine learning (ML) algorithms (Huang et al., 2019). This comes as result of Industry 4.0 cost cutting strategy and integration of the customer into the production process (Oztemel & Gursev, 2020). With each Internet search, humans are training AI to be better (Llansó, 2020). Hence, the most important pillar of AI is Big Data (Huang et al., 2019), intelligent data systems that have the power to disrupt any industry (Oztemel & Gursev, 2020). Even though AI is not human, it has already been given a lot of responsibilities. For example, AI already dictates the lives of Uber drivers around the world. The fact that classification is not carried out in Industry 4.0 reflects that, while the amount of academic literature on artificial intelligence has tripled in the past decade, it still refers to AI as a thing of the future (Oztemel & Gursev, 2020).

There is a misconception that AI is a one-button technology or machine that solves all problems. This stems from the industry-wide lack of a clear understanding of what AI is. AI involves a machine that is able to capture information, process it, learn from it, and make quickly valuable decisions than a human (Grønsund & Aanestad, 2020). Hence, AI is as good as the data that you feed it (Llansó, 2020). Thus, solving issues of data ethics may be the first step toward a clear AI path. To implement AI, we need to understand its ethical foundations. Moreover, we must ask what the lines of accountability are for AI and if it can be held accountable for its actions. As AI is being discharged from labs and becoming a reality, it is becoming a management issue (Klumpp & Zijm, 2019). Moldenhauer and Londt (2018) noted the crucial importance of leadership and AI, because leaders are the gatekeepers to the financing of AI projects. AI offers a unique opportunity to combine labour and capital on a vast scale by identifying areas of inefficiencies in an organisation and streamlining them (Plastino & Purdy, 2018). The power of artificial general intelligence is that it harnesses these capabilities and standardises them across the industry.

Despite the recent technological advancements and apparent benefits that AI offers to the private and the public sector, the rate of AI adoption has been surprisingly slow, with many businesses not seeing it through to large-scale implementation. This fact is evidenced by the recent survey by McKinsey, which found that only 20% of the 3000 AI-aware C-level executives surveyed are using AI. Noting the slow adoption rate of AI, this paper will review the fundamental issues that are the main causes of this rate (Bughin et al., 2017). These issues include a lack of trust in AI as well as management structures that are not ready for AI. In doing so, this paper intends to show what an organisation can be aware of when it comes to what could go wrong with AI adoption, so that it can take preliminary steps to ensure that it avoids those costly mistakes.
The purpose of this paper is to address the following research questions:

1. Why is the rate of AI adoption slow?
2. What is the best way to implement AI?

3. How to prepare an organisation for AI?

This paper uses the Technology-Organisation-Environment (TOE) framework to review the factors that are slowing AI adoption. This paper will also add value in the field of business management through a qualitative review of the fundamental issues emerging due to AI, highlighting the artificial divide that is increasing through the slow adoption of AI (Klumpp & Zijm, 2019).

The remainder of this paper is organised into five sections. Section 2 presents the methodology employed, while Section 3 lays out the benefits of adopting AI. Section 4 then provides theoretical reasons for the slow adoption of AI and its barriers. It also discusses ethics and trust issues that prevent AI adoption. Section 5 relays how to best adopt AI through examples from the papers below; it also entails the reasons for efficiently managing the AI revolution and the best practices for AI adoption. Finally, Section 6 concludes by reflecting on the implications for theory and practice, as well as the limitations of this paper and directions for future studies.

2 Methodology

2.1 Eligibility

The objective of this literature review is to understand the factors that may influence and, ultimately, slow the adoption of AI. To attain this objective, a set of criteria was identified to categorise the papers, namely, how to best adopt AI, TOE framework, ethics and trust in AI, awareness and roles required for AI, change management, enterprise architecture, and scalability. Four bibliographic databases, namely, Google Scholar, Scopus, Springer, and UHasselt databases were explored to find relevant articles. The internet also revealed grey literature, such as publications from corporate organisations. Only English language publications were included in this paper. The Scopus database contributed significantly to obtaining credible and high-quality papers in this domain. A thorough search strategy was developed with key terms searched across titles and abstracts, or as business management subject headings using the Boolean operator 'AND' combining key concepts, and 'OR' for synonymous keywords. This search was done during the period of November 2020 to May 2021. The search terms used were "artificial intelligence" AND "management" OR "adoption" OR "inhibitors" OR "barriers". Moreover, a business management filter was implemented in order to ensure the information was relevant. A total number of 1,018 articles surfaced from the search. This list was scanned to check for articles that address the research topic according to the aforementioned categories. After this process, a total of 63 papers remained.

2.2 Snowball search

The initial readings from the supplied articles of Klumpp and Zijm (2019), Bughin and Hazan (2017) and; Elliot and Andrews (2017) were the main starting point of understanding. Through these articles, a snowballing sampling method was used to obtain more research papers. This process of snowballing provided an understanding of the many variables that can add value to the study. This step yielded 27 quality papers, including articles and review papers.

2.3 Systematic search

A purposive search was also conducted to find articles regarding AI ethics and employees. The article "Human Values in the Loop', from one of the Big Four companies (Deloitte), discussed two renowned AI researchers, Luciano Floridi and Matthew Salganik. From their websites and books, further research papers were found regarding how to imple-ment AI with human-centric values. The reason for looking at this literature stems from the taxonomy performed by (Oztemel & Gursev, 2020), which reflects a significant increase in research on intelligent technologies. Based upon these finding, the (Webster & Watson, 2002) method of focusing concepts was applied to access select related articles.

3 Benefits of AI adoption

AI is a generic name for computer systems which are cognisant of their environment. These systems are able to process, comprehend, and make decisions in relation to the data they are observing and sensing. This definition encompasses machine learning (ML) and Deep Learning which are subsets of AI (Joshi, 2019). It is best visualized as shown in Figure 1 (Joshi, 2019). Although the term AI was coined 65 years ago, it didn't see a lot of development for the first 40 years, even though people such as Alan Turning added significant knowledge to what we know now (Siddique, 2018).

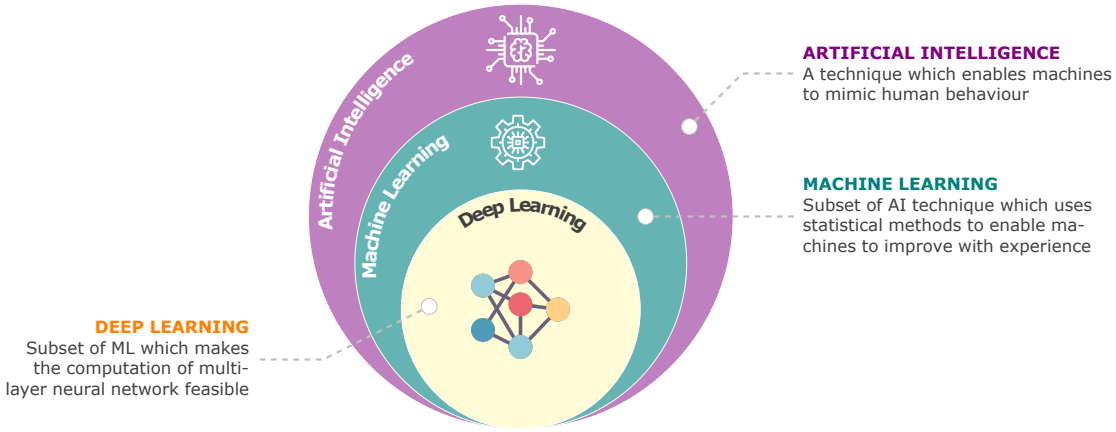

Figure 1: Relationship between AI, ML and Deep learning

AI systems can be broken up into two i.e. hard wired and adaptive. Automated intelligence and Assisted intelligence systems fall under hardwired AI systems. Augmented intelligence and Autonomous intelligence systems are adaptive systems (Rao, 2017). The slow adoption of AI has also led to large-scale intelligent process automation (IPA). IPA is a new wave of AI that aims to replace all manual, laborious tasks that humans traditionally had to do. This technology is aimed at helping a skilled worker become more agile (Berruti et al., 2017). Digital assistants, chatbots and machine learning (ML) are some of the common AI applications. Moreover, AI has been crucial to the speedy discovery of the mRNA Covid 19 vaccines through the use of ML algorithms (Zhou et al., 2020).

What makes AI models unique is their ability to learn. AI can learn in three major ways: supervised learning, unsupervised learning, and reinforcement learning (Kaplan & Haenlein, 2019). Supervised learning models receive data and labels with observation, features, and attributes to help them predict outcomes e.g., regression models loaded with tabular data. In unsupervised learning, the model uses filters to predict outcomes without any labels e.g., recommendation engines (e-commerce and streaming services). Reinforcement learning pertains to AI models that can decipher that winning is the ultimate goal of playing a chess game or other outcome optimization tasks. Each time a robot can successfully perform a task e.g., win a game of chess or pick up an item, all the other robots learn the same skills, and if it makes a mistake, it is not reinforced.

In recent years, there has been a dynamic digital transformation in almost every industry all over the world. This transformation is fueled by high volumes of qualitative research

in the domain of artificial intelligence (Agrawal et al., 2018). It is, however, concerning that, despite the fast pace of the innovation and the influx of scientists in artificial intelligence research, very few organisations have adopted artificial intelligence so far. About a tenth of the firms had adopted artificial intelligence for their operations in 2016, this figure more than doubled in 2019 (Rettas et al., 2019). Enterprise Digital Research has predicted that, by 2024, artificial intelligence adoption will have risen by two-fold. Artificial intelligence is important because of its use as a strategic technology by organisations. One of the main factors that has facilitated the availability and adoption of artificial intelligence is developments in the domains of networking and data processing. These developments have led the course of the digital transformation (Rettas et al., 2019).

Artificial intelligence has proved to be a vital business solution, with its potential to enhance economic growth evident from the fact that countries which have increased the adoption of artificial intelligence have reported a splendid rise in their economies. These countries include the US, India, China, and Australia, among others. The potential of artificial intelligence adoption in facilitating economic growth is noted in the Rao (2017) by PWC, which states that artificial intelligence adoption can provide leverage to the Australian economy, increasing it by as much as 2.2 trillion USD by the year 2030. As reported by Elliot and Andrews (2017), the introduction/adoption of artificial intelligence in organisations can create a competitive environment that contributes towards positive growth in overall performance, increase in revenue generation, and cost reduction of various organisational operations, as well as greatly enhanced efficiency in business.

Moreover, AI has become the driver of improving supply-chain processes and accelerating both automation and business innovation (Oztemel & Gursev, 2020). AI learns and accumulates data about the customer, optimizing prices accordingly to increase profit. The importance of facial recognition, pattern recognition, and digital content analysis will be enormous. Academic research, health sciences, and technology companies will all benefit. By using search algorithms that provide personalised knowledge, artificial intelligence improves users' lifestyle choices. All mundane activities, such as data entry and responding to emails, will be performed by AI. Smart homes powered by AI can save energy while also improving security. Information processing would be quicker, which is a welcome advantage of AI in the justice system; algorithms may be used to look up someone's criminal records or other public documents on the internet, and shorter lines at the courthouse or police station will relieve pressure on police officers and court officials (Re & Solow-Niederman, 2019). Artificial intelligence has the potential to open new avenues of decision-making in business, and can, therefore, provide us with unprecedented ways of creating value (Alsheibani et al., 2019).

A use case example of AI is illustrated by Bollard et al. (2017) from McKinsey, whereby AI improves the insurance claims process. The insurer installs AI sensors in the customer's vehicle. These AI sensors have live data linked to the customer's mobile devices, and as the client drives, the sensors can advise the client of the possible upcoming dangers such as storm or snow conditions. Moreover, insurance companies such as Discovery in South Africa have shown that the use of these systems can save lives. This is because these systems have an impact alert that automatically sends live messages to the insurance

company if the customer is involved in an accident. This also improves the claims process because the incident is immediately registered as soon as the impact occurs. Live cameras can send live images of the damage and reports, which is liable for the accident. This sensor is able to send recommendations for nearby car repair garages. The client is thus able to receive the car rental while the car is being towed away for repairs. This leads to a seamless and transparent process for all parties involved.

4 Barriers to AI adoption

Despite all of the advantages of artificial intelligence, its adoption has not become common. Artificial intelligence adoption has suffered from a hiatus, causing its pace to be very slow and preventing the achievement of conventional artificial intelligence adoption (Ramaswamy, 2019). These factors can be considered either ”inhibitors” or ”barriers” to the adoption. The slow adoption can be accredited to a number of diverse factors that involve the willingness of organisations to embrace the change and make the digital transition from conventional technologies to artificial intelligence systems. Although many organisations are now willing to adopt artificial intelligence, most of them are still at a pre-adoption phase, and the pace of the process is not what it was expected to be. During the pre-adoption phase, the organisations try to collect as much information about artificial intelligence as possible, make policies, and figure out the course of their artificial intelligence adoption. Still, there are many other organisations that have been stuck at the stage of deciding how to implement artificial intelligence, including which organisational operations need to be shifted from conventional systems to the artificial intelligence system. Other organisations, however, are still confused about how they can use artificial intelligence in the context of their business (Bundy, 2017).

In addition to these aforementioned factors, there are several other factors that have wreaked havoc on the pace of artificial intelligence adoption. These barriers have caused a decrease in the pace of adoption as they have a negative impact on the organisation’s ability to make and implement the decisions and policies governing the transition to AI systems from the conventional methods and systems. The barriers to the adoption of artificial intelligence have been investigated by a wide range of researchers in relation to the domains of information sciences and information technology (Alsheibani et al., 2019).

It is important to know which barriers affect the pace of artificial intelligence adoption, because the identification and classification of these barriers can help induce an increased awareness and understanding of AI adoption amongst the masses. This will ultimately pave the path towards the increased adoption of artificial intelligence (Alsheibani et al., 2019).

4.1 Technology-Organisation-Environment framework

A framework known as the Technology-Organisation-Environment (TOE) has been established to classify barriers to artificial intelligence adoption into three major categories (Tornatzky et al., 1990). According to this framework, the barriers (the factors involved in slowing down the adoption of artificial intelligence in organisations and firms) can be divided into three diverse categories, including technological barriers, organisational barriers, and environmental barriers. Further research into this framework revealed that company size and industry type play pivotal roles in the whole process of AI adoption (AlSheibani et al., 2020). This framework can be visualised as shown in Figure 2.

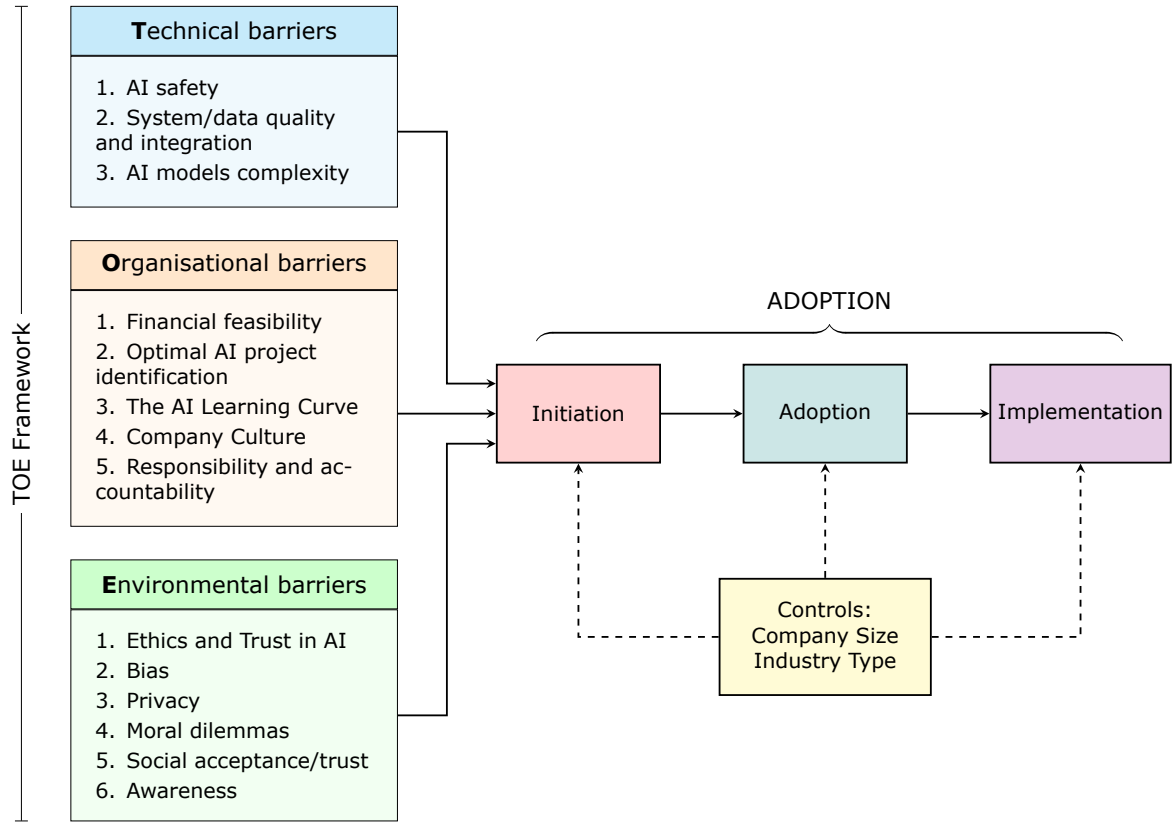

Figure 2: TOE Framework Illustration

4.1.1 Technical barriers

Technical barriers are the first type of barriers that have slowed the adoption of artificial intelligence in organisations. Technical barriers include the limitations of the technologies which are available to the organisations, as well as the external technologies which indirectly influence the operations of the organisations. Some of these technological barriers are the limitations of the security and surveillance systems employed in the organisations as well as the absence of organisational resources necessary for the adoption of artificial intelligence. No matter how technologically advanced an organisation is, its digital transition to artificial intelligence systems is not instantaneous; rather, it is a gradual process by which one generation of innovation builds upon its predecessor. There have been grave concerns about security issues associated with artificial intelligence technologies around the globe, which also impacts the pace of AI adoption. Other technical barriers include the potential of the artificial intelligence algorithms to exceed the level of human intelligence, possibly even creating the perception of AI being dangerous to humans. It is, therefore, quite difficult to adopt artificial intelligence until a proper security and surveillance system has been developed (Alsheibani et al., 2019).

1. AI safety

Like the concerns faced by almost all the newly launched technologies, AI faces a

number of concerns regarding safety and security (Boyd, 2017). The idea not only encompasses IT security-related issues, but also security as a whole. As AI is continuously modified according to its input data, there is a probability of acquiring negative behavioural inputs that might alter its output according to the false input (Conn, 2017). In this matter, (Bostrom et al., 2016) pointed out the importance of AI being tough and durable to withstand devastating human manipulation. Google, a multifaceted company and a pioneer in AI, has addressed the attention paid towards various security-related AI issues in practice. The reinforcement learning type of AI must be programmed not to execute devastating actions. Other than that, it is mandatory to fix any distortions in a working environment made in correlation to AI, while using it to accomplish the task it is meant for. For instance, a robot performing a human surgery must not test further cuts or methods based on its learning. In a nutshell, the advancements in the field of AI are desirable only as long as the benefits for humankind are manifested, neither more nor less (Wirtz et al., 2019).

2. System/data quality and integration

This factor is of primary importance. AI learns and responds to a certain type of input. Thus, the smartness of the system is only as strong as the input data allows. At present, it is a well-established fact that data is basically "the fundamental driver of current AI systems". Related issues, such as poor quality and untrusted data, are some of the biggest concerns in the development of AI systems. Due to this, the accumulation, aggregation, processing, and storage of impartial, prudent, and important data is vital for the successful establishment of AI in an organisation. The reverse situation, where AI systems constantly crash, may happen if the data is of poor quality. In light of such facts, a reasonable and trustable AI system can only be established if all these challenges are resolved with greater diligence and responsibility (Wirtz et al., 2019).

3. AI models complexity

AI is a complex technology aimed at solving complex most of which are beyond humans compression. To add the complexity is the reality that building reliable AI models can be very complex. This process mostly requires specialised labour force and exorbitant computing power (Alsheibani et al., 2019). Moreover, keeping AI systems running with limited downtime still proves to be a big challenge for most the AI-aware C-level firms (Bughin et al., 2017).

4.1.2 Organisational barriers

The second major type of barrier that is slowing down the pace of artificial intelligence adoption is organisational barriers. The main organisational barriers include factors such as lack of interest and lack of support from the upper management of the organisation, as well as the workforce's inefficient and out-dated artificial intelligence skills, and a prevailing reluctance to embrace change. Managerial skills are sometimes lacking amongst the top management of the organisation, which, therefore, causes a lag in AI adoption. Research has made it clear that no industry or organisation can embrace innovations and transitions from conventional to contemporary technologies unless the top management possesses a broad insight and interest in innovation. Similarly, artificial intelligence adoption directly depends upon the managerial skills and support of AI by the organisation's top management. Apart from managerial skills, the artificial intelligence skills of the workforce (including the employees) play an important role in determining the pace and extent of artificial intelligence adoption by an organisation. These artificial intelligence skills involve skills which are necessary for the creation of AI technologies, data processing techniques, and developmental skills (Alsheibani et al., 2019).

1. Financial feasibility

Introducing a new technology on a public scale demands a huge amount of financial commitment. Similarly, the initiation of the AI system requires the allocation of a big budget. The management of finances in the organisation is a challenge itself. Revenues and maintenance costs must be kept in mind before developing and launching systems at the public level. This will ultimately lead to being able to foresee the feasibility of establishing the system in any sector. The main issues that need to be addressed are the building of an infrastructure for storing and collecting data, as well as the allocation of AI technology experts and the increase of expenditures on salaries and training (Wirtz et al., 2019).

2. Optimal AI project identification

Identifying the right AI project is an intensive and risky part of AI adoption because most organisations are still trying to understand what AI is. Most organisations fail to strategise an optimal AI business case and how AI will integrate with their traditional systems. They do not have a plan beyond a few use cases, and they're handling AI on the fly, without realizing the big-picture opportunities and challenges it poses to their environment (Fountaine et al., 2019). Moreover, they do not balance the long-term gains with short term setbacks.

3. The AI Learning Curve

Broadly speaking, artificial intelligence experts can make the platforms easier and more convenient to use. There are still many issues to teaching the artificially intelligent machines. Let us consider the applications of AI in a clinical setup, as doctors and healthcare facilities are already using electronic systems to store their data. So, a reasonable coordination must exist between machines already in use and newly implemented AI appliances. Another fact that will tarnish the successful use of this technology is that all healthcare

providers would not have equal and sufficient technology skills; hence, this would create a huge challenge to keep up with newly embedded AI technology. Learning to interpret artificial intelligence algorithms will add up into new responsibilities and may consume the physician's mental and physical abilities. Physicians would additionally be held responsible for educating the patients regarding the use of artificial intelligence services. One good aspect of AI systems is that they would be far better in alerting healthcare providers in case of any abnormal conditions, which would certainly save time in comparison to seeing and observing the patient in person. Due to the higher sensitivity of AI machines, however, the system could make alerts due to any minor or ignorable changes, which would leave the physician at risk of alert fatigue. All such issues may result in exasperated feedback from both the physician and patients, causing mishandled and improper services. Therefore, a coordinated panel must be devised in order to collaborate a better communication system between artificial intelligence, technical personnel, and users in health setups (Cubric, 2020).

4. The Role of company culture in Embracing AI

There exist different behavioural patterns of various organisations towards adopting artificial intelligence technology in their setup. Generally, firms do not have any proper awareness workshops, thus, there are unanswered questions all throughout the organisational structures. This impacts artificial intelligence embedment, and has an impact on the daily routine activities of any department in any organisation. One of the major problems to be addressed is the insufficient understanding of business leaders' behaviours towards AI, which serves as the main hurdle in the successful implementation of this technology. The possible and better implementation of AI technology, however, would require a planning scheme, efficient communication, and sufficient time. Most organisations lack insight on the future of AI, which creates hurdles for AI adoption (Cubric, 2020).

5. Responsibility and accountability

Responsibility and accountability has to do with who is behind the legal decision-making for the AI. For example, if a pedestrian gets hit by a public transport vehicle, the question will arise over who is responsible. So, in the case of AI, this calls into question who should be to blame, whether it be a hardware engineer, software engineer, the authorities, the operator, or even the AI application. An AI application or system works on reinforced learning and can only be tested when operating; in that case, the operators and developers have no control over the responsiveness of the application (Johnson, 2015). Thus, AI systems lack the proximity of human control over the distinct actions by the system, so the condition remains vague (Matthias, 2004). On the contrary, DeGeorge (2003) debates that technology can never surpass human control. To deal with this situation, many proposals and approaches have been introduced to get a human grasp and control over the AI so that it is not a matter of conflict when it comes to overcoming the responsibility gap.

No practical approach has been found to resolve this issue as of yet (Wirtz et al., 2019). Johnson (2015) points out that overcoming this challenge is a matter of valuing human decisions over the technological decisions made by AI for strong political and social

infrastructure purposes by saying "that whether or not there will ever be a responsibility gap depends on human choices, not technological complexity" (Johnson, 2015). Still, as AI decision-making is becoming a norm, it will become clear to employees how AI has reached a certain conclusion. Huang et al. (2019) contends that the organisation board must set up an AI expert team to deal with this conundrum. Moreover, management needs to balance the three P's, which are people, planet, and profit; according to Klumpp and Zijm (2019), these can be addressed by correctly integrating AI into a firm. The management implication here is that managers have to be the bridge between AI and human resources. They notably need to efficiently allocate intellectual tasks to AI and emotional tasks (such as conflict resolution) to humans (Huang et al., 2019).

4.1.3 Environmental barriers

The third type of barrier according to the TOE framework is environmental barriers. Regulatory acceptance and the trust consumers have in artificial intelligence technologies constitute the category of environmental barriers. Artificial intelligence technology depends upon the data of the consumer, so the customer's trust is the main factor in artificial intelligence adoption. When consumers do not trust how their data is handled, this can cause an organisation to lose its customers. No organisation wants to lose customers, so these organisations are reluctant to adopt artificial intelligence. As long as customers do not trust artificial intelligence, the organisations will not make the digital transition towards artificial intelligence systems. Therefore, a lack of consumer trust in regards to artificial intelligence also halts the pace of AI's adoption. One of the main characteristics of artificial intelligence is that it can mimic human intelligence, which gives rise to plenty of legal concerns. In addition, governmental regulatory policies and standards also need to be met before adopting artificial intelligence. Meeting these standards is a gradual process, which has been a hurdle in the way of artificial intelligence adoption (Webster & Watson, 2002).

1. Ethics and Trust in AI

When talking about the privacy and security of AI, ethics is a widely discussed topic. The primary ethical concerns of AI ethics are machine ethics and robotic ethics. Ethics are a vital component in the formation of the moral system of a society. They must never be compromised. The ethical issues with AI learning and systems are of genuine concern. The question arises whether the use of certain AI tools are morally justified, such as in, for example, the case of lethal autonomous weapons. It is indeed a never-ending debate, but a matter worth deep investigation. It is important to link moral ethics with AI to ensure the system does not distort the moral fabric of society (Anderson, 2011). People have shown concerns about AI ethics and have reservations about whether the AI will follow the legal code of conduct, living up to the standards of honesty and loyalty, with no human harm intended. A detailed study of moral and ethical values from every perspective and custom is necessary to formulate a legal license to use the AI system. Keeping in view the requirement and standards that AI must meet, the thorough study reveals that AI covers a wide range of ethics, including human behaviour, values, prejudices, and value judgments (Wirtz et al., 2019).

2. AI embedded with bias

Fears are on the rise regarding AI being given the opportunity to make decisions for humans, which is considered one of the biggest ethical concerns to date. Humans, out of curiosity and to decrease their labor, ended up creating an intelligence that is equally smart as them (or smarter). To achieve and observe results that are more similar to human outcomes, AI reportedly imitates human brains to make decisions. The results, shockingly, have fewer errors and are nearer to logical reasoning, as no emotions have been involved. The system is programmed to think and act rationally to replicate the natural process of decision-making. Still, there can be flaws, as AI can never be programmed to be discerning like humans (Krausová, 2017).

A weakness on the side of the humans is that they involve bits of emotions in their judgment process. Such attributes or concepts are important requirements for getting what Solum (1991) called ”constitutional personhood”, representing the equality of humans and AI (Krausová, 2017). Since AI systems do not include all human attributes, they are far away from being entitled to the rights associated with constitutional personhood (Solum, 1992). With all the facts and data discussed above, it is still a question of whether it is justified to let AI make rules for human systems. No decision is perfectly unbiased, and all the decisions encompass some human emotions. Humanity indeed plays a crucial role in making so many decisions. One drawback about AI is due to its self-learning capability, which makes it an unpredictable mode to be used in such situations. In light of the discussion above, it is very likely that an AI-based decision might include rejecting an immigration application, but a human, in contrast, tends to accept it depending on the varying details (Wirtz et al., 2019).

Another major concern that must be dealt with in this approach is AI developer bias. The in-person method of taking data from the patient and the manipulation of this data is still considered more useful and productive than artificial intelligence algorithms. AI systems work only according to the data that has been programmed into their algorithms, and this data might be directional, leading to a bias as a result. Sometimes, a physician has to consider many aspects, thinking outside of the usual ways of dealing with a patient’s condition. He is expected to consider socio-demographic properties which might not be available in artificial intelligence systems; these properties include socio-economic status, race, ethnic group, gender, and the family’s terms of living. In a study conducted by Framingham Heart the aforementioned fact was observed in predictions about cardiovascular disorder occurring in the black race, where some bias in play. Hence, a physician may be reluctant to rely solely on AI systems, but rather, should develop a keen conscious and aware approach to eradicating hidden biases. Sometimes a physician has to reject a therapeutic strategy suggested by AI therapeutic models to combat bias (Cubric, 2020).

Lastly, the recent Amazon scandal regarding AI recruitment algorithms’ bias in favour of white males attests that bias-free AI is still not imperfect. The initial intention in adopting AI in the recruitment process was to eliminate the discrimination that exists in the recruitment world. By 2015, however, Amazon started to notice that the AI systems were giving preferential treatment to white males. This is because these systems were trained to screen applicants over a decade by looking for trends in resumes submitted to the company. The bulk of the submissions were from men, suggesting male supremacy in the tech industry. In this case, the AI models, with the help of machine learning, had trained themselves to ignore applications received from women. The company modified the models to make them unaffected by these terms. Nevertheless, the general consensus remained that there was no guarantee that the computers would not invent any other unfair methods of sorting candidates. The company eventually had to put a stop to the whole project. When looking for new recruits, Amazon’s recruiters looked at the tool’s suggestions, but they never focused solely on AI rankings. Some of the lessons learned from this failed AI experiment were salvaged by the company. This case has served as an example to other

industry giants, such as Hilton and the Goldman Sachs Group, who had hoped to deploy this technology on a large scale (Dastin, 2018). Additional reports reveal that there are cases in Silicon Valley in which AI has failed to recognise black candidates in the recruitment process due to inbuilt AI biases (West et al., 2019). In essence, the implication here is that a firm needs to be aware that there may be historic data bias or limitations, working with external AI consultants to ensure inclusion.

3. Privacy

The preservation of human privacy and ensuring security have been some of the major concerns in the AI revolution. AI has become a threat to human privacy, as per general opinion. It is suspected that the personal data of users is collected in compliance with respective laws, but privacy invasion can occur in three ways: "as illicit interference in one's actions, as illicit surveillance, as illicit intrusions in rooms or dwellings," all of it attributing to the AI (Calo, 2011). For example, AI systems that include robot applications are likely to be attacked by cyber invasions. This is one of the biggest security threats, as the attacking system gets access to the environmental conditions, preferences, and psychological and physical areas of a human personality. Other than that, a great privacy breach concern may also arise related to AI-based government surveillance (Gasser & Almeida, 2017). Considering these probabilities, it has been reported that, according to the studies, most of the population is worried regarding this threat posed by AI towards the privacy of the masses.

Privacy is the major area of opposition concerning AI policies, and it is taken as a challenge to overcome (de Montjoye et al., 2018). de Montjoye et al. (2018) continues to note that there is currently insufficient guidance regarding privacy parameters, and that historical modes are failing due to the scale of data and the dire need to customise data. This challenge particularly refers to technological and legal concerns. In contrast, AI systems must have reasonable cybersecurity licenses to ensure the safety and security of users. Also, measures must be taken by the policymaking departments to develop a safer and more reliable mode of AI to gain the trust of the masses (Krausová, 2017). This also includes, for instance, the management of discrepancies within jurisdictions in regards to privacy standards, amongst other factors (Gasser & Almeida, 2017).

4. Moral dilemmas

One of the key inhibitors to the rapid adoption of AI is its moral code, which can be questionable depending on how the AI is used (Bostrom & Yudkowsky, 2014). Even though most of the basic AI systems do not pose this conflict, humans continuously abdicate and delegate their responsibilities to AI, the organisation loses its accountability to society. Currently, the employees of the firm are the ones that have a moral status, and they have to exercise this authority for the greater good of the society. For example, a human may exercise human judgment to be extra cautious when they are dealing with a child during a transaction. It is still up for debate whether AI can exercise this ability. AI is also used in situations where a choice must be made between conflicting alternatives. A moral choice is made to ensure desirable consequences. The situation arises, however, when one has

to choose between two negative alternatives. This is seen in the case of healthcare robots and autonomous driving cars (Deng, 2015). If an autonomous driving robot encounters an accident, it is programmed to go for a solution that still results in two bad options. Should it protect the driver of the vehicle at all costs even if several other humans from another vehicle involved could otherwise be rescued? It is quite evident from this example that making life-and-death decisions involves ethical reasoning, and AI is still not capable enough to perform that form of reasoning (Wirtz et al., 2019).

Again, this raises a lot of questions in view the above discussion when it comes to AI acquiring control of decision-making in accordance with human behaviour. There are a number of human factors that go into making a judgment, such as rationality, emotions, consciousness, and advanced thinking and reasoning that AI is hardly expected to do presently; this discrepancy is because of the fact that judgment is different in varying situations, and some details need to be addressed that software might otherwise overlook. Creating ethical consistency for AI systems is still a challenge. Turilli (2007), for example, suggests the importance of binding AI systems to the same ethical principles that govern humans. Individuals achieve ethical consistency for an organisation's overall behaviour or performance (Turilli, 2007). Despite the current debates over embedding algorithms of ethics and morality into the AI systems to make them very much like human's systems, human qualities are still believed to be not computable. It has proven to be very difficult to imitate humans in every aspect and detail (Anderson & Anderson, 2011). In this context, self-learning may harvest some extremely unethical consequences that are incompatible with a human frame of reference. In the worst-case scenario, AI software might decide exactly the opposite of what actually must be right according to humans, which may lead to the actualization of the most feared notion: AI ruling humans (Wirtz et al., 2019).

5. Social acceptance/trust

In order to launch AI to become more successful and acceptable, the system needs to meet certain social challenges. Firstly, AI developers must find adequate answers and solutions in order to end any debates. The world needs to see its positive social impact with all the privacy and safety of which it is capable. There must be a breach-free policy that will help in developing the trust of the users. Issues such as aggressive debates, ethical concerns, and negative impact on the workforce have increased (Fast & Horvitz, 2017). Recent studies have suggested that people are now becoming more accustomed to letting AI help them in their daily lives only if their personal details, health, and life are not affected. As long as AI is working based on privacy, maintaining ethics and morals, safety, and workforce management, it is more likely to gain acceptance in society. The presence of the contrast between society and the AI norms is conflicting, resulting in a loss of harmony (Hameed et al., 2016).

Secondly, if people sense any kind of discrimination or, in the worst case, that their privacy and safety are threatened, they will remain resistant to AI implementation. A major concern is replacing of human employees with AI, which would certainly lead to an outburst of unemployment. This would be the last thing that a career-oriented person would accept (Boyd, 2017). In order to gain the trust of the public, they must be confident that choosing

AI will not risk any of their assets or moral values (Petit, 2018).

Take a case from a clinical setup. Patients willingness to the use of AI technology regarding their welfare and healthcare facilities is the key factor in the establishment and success of this technology in the health sector department. Moreover, information gathering and symptoms analysis, consoling, and revealing painful or positive perspectives of treatment will also change. A patient's will is questioned if he/she relies on a computer-generated diagnosis instead of one from a human. Nevertheless, it would consume less time and money, though reliability is still questioned. Patients may feel less comfortable having what could be considered mechanical and heartless advice. Who will pay attention to these patients and respond to their befuddled attitudes and sometimes illogical questions? After all, a machine certainly cannot provide more compassionate and humane behaviour. Even though the above-mentioned hurdles are worthy of pondering, the aspect that needs the most attention is the issue of trust. Mechanical tools for data collection will instill sheer mistrust and insecurity among patients. Who would trust artificially intelligent software gaining access to everyone's health and disease-related information? This issue was raised in a survey in the United States of America, where data was gathered regarding this issue.

The major concern revealed here was the privacy issue of AI machines. Analysts gave the opinion that artificial intelligence may breach patient-physician confidentiality. Letting any third person or machine know all the data concerning a patient's progress would never be considered safe, as any software developer may get access to data without taking traditional confidentiality limits into account for both the patient and physician. According to the results obtained, artificial intelligence technology implementation at other places within health facilities (for instance, in a pharmacy store) may be considered somewhat more reliable than in a room of a clinic.

Hence, we may conclude that trust is the first and main step in the hierarchical implementation of artificial intelligence technology in an organisation.

6. Awareness

Fountech, an AI organisation, conducted research on the public opinion of AI. Several interesting results came out of that research. First, it was revealed that 67% of the participants had reservations about AI, opining that it will force them to forfeit their jobs to machines; 58% of British citizens consider AI tools that recommend products to customers to be strange; and 59% of participants had reservations about how their personal data has been collected and manipulated since AI has emerged. Despite having such grave concerns about AI, 62% of people still believe that AI will positively affect society. 37% of the adults did not understand the term "artificial intelligence", while the remainder that said they do have also fallen to the trap of thinking of AI as one big robot. It can be deduced that the majority of the public is confused about AI and AI adoption (Fountech, 2020).

Second, for the implementation and adoption of AI, there is a dire need to educate non-scientific people who have very limited knowledge and insights into the domains of science and technology. To make people trust AI, they must be aware of how it actually works. Moreover, it must also be made clear to the people what AI can really achieve.

People need to be made aware of the fact that proper regulation and legislation are being made to determine the limits that AI researchers can reach. These regulations must be made by very intelligent and highly educated people belonging to multiple educational, philosophical, and professional niches. This group of people is known as the AI ethics community, and they come from the various niches of the profession, including tech experts, policymakers, think-tanks, legislators, professors, human rights organisations, and social justice organisations. The AI community has devised many principles to ensure a fair and hazard-free AI. Despite these rules and principles, there has still been a very slow development in the adoption of these ethical principles. Effective legislation and governance have failed to keep the pace of the advancements in the proliferation of AI. Private firms have also been developing their own AI systems. With such haste, the principles set by the AI community seem to have been ignored (Fountech, 2020).

Third, public awareness of AI is also needed, because the public voice is very crucial whenever society needs to effect a change or transformation. This change can be include changes in the behaviour of the business imperatives, consumers, and legislation. If any one of these areas fails to change, the AI will be polarised. Thus, the public voice matters a lot, and the public will not widely support AI as long as it does not understand it. Therefore, it is very important to simplify complicated concepts, such as neural networks, algorithms, and deep learning, so that a layman can understand them. Improper understandings and vague conceptualizations about AI have misled most members of the public into thinking that AI is their enemy. Awareness needs to be ensured at both the organisational and governmental levels. Some countries have been teaching proper awareness courses in their educational systems to make their students aware of AI; for example, the program "Elements of AI" has been educating the non-technical population in the US about the basics of AI (Tania, 2021).

To conclude, no technology may be launched at the full-scale level unless specialists are available in case of any potentially harmful consequences. These specialists are required to maintain the flawless operation of the system, as well as to promote its development. Because of their high demand during this technological revolution, specialists are being readily hired all over the world. Still, there is a lack of available experts, creating a void in overcoming AI's developmental challenges. Thus, it is becoming harder to overcome all the challenges we are facing at the global level. In this situation, more pressure is put on the government to spread awareness to empower the generation of a competent workforce (Holdren, 2016).

5 Guidelines for AI adoption

The best way to adopt AI is to understand that it is a process instead of a one-time event. This means that organisations must be willing to integrate AI into their business practices. As this takes time, it is best to follow guidelines to ensure sustainability.

5.1 Best practices for AI adoption

Industry comprehensive guidelines have been suggested, but since there has not been a lot of collaboration, there are no standards set (Bughin & Hazan, 2017). This being said, the below practices seem to be consistent for most publications.

1. Change management

To manage change in its systems, an organisation needs to understand and define what change is. According to the renowned DevOps, novel change is "any activity that is physical, logical, or virtual to applications, databases, operating systems, networks, or hardware that could impact services delivered" (Kim et al., 2014). Change management means the monitoring, management, and regulation of a digital transition to AI systems. This is vital because the role of the change management process is to control the lifecycle of all changes, enabling beneficial changes to be made with minimal interruption to organisational systems (Agutter, 2019). It also addresses the questions relating to whether the workforce is ready for the workload and new way of working. Once AI has been implemented, is it the responsibility of the chief information officer/IT to make it work, or is AI similar to a human worker in an organisation, managed by a line manager? What work are we asking AI to do in relation to our strategy and business values? What are the rights of the employees impacted by AI? Answers to these questions should be included in organisation's change management manuals. For a while, IT departments had to rely on the Information Technology Infrastructure Library (ITIL) guidelines to manage IT transitions. However, the ITIL framework has been updated to catch up with the new AI business environment (Agutter, 2019).

2. AI roles and responsibilities

Assigning of roles and responsibilities is part and parcel of a sound AI adoption process. However, this is still a "black box" as most organisations are still stuck on the traditional hierarchical organization structures (Elliot & Andrews, 2017). Role assignment has to do with setting the course for AI projects, evaluating the problems they will solve, developing the algorithms, designing the tools, checking them with end-users. It also depends on who will be managing change and building the supporting IT infrastructure; these are all activities that can be owned by either the hub or the spoke, shared by both, or sharable. The process of assigning roles relies on how advanced an entity is in its AI capabilities, business structure, and the level of innovation needed (Fountaine et al., 2019).

3. Higher level management buy-in

As AI becomes the core of the business, it is becoming clear that those who adopt AI experience strong higher-level management support. This is demonstrated in a McKinsey survey, which shows that only 20% of the organisations that adopted AI at a large scale enjoyed strong executive buy-in (Bughin et al., 2017). The board of directors plays a massive role in AI capital investment. If executive management articulates critical areas that need AI investment, it is more likely that these projects will receive a favorable vote from the board. Thus, the top-level executives play a crucial role in AI adoption because leaders are the gatekeepers to the financing of AI projects (Moldenhauer & Londt, 2018).

4. AI governance

Laws and regulatory policies need to be created to set the limits and parameters of AI's advancement. AI laws and regulations have their vast range of socio-economic impacts; thus, general governance should show some concerns regarding its management. Because of its broad usage and scope, the government must regulate the legal concerns related to data, algorithms, infrastructures, and humans (Gasser & Almeida, 2017). Operating AI in a responsible and beneficial manner is crucial part of adopting AI. Insights are being forwarded from renowned research institutions, including the Future Society at Harvard Kennedy School and the Future of Humanity Institute at the University of Oxford; such insights point out the critical role of AI-related policy-making and some form of global governance board (Boyd & Wilson, 2017). Getting this step right will not only ensure smooth business processes and operations but also data integrity.

5. Enterprise architecture and Scalability

It is said that the only constant is change. This proverb can be proved by the way AI is reshaping organisational structure. This changing business environment has, however, given birth to challenges for developers to bring new products and services to the market that leverage AI and ML. Keen and Qureshi (2006) framework on rewiring an organisation through business models allows a business to easily embed technology, reduce errors, and to become more agile and scalable. This framework iterates that a business model is the core statement of direction and identity for an entity. It also places the customer at the organization's center by noting that business models balance value to the firm and the customer. This comes from technology giving power to the consumer to choose who they want to buy from at the fingertips.

Since it can be said that scalability is the new norm, developers, as well as engineers, now have to design AI systems, which have the potential to be scalable. AI systems must be developed in such a way that they can dynamically adjust the types of processing resources they deliver based on the task at hand (Manoj et al., 2019). Employee productivity can increase as AI systems take over routine tasks or empower workers to control the equipment of AI systems programmed to cooperatively execute complex tasks with minimal human intervention (Hoadley & Lucas, 2018). The scalability of AI involves helping/encouraging the people, processes, partners, and software to repeatedly deploy and manage the enterprise's AI at scale. As an example, an AI-based debt risk advisor is used in a hospital system can identify the patients with a "bad debt" risk. It can, however, si-

multaneously conduct the patient scheduling, hence affecting much better satisfaction for the patients and more efficient utilization of the resources (Manoj et al., 2019).

5.2 Phases of AI adoption

It is now evident that AI gives considerable benefits in processing speed, accuracy, and consistency, and, because of this, many professionals now rely on it. More data shows that workers still fear that machines will replace them. The pervasiveness of such fears suggests that the management must be involved when introducing AI to an organisation. Accenture discovered that, when it is made clear to the workers that the machines would not replace them, the workers perform better in terms of administrative efficiency, notably in the speed, scalability, and efficacy of decision making (Babic et al., 2020). According to (Babic et al., 2020), there are four phases that must take place in order to embed AI to an organisation, i.e., assistant, monitor, coach, and teammate phases.

1. Assistant phase

The assistant phase is merely similar to the process of training an intern. You teach them new techniques by assigning them easy but time-consuming tasks so that you have ample time to focus on other tasks. They will learn by observing you keenly. A common task for the trainee is to sort data; for instance, the Covariant Brain employed by the Belgium Postal services is a universal AI that enables ”robots to see, reason, and act on the world around them” (Abbeel, 2019). This technology helps Bpost to filter thousands of parcels and find the most relevant. This kind of manual sorting is in demand by many companies. Bpost, for instance, tries to filter for shirts wrapped in plastic polybags, pill bottles, and boxes of band-aids. Every situation is different at Bpost, and this could be a challenge for most sorting robots. The new Covariant Brain, however, is able to make connections between millions of data points and still handle heavy lifting tasks. This is beneficial for human workers, especially for both their physical and mental health (Bpost, 2019).

2. Monitoring phase

The next step is to establish a real-time feedback system through the monitoring phase. With the help of ML and neuroprediction, AI can be trained to forecast what would be the user’s exact decision in each situation (Tortora et al., 2020). Neuroprediction is a new AI technology which studies brain connections to estimate what a human could do (Tortora et al., 2020). This helps organisations predict and reduce risk. Humans have limited and imperfect reasoning abilities, especially when it comes to statistical and probabilistic problems which are global in scale for businesses (Tortora et al., 2020). Different studies showed that justice might be better served if AI could assist judges by showing them that the decision they were planning to make was inconsistent with their prior decision or with the suggested decision based on an analysis of purely legal variables (Re & Solow-Niederman, 2019).

3. Coach phase

The coaching phase plays an important role because it creates feedback loops within the organisation. People think that they know what they are good at, but they do not; hence, companies are now starting to employ AI to uncover tacit knowledge deeply em-

bedded in the organisation (Wilson & Daugherty, 2018). The only way to discover strengths and weaknesses for improvement will be through careful analysis of decisions and actions, and then by comparing them with expectations and reality after the span of nine months to one year. Such problems can be solved with the help of AI, as they generate feedback that enables them to look at their performances and errors (Tortora et al., 2020). Organisations should thus create an environment of learning and self-improvement for their workers (Graßmann & Schermuly, 2020).

4. Teammate phase

The teammate phase is supported by the cognitive anthropologist (Hutchins, 1995), who established the theory of distributed cognition, which is based on ship navigation. This theory posits that cognitive processing and related mental acts are not necessarily limited to the brain or even the body. This is the final phase of AI implementation, in which organisations would establish a coupled system of machines and humans, with both contributing their expertise (Babic et al., 2020). It is said that AI can improve their decisions by linking them with the individual user and analysing their past behaviours and decisions (Tortora et al., 2020). This phase is full of problems and challenges. Understanding, however, is the best approach to building trust in the workplace. The trust model states that someone can be trusted if we understand their values, desires, and intentions (Danks, 2019). This approach is probably the best one for cultivating human-AI partnerships (Wilson & Daugherty, 2018). In short, organisations must ensure that, in terms of transparency, decision autonomy, and privacy, the AI designs should be reasonable and responsible.

6 Conclusion

This paper aimed to review the fundamental barriers to AI adoption into an organisation. Even though there are some limitations to AI, it increasingly plays a critical role in our daily lives. One of the main limitations of AI is that it is heavily dependent on data. Qualitative data, therefore, needs to be gathered and processed. It must also be ensured that technologies are being used for the better processing of data. Machine learning is an element of AI that will enable the processing of unprecedented amounts of data with enhanced accuracy and precision. Secondly, AI, as for now, lacks emotional intelligence and, thus, can lead to illogical decisions and the failure to make radical decisions when needed. AI needs to be trained to develop emotional, as well as situational, intelligence in the future, so that it might not result in any type of misjudgment and misadventure for humans and the environment. Thirdly, AI algorithms have been also found to possess biases, which also limit the extent of their intelligence. The AI algorithms need to be trained so as to get rid of their inherent biases so they can make decisions based on ethics, not on their personal biases. When it comes to profiling people and clustering problems, AI must be able to understand what people need.

Therefore, it is clear that the future belongs to AI. AI has the potential to perform a diverse range of roles, including driving the economy, use in personalised and targeted marketing, as well as in its brisk scientific and technological advancements. To get the benefits of these positive sides of AI, implementation and adoption of AI is mandatory. The adoption is eminent, and the digital transition from conventional technologies to AI systems has been taking place gradually. The pace of AI adoption, however, needs to be improved by coping with the challenges that have halted the pace of AI adoption.

6.1 Recommendations

Future research needs to focus on AI risk mitigation strategies, which are still lacking in this paper's writing. More research must also target ways of adopting more accessible and more reliable modes of gathering high-quality data. These studies can also look into how companies can address the new class of unskilled laborers that AI will create. Another area that has emerged from this research is the environment, which plays a significant role in AI adoption. Data shows that there is also an East versus West mentality, because adoption is faster in China compared to the Western world; hence, most of the big tech giants are moving to China. More research in this regard will clarify this phenomenon. Proper legislation and policies must be drafted in order to facilitate the implementation of AI while preventing its ethical dangers; in addition, awareness needs to be spread amongst the public about the fundamentals of AI so that public approval can be achieved.

Moreover, efforts should be made in support of the scalability of AI, without which AI cannot reach the level it has been predicted to reach. It must also be ensured that the upper management teams of companies pay heed to the AI shift and support the ideas related to AI adoption. The organisations must allocate generous funds, as well as incentives for the research and development in the field of AI. The AI learning curve needs to be flattened to

facilitate AI adoption and implementation. The consumer data which is being fed to AI for training their algorithms must be securely handled so that the privacy of the consumers is not compromised. Furthermore, organisations need to cater to inclusivity in their models. This starts with problem framing, because, fundamentally, good AI implementation starts with defining and understanding the problem you are trying to solve. Humans need to know how to leverage AI, but they do not need to know the code in order to do this. A firm also needs to leverage it with industry expectations so that it does not blindly apply AI; they must ensure that knowledge is readily available and shared throughout the organization, thereby requiring that the knowledge acquired be properly documented. Finally, it is vital to define AI's success measurement models. For example, how is success defined if Google gives answers that are biased towards what Google wants humans to find?

6.2 Limitations and future research

In an attempt to review the topic of AI implementation, this paper may have missed some key research papers that were not published in the English language. AI implementation strategies may be part of the strategic corporate operational plan and are not a field of (open source) research alone. Therefore our data retrieval may have been limited by not finding exclusive and discrete intellectual AI project articles. It may also be the case that papers from less developed countries would have been left out, as they did not form part of the high-quality literature. There may also be selection bias of papers that dealt with concepts that were mostly mentioned in recent publications. Moreover, the TOE framework is not exhaustive, and there may be other factors that fall out of these parameters that future research needs to investigate. Some of the TOE factors are not easy to distinguish as they may stem from both the environment and organisation.

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