# THE FRAMEWORK OF ARTIFICIAL INTELLIGENCE (FAI): DRIVING TRIGGERS, STATE OF THE ART OVER TIME AND INDUSTRY ADOPTION INFLUENCERS

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***ABSTRACT***

*The authors present a new Framework of Artificial Intelligence which analyzes the key elements of transformational AI in industry. The State of the Art of Artificial Intelligence is gleaned from an examination of what has been done in the past, presently in the last decade and what is predicted for future decades. The paper will highlight the biggest changes in AI, important influencers to adoption/diffusion and give examples of how these technologies have and will be applied in three key industrial sectors, including agriculture, education and healthcare. Next the research examines seven driving triggers of cost, speed, accuracy, diversity/inclusion, interdisciplinary research/collaboration and ethics/trustworthiness that are accelerating AI development and concludes with a discussion of what are the critical success factors for industry to be transformational in AI.*

***KEYWORDS***

*Artificial Intelligence, Technology Adoption and Diffusion, Driving Triggers, Technology Trends, Applications of Technology Development.*

## 1. INTRODUCTION

Artificial Intelligence (AI) is an evolving science and art. Developments come in flashes and spurts over time. The scientific community changes its focus on different topics and applications. Technological developments can and will continue to expand the problem solving and innovative capabilities of AI. Researchers build on what has been done in the past, implement in the present and dream about what can happen in the future. Together, these developments over time lead to the state of the art of a technology like AI.

This paper presents a time-evolving Framework for AI (FAI) based on past and present adoptions and future expectations of technology uses. Triggers such as cost, speed, accuracy, customization, inclusivity/ diversity, cross discipline/collaboration and ethics/trustworthiness are factors that push an organization to adopt and transform to a new technology. When there are dramatic changes in the environment, what the customer needs, competitiveness in the industry and increased resources to implement a new technology, these become influencers in how rapidly technology becomes transformational as well. In this framework, the state of the art of AI is impacted by triggers, influencers and time. Three distinct industrial sectors including agriculture, education and healthcare illustrate the sector-dependent nature of AI application development

DOI: 10.5121/ijaia.2022.13307

over time, spanning the past, present and future. The authors conclude with an in-depth discussion of the seven driving triggers of AI and how far along the AI transformation continuum industry has come.

## 2. RELATED WORKS

This section briefly reports the most related works to examining the triggers and influencers of AI technology adoption over time based upon a variety of theories and research models. The first group of theories and models pertinent to the development of artificial intelligence include those related to technology acceptance and adoption. The 3 most used acceptance/adoption models/theories are the Technology Acceptance Model (TAM), Diffusion of Innovations Theory (DOI) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [1].

TAM, the most widely tested empirical model, touts three technology acceptance factors including 1) "perceived usefulness", 2) "perceived ease of use" and 3) "attitude towards use" and focuses on the individual [2]. In contrast, DOI focuses on both individuals and organizations and four factors of time, channels of communication, social systems and innovation which impact technology diffusion and adoption [3]. Differences in adopter characteristics in the DOI model categorize firms and individuals within firms as early adopters, innovators, laggards, late majority and early majority leading credibility to industry sector differences discussed in this paper [3].

The UTAUT model is a built upon 8 former models (including TAM and DOI) emphasizing effort expectancy, performance expectancy, social influence, and facilitating conditions [4]. "Facilitating conditions" mean removal of barriers impeding technology adoption. When the UTAUT model was applied to adoption of new technology in e-learning, "facilitating conditions" were providing financial resources, new infrastructure, more human resources and innovative educational content [5]. "Facilitating conditions' are included in this study under the "influencer" construct subcategory called *resources*.

Both TAM and DOI models use the constructs of "perceived usefulness" and "relative advantage" [6]. A new construct of "perceived benefits of technology adoption" incorporated into the International Technology Adoption (ITA) model combined the previous constructs of technology utility to the individual with benefits to the company's well-being and corresponds closely in this research to the "triggers" of *speed*, *accuracy*, *cost*, and *customization* and the "influencers" of *competitive advantage* and *customer needs*.

"The Digital Transformation Journey" [7] is a framework that describes how digital technologies can transform an industry. A major construct in this model is called "mounting challenges and drivers" which is defined as finding ways to use technology to do business in new and better ways [7]. Coronavirus (Covid-19) in late 2019, for example, is considered a pressure point or "driver" of technology transformation in a variety of industrial sectors [7].

An example in the healthcare sector of a "driver" or "influencer" of AI technology is the coronavirus in Wuhan, China in 2019 which used AI tools to provide early detection of the coronavirus, isolating those areas with the virus [8]. It is likely the experience of a global pandemic will have a long-lasting and global impact on AI diffusion finding new ways of early detection which will help prevent future pandemics and influence health policies worldwide [8]. Increased competition is another "challenge" creating market pressure that if not addressed, can lead to loss of market share and revenues [7]. The Framework of AI uses the construct of "influencers" of *changing environments* and *competitive advantage* which correspond to transformational "mounting challenges and drivers".

Building on the previous construct of "benefits", this overview uses "triggers" which add value, usefulness and benefits to the individual (less time to do a task) and organization (reducing costs and mistakes). In addition, this paper addresses both "facilitating conditions" and "mounting challenges and drivers" constructs from previous theories as "influencers", particularly *changing environments*, *resources* and *competitive advantage*. This research contributes three new constructs under "triggers of AI technology adoption" – *diversity/inclusion*, *cross-discipline/collaboration*, and *ethics/trustworthiness* in its Framework of Artificial Intelligence (FAI). Addressing these essential issues can increase transformational adoption of AI.

The more leaders understand the biases in technology [8] and the need for collaboration across disciplines/fields and how ethics/trustworthiness define an organization's value system, the better they can improve AI's acceptance and therefore, increase its transformational adoption [9]. AI technology is a dynamic phenomenon affected by time; a better understanding of technology changes through past, present and future developments can help increase individual and organizational ability to build their AI maturity level [10]. Figure 1 categorizes constructs used from related research works, reimagined constructs in the FAI that align with previous works and brings new constructs in its FAI.

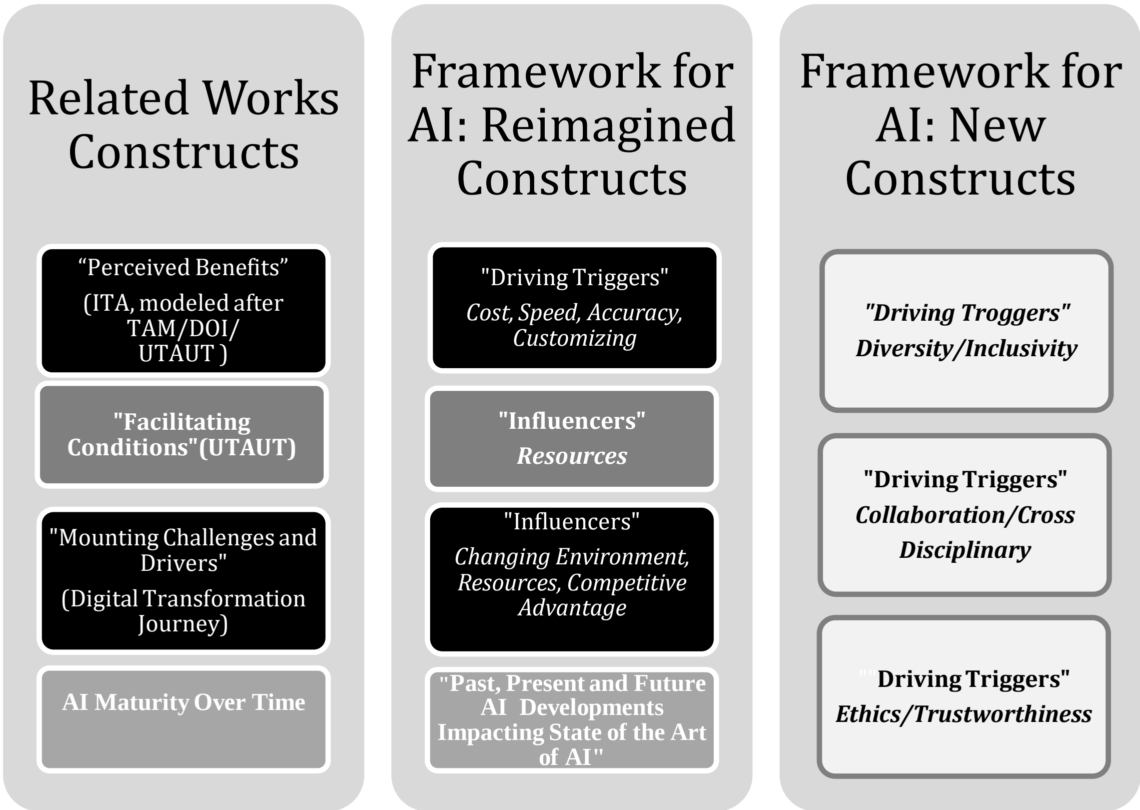


Figure 1. Related Work Constructs Used, FAI Reimagined Constructs and New Constructs from FAI

## 3. FRAMEWORK FOR ARTIFICIAL INTELLIGENCE

Successes in one industry spur interest in another sector. Some sectors are quick to adopt new technological applications such as AI and others are more cautious. Factors that can prompt or influence adoption include changing environments such as climate change or a pandemic event like the 2019 coronavirus (covid-19) or evolving customer needs for a product or service [11][12][13].

Often, organizations within a particular sector are searching for a better way to compete such as cost, quality, or catering to a special niche of consumers. For example, a recent McKinsey study showed advanced AI adopter firms were 52% more likely to increase their market share by 52% and 27% had growth in their marketplace compared to those who were testing or moderately implementing AI [14]. Lastly, there are changing priorities in the allocation and budgeting of resources depending on societal expectations and organizational readiness [15]. Figure 2 gives a schematic of the Framework for AI (FAI), from development triggers to adoption influencers based on past, present and future AI technology trends, which define the State of the Art in AI.

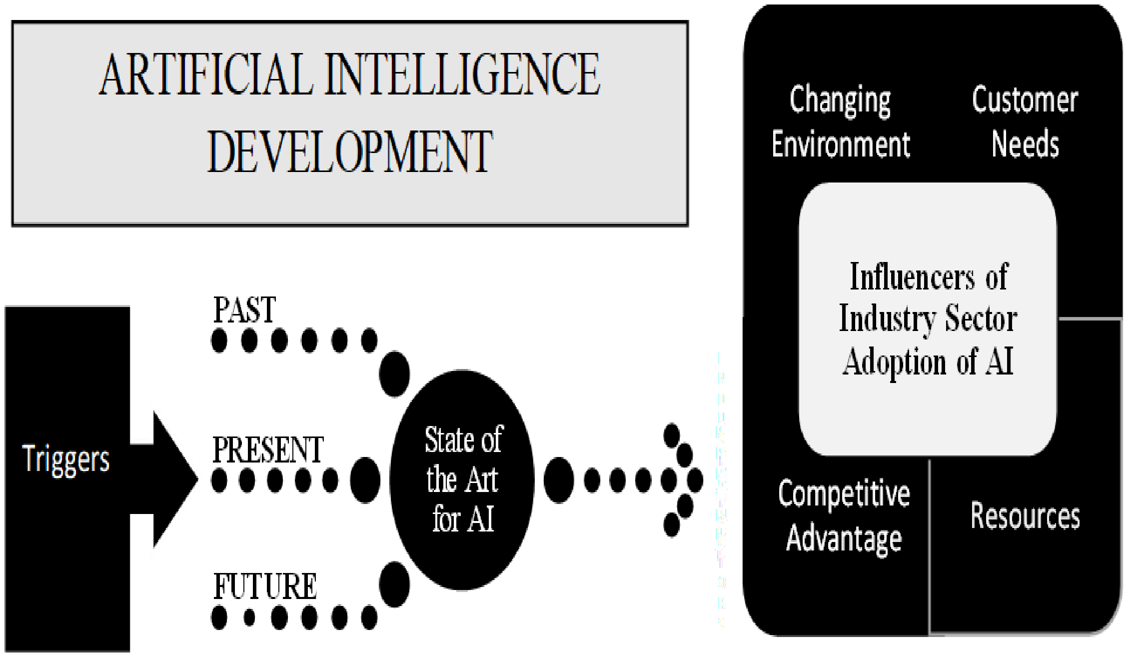


Figure 2. Framework for Artificial Intelligence (FAI): Driving Triggers, State of the Art of AI Over Time and Industry Adoption Influencers

### 3.1. Past

AI began in the 1940s, demonstrating that a new form of computing was possible, with an approach derived from known cognitive processes and neurobiology. The initial purpose of AI was to automate, through computers, non-analytical human knowledge, from symbolic computation processes, connectionist ones, or a combination of both. AI was initially considered a branch of computer science with limited application and restricted by the capabilities of the hardware of the time.

Turing, a British mathematician, developed a code breaking computer called the *Bombe* in the early 1940's that successfully broke the Enigma code used by the Germans during World War II, a task thought impossible by most human mathematicians at the time. He also developed the Turing Test, that states "if a human is interacting with another human and a machine and unable to distinguish the machine from the human, then the machine is said to be intelligent" [16].

In 1956, John McCarthy offered one of the first and most influential definitions of AI: "The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" [17].

One of the most famous AI examples is IBM's Deep Blue chess playing program, which beat the world chess champion Gary Kasparov in 1997. This expert system processed 200 million possible moves per second and determined the optimal next move looking 20 moves ahead [18].

### 3.2. Present

The current definition of artificial intelligence (AI) has transformed into "computing systems that are able to engage in human-like processes such as learning, adapting, synthesizing, self-correction and use of data for complex processing tasks" [19].

AI has become a vital element for the development of many services and industrial sectors in the 21st century. This discipline of computer science studies algorithms to develop computer solutions that copy the cognitive, physiological, or evolutionary phenomena of nature and human beings. The data, examples of solutions, or relationships between these facilitate the resolution of diverse problems [20]. AI exhibits, in certain aspects, "an intelligent behavior" that can be confused with that of a human expert in the development of certain tasks [21].

The Deep Blue project inspired the development of Watson, a computer that was able to beat the two best Jeopardy Game players in the world in 2011. Its software could process and reason using natural language, and draw from a massive supply of information poured into it in the months before the competition [22].

At present, AI has been redirected towards the construction of solutions to problems analyzing large volumes of data which change over time. Currently, the systems for approaching functions using iterative techniques, and the neural network architectures interconnected with each other, make up most of the techniques, which are grouped under the terms "Machine Learning" and "Deep Learning".

AI is becoming a growing presence in our society. From the intelligent sensors that make a car drive autonomously to mobile assistants, we are already surrounded by AI in some way or the other at all times [23]. Alexa, Siri, Cortana, security surveillance, fitness/dieting apps and online customer service are all examples of AI [24]. A large portion of the global population use these products/services in their everyday lives and the demand and popularity are ever growing [24].

### 3.3. Future

AI is a game changing technology and disruptor. Within 10 years, it is predicted 375 million workers will need to change occupations as a result of widespread use of AI [24]. AI and machine learning are predicted to reshape most sectors but particularly manufacturing, energy, transportation, agriculture, labor markets, and financial management [25].

AI will not only impact our personal lives but also fundamentally transform how organizations make decisions and interact with employees and customers. One of the most vital questions will be how AI systems and humans can coexist with each other. Which decisions should be made by AI, which ones by humans, and which ones in collaboration will be an issue all companies need to address in the future [22].

### 3.4. State of the Art of Artificial Intelligence

From basic computational skills and automation in organizations, Artificial Intelligence has expanded to learning and adapting through the use of neural networks and iterative techniques that mimic human intelligence. The future is about connection and how to use AI to transform our workplaces and our lives. Please see Figure 3 for The Schema of AI Technologies which summarizes how these new AI technologies affect the State of the Art of AI over time.

# 4. KEY SECTOR APPLICATIONS: AGRICULTURE

## 4.1. Past

Agriculture is a sector that includes studies in science, engineering, and economics. The deductive techniques of AI expert systems have been used in the field of agriculture to integrate crop management which encompassed irrigation, nutritional problems and fertilization, weed control-cultivation, herbicide application, and insect control/insecticide application. Additional subject areas were plant pathology, salinity management, crop breeding, animal pathology, and animal herd management [26].

Agricultural applications of expert systems and decision support systems have also benefited the simulation of processes and the management of supply operations [27][28].

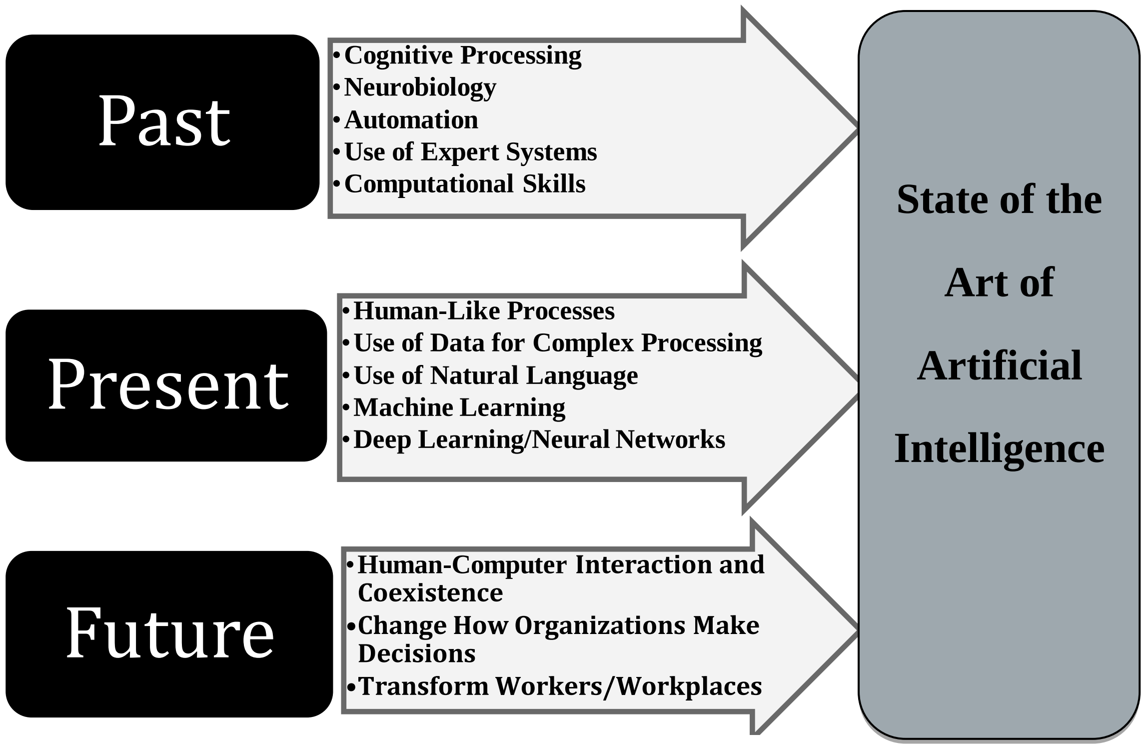


Figure 3. Schema of AI Technologies From Past, Present and Future: Impacts on the State of the Art of Artificial Intelligence

In other studies, AI has been used in quality control processes, whether or not they are supported by artificial vision [29] or in processes of justification of food policy decisions, such as when the use of AI is analyzed as a collaborative tool between the different actors that supply the agri-food chain, using distributed computing processes [30].

In the field of science, climate aspects are studied through modeling and solar radiation is predicted using neural networks [31][32].

### 4.2. Present

Interest in the application of AI to the world of agriculture and its multiple facets has been growing in recent years as it has proven to be a powerful tool for data analysis [33].

Current AI technology investigates the price behavior of agri-food products [34][35][36]. In these cases, artificial neural networks and machine learning techniques are applied to investigate the price variations of agricultural commodities.

The expansion and intensification of industrial and technological agriculture have increased production, decreased the number of people suffering from poor nutrition and ensured richer and more resource-intense diets around the world. Industrial agricultural activities also generate employment, improve economic growth and boost the service sector in industrial regions [37].

Agriculture 3.0 brought robotics and automation to the agricultural world, as evidenced by agricultural machinery that performs complete cycles of agricultural work such as planting, spraying, and harvesting [38][39][40][41].

### 4.3. Future

Now, agriculture 4.0, combines intelligent farms and the interconnection of machines and systems, and seeks to adapt production ecosystems by optimizing the use of resources such as water, fertilizers, and phytosanitary products. In addition, it uses big data and imaging technology to arrive at “precision agriculture” [42][43][44][45].

Combined with genetic engineering and the use of data, it can solve an important part of agriculture by maximizing efficiency in the use of resources and adapting to climate change and other challenges [46]. To this end, the use of big data in decision-making is essential [47][48]. The technification of agriculture, decision support systems and the inclusion of concepts of Industry 4.0 by agri-food companies will continue to generate increased innovation in AI [49].

## 5. APPLICATIONS IN EDUCATION SECTOR

### 5.1. Past

The IBM supercomputer Watson was watched across school and university campuses and all were delighted with the computer besting the 1994 world chess champion. In 2011, Watson with its victory in the game show *Jeopardy* against the two highest winners, heralded the era of cognitive computing with its potent natural language processing, knowledge representation and reasoning capabilities.

The educational interest in AI was initially captured through computers playing games but early versions of educational tutorials, learning management systems, simulations and iterative computer learning in the 1900s and early 2000s started the AI revolution in education [50][51][52].

### 5.2. Present

Universities have been particularly impacted by the 2019 coronavirus pandemic due to the in-person nature of traditional education. They are responding to this threat by investing in digital technologies such as cloud, AI, analytics, immersive learning spaces, and digital curricula.

In fact, more than 80% of institutions are allocating over 25% of their 2021 IT budgets toward digital initiatives [53].

“Customization of learning has been happening through rising numbers of adaptive education programs, gaming, and software. These systems are personalized by enabling repeated lessons that students haven't mastered, and generally helping students to work at their own pace, space and liberty” [23].

Individualized automated tutoring has been developed to help students to learn easily and on their own schedules [54]. At Colorado State University, online students and tutors are using AI powered by Cognii, an Edtech company, to improve learning and assessment tools [55].

Another recent example of AI advancement is AlphaGo—a software or ‘machine learning’ developed by DeepMind, the AI branch of Google—that was able to defeat the world’s best player at Go, a very complex board game considered more difficult than chess [56]. The AlphaGo program proved that the computer and deep learning can reach new heights and further advance human understanding in certain topics.

‘Machine learning’ is a subfield of artificial intelligence that includes software able to recognize patterns, make predictions, and apply the newly discovered patterns to situations that were not included or covered by their initial design.

## 5.3. Future

AI has the potential to modify the quality, quantity, delivery, and nature of education. It also promises to change forever the role of parents, students, teachers, and educational systems. Using Artificial Intelligence systems, software and support, students can learn from across the world at any time. These kinds of applications are taking the place of certain types of classroom instruction and may replace teachers in some cases [23].

AI can contribute to changing education via the automation of administrative teaching tasks, software programs that favor personalized education, the detection of topics that need reinforcement in class, the guidance and support of students outside the classroom, and the use of data in an intelligent way to teach and support the students [57].

Three techniques of AI are particularly relevant for future educational developments - personalization systems (knowledge and individualized adaptation of the student), software agents (intelligent programs and robots with autonomy and the ability to learn) [58] and ontologies and semantic web [59].

When developed and applied in education, these systems and techniques can be powerful resources for improving the teaching–learning process, since they are able to generate a kind of virtual teacher who is fully trained and has human characteristics, yet is able to interact ubiquitously (that is, at any time and place) [54].

By harnessing the power of AI and deep learning, educators can gain insights from the vast quantities of data collected from their students, make better decisions and improve student retention. Teachers can access detailed feedback on how learners are processing information. Big data can help answer key online learning questions—what are the best ways to teach complex ideas and which parts of a course are best taught in person instead of online. Big data helps students find the right courses; customize them to their needs and keep them on the right track [55].

Most EdTech products will have an AI or deep learning component in the future. AI could help online learners self-assess, increase connectivity in global classrooms and create social simulation. Limitations include the uncertainty of how humans learn and fears among faculty that they must be retrained or could be displaced completely [55].

"Remote learning will coexist with on-campus education. As institutions accelerate their focus on student diversity and address unique educational needs, it is critical for them to make necessary technological investments to support their teaching models" [53].

In the future, higher educational institutions should expand outreach by using online courses and digitization of content to enable on-demand access by students across different geographies for remote learning, self-directed learning or specialized skill development. Secondly, increase funding to facilitate online learning, particularly enhancing IT capabilities – cloud platforms, collaborative tools, data security measures, AI bots and assessments. Lastly, educational organizations must learn to mine data assets and use AI's analytical solutions to develop personalized content, upskill faculty and enable remote proctoring, communications and virtual assistants [53].

# 6. APPLICATIONS IN HEALTHCARE SECTOR

## 6.1. Past

A recent review of the history of clinical decision support states the dramatic improvement in the medical sector due to the advent of cognitive aids to support diagnosis, treatment, care-coordination, surveillance and prevention, and health maintenance or wellness [60][61].

Some studies highlighted the importance of AI in healthcare, especially in medical informatics but there is still work to be done on examining the impacts and consequences of the technology [61][62].

## 6.2. Present

In the medical profession, image recognition tools are already outperforming physicians in the detection of skin cancer [63]. Molecular imaging modalities have also been effective in diagnosing neurodegenerative diseases [64].

Digital medicine and wearable devices are presently used by healthcare professionals by mining data for anomaly detection, prediction, and diagnosis/decision making. Wearable devices and sensors have been used to continuously track physiologic parameters which guided patient care strategy that improved outcomes and lowered healthcare costs in cardiac patients with heart failure [65]. They also have been effective to improve diagnosis and management in neurological disorders such as Parkinson's disease [66].

Machine learning applications in healthcare have been helpful in earlier disease detection and prediction. For example, machine learning models were used in identifying stable subsets of predictive features for autism behavioral detection and blood biomarkers for autism [67][68].

Machine-learning algorithms were also used in the prediction of periventricular leukomalacia in neonates after cardiac surgery [69].

### 6.3. Future

Deep learning for automated and/or augmented biomedical image interpretation will continue to be used in radiology, pathology, dermatology, ophthalmology and cardiology with strict protocols and benchmarks in place to ensure data integrity and fairness. However, sensor-based, quantitative, objective and easy-to-use systems for assessing many diseases has the potential to replace traditional qualitative and subjective ratings by human interpretation in the future [70].

Future AI in healthcare must be able to use machine learning to handle structured data such as images, data, genetic data, and natural language processing to mine unstructured texts. Then it must be trained through healthcare data before it can assist physicians with disease diagnosis and treatment options [71].

AI in medicine will continue with informatics approaches from deep learning information management to control of health management systems, including electronic health records, and active guidance of physicians in their treatment decisions. Also in the future, healthcare will increase its use of robots to assist elderly patients and targeted nanorobots, a unique new drug delivery system [72].

## 7. Driving Triggers

Certain factors are accelerating the growth and use of AI throughout our society and will continue to be the driving triggers for AI's transformative impact. AI can be used as a competitive strategy in all economic sectors particularly in cost/pricing advantages, customizing or personalizing products and services, and research using data mined from present and potential customers.

In addition, many AI advances have been accomplished by finding ways to increase the speed and accuracy of data resources and data research which can accelerate innovations while increasing the level of quality for consumers. Lastly, in the pursuit of the positive contributions of AI, leaders must be mindful of creating products and services that appeal to an inclusive and diverse group of people. Another way to increase the potential of AI is to use collaboration and reach across disciplines and sectors. Without ethical application of AI and building trust with stakeholders, the organization will not succeed in its quest to fully develop the transformational power of AI. Please see Figure 4 for the critical triggers driving AI development.

### 7.1. Speed

Artificial intelligence systems can take control of many factors in an organization. For example, in an educational classroom – AI can control time-consuming tasks like accounting processes, record keeping, filling out forms, producing documents and automatically grade assignments freeing up time for teachers to improve the quality of learning, increase active learning and help students when needed [73].

In a survey about the benefits of AI in the workforce, 61% of respondents said it helped them have a more efficient and productive workday [74]. Almost half (49%) felt it improved their decision-making and accelerated time to insights, while 51% said they believed AI enabled them to achieve a better work/life balance [75].

The three highest rated tasks to benefit from AI adoption were: 1) understanding trends and patterns; 2) moving data from one place to another and 3) accessing data residing in different places across the organization [74].

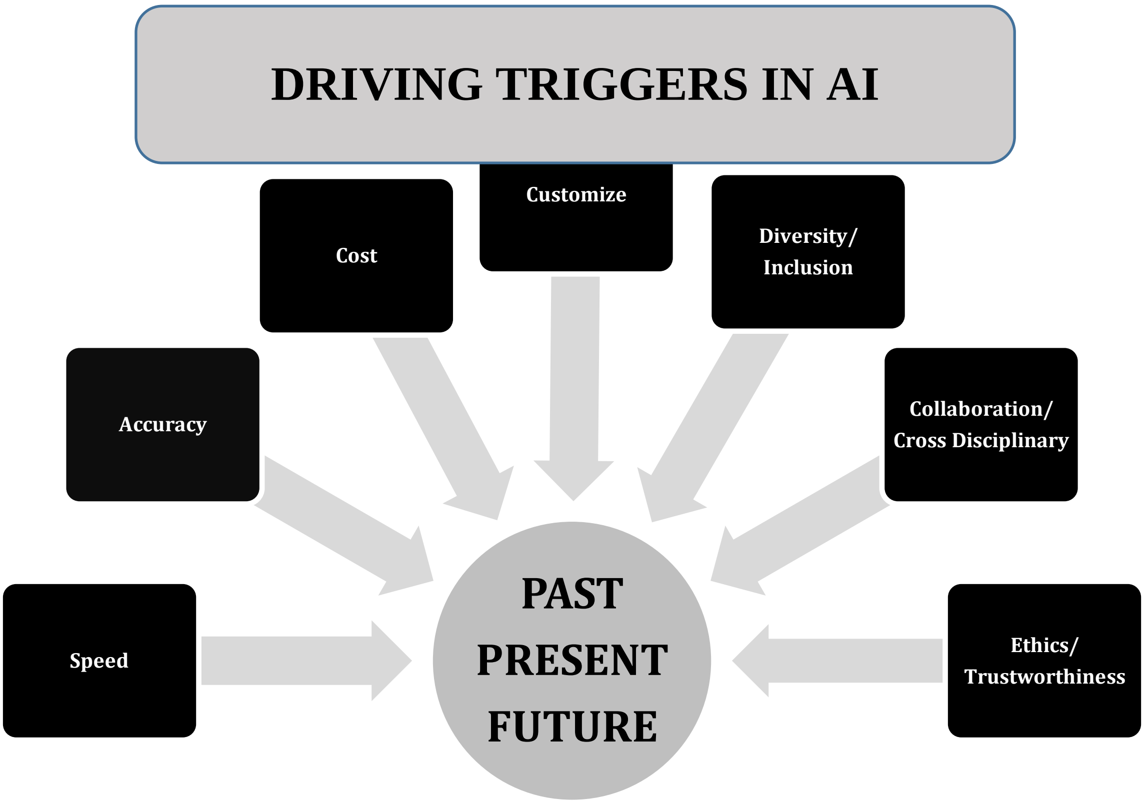


Figure 4. Driving Triggers in AI: Past, Present and Future

## 7.2. Accuracy

It is also predicted that 70% or more of companies will use some type of Artificial Intelligence in their operations because AI builds efficiency and effectiveness [24].

In the healthcare field, for example, AI can use sophisticated algorithms to ‘learn’ features from a large volume of healthcare data, which can bring about insights for clinical practice and because it can be equipped with learning and self-correcting abilities, will improve its accuracy based on feedback over time [71].

Machine-learning-based methods provide a collection of strategies that are efficient and deliver automated cerebellum parcellations with a high accuracy, surpassing previous work in the area of neural medicine [76].

In breast cancer, the combination of computer-aided diagnosis of image-omics and functional genomic features improved breast cancer classification accuracy by 3%. The entire biomedical imaging informatics framework consisted of pathological image extraction, feature combination, and classification [77].

In a recent interview with Susan Kaplan, the VP of a high-tech firm called Modal Technology located in Minneapolis, a joint venture partnership between Modal Technology (inventor and founder Nate Kaplan) and McGill University Health Center Research Institute (scientists – Drs. Lazaris and Metrakos) in Montreal, Canada enabled the partners to compress the network, use less data, get a non-statistical mathematically provable training solution in a single run and answer the researchers' hypothesis[78].

That means they were able to get 100% accuracy in the training with a limited amount of data. The project successfully identified (100%) cancer vs. non cancer patients and also as part of the training run rank ordered over 1200 biomarkers (from most important to not important at all) of the disease, which was an important and not seen before capability. Clinicians can be more confident as they diagnose and treat patients and meet their goal of developing a feasible point of care lab kit to better diagnose and treat patients more quickly and at a lower cost [78].

## 7.3. Cost

Three cost-saving AI solutions include virtual assist (chatbots), human assist (which routes complex customer questions to a human), and screen assist (which provides common answers to humans) [79].

These AI technologies can save millions of dollars for financially stressed businesses in today's challenging times by enabling them to address issues that affect customer service, costs and revenues [79].

AI has already increased productivity and efficiency in healthcare delivery, which has helped improve care outcomes, patient experiences and access to medical services [80].

## 7.4. Customization

Customization is the name of the game – industries are using AI to humanize, personalize and customize products and services to their clients and expand their outreach and engagement [81].

Hyper personalization is the use of customer data to create and present customized contacts, information, or recommendations to customers. These customizations are created based on individual customer profiles. Profiles are created using data from browsing patterns, purchase histories, geographic location, demographic data, and behavioral data [82].

For example, Thread, a UK-based fashion retailer, offers customers AI-based product recommendations as a "personal stylist", from information collected from style quizzes and ongoing reactions to product recommendations and they do this with minimal additional effort or staffing [82].

Hilton Hotels currently uses a robot concierge named Connie in its lobbies to greet guests, answer questions and provide concierge-like answers to guests using natural language processing capabilities to interact with guests and develop meaningful profiles [82].

Although Under Armour is known for clothing, they reach customers through lifestyle activities of health and fitness, so they created the Record app, which collects user information on sleep, diet and physical activity. They then create personalized health goals and workout plans and after customers work out will provide feedback on the user's workout effectiveness to help maximize their future efforts [82].

## 7.5. Diversity/Inclusivity

While AI is quickly becoming a new tool in the CEO tool belt to drive revenues and profitability, it has also become clear that deploying AI requires careful management to prevent "unintentional but significant damage, not only to brand reputation but, more importantly, to workers, individuals, and society as a whole" [83, p1].

Recent research shows that AI bots and voice assistants promoted unfair gender stereotypes by featuring gendered names, voices, or appearances. In the United States, Siri, Alexa, Cortana, and Google Assistant—which collectively total an estimated 92.4% of U.S. market share for smartphone assistants—have traditionally featured female-sounding voices due to the designers' inate biases that female voices are more helpful, pleasant and accommodating than male ones [84]. In addition, racial and cultural biases also make it difficult for many people to interact easily with AI assistants around the world [85].

AI chatbots, recruitment software and risk assessment tools in the past caused harm by being racist, gender-biased or selecting the wrong people to put into jail [76]. People may not care how Facebook identifies who to tag in a given picture, but when AI systems are used to make diagnostic suggestions for skin cancer based on automatic picture analysis, understanding how such recommendations have been derived becomes a critical issue [63].

Experts say that AI is still "fragile, opaque, biased and not robust enough" to provide trustworthiness [87]. Leaders need to take the necessary steps to ensure that AI is being used in an ethical manner by consistent reliance on organizational values.

Three ways to accomplish this are: 1) Clarify how values translate into the selection of AI applications, 2) Provide guidance on definitions and metrics used to evaluate AI for bias and fairness, and 3) Prioritize organizational values [83]. Expanding the concept of AI to 'Responsible AI' is essential to ensure fairness, ethics, security/safety, privacy, transparency and accountability issues are considered [88].

"Business leaders may claim that diversity and inclusivity are core goals, but they then need to follow through in the people they hire and the products their companies develop" [19]. Ensuring minorities are well represented among both users and evaluators of AI will make AI more accessible and inclusive [88].

The covid-19 pandemic first discovered in 2019 has accelerated the need for the adoption of digital tools in education, particularly in the science, technology engineering and mathematics (STEM) arena. The majority of software developers are still males with only 25% women in the U.S. and minority racial groups are totally underrepresented in technology fields [89].

The goal is to create a stronger foundation for STEM literacy, inclusion, and diversity of STEM students and preparing the STEM workforce of the future. With the growing demand for advanced skill sets, educators can provide creative and more targeted learning rather than focusing on the repetitive tasks of creating problem sets. The net result is better learning outcomes for a wider group of students and requires collegial partnering, ongoing development, and thorough testing to implement [84].

## 7.6. Collaboration and Cross Discipline

"Creating differentiated experiences through personalization and immersive education will play a crucial role in the growth of remote learning," said Avasant's Research Leader, Pooja Chopra [53]. "Educational institutions should collaborate with EdTech companies and progressive service providers to accelerate digital transformation" [53].

Bibliometric studies that connect different disciplines are of growing interest in the analysis of the impact of AI synergies and their future within the research community. An example of this is a paper [91] which shows that the structure and model of the scientific production of researchers worldwide and the relationships between quality, references, and synergies among authors increases as collaboration across disciplines is applied. Multi-disciplinary research is vital to effective and natural human-robot connections [92].

Interdisciplinary research in artificial intelligence is a way to garner synergistic outcomes across industries from the AI field. To that end, researchers [93] recommend three strategies: 1) Collaborate on ways AI can impact other fields and look to new ideas from other fields to apply to AI; 2) Explain how decisions are made, be transparent about data biases, and use high level evaluators and regulators to evaluate processes; and 3) Scientific and educational experts should increase their AI educational levels.

Human-robot interaction challenges AI in many regards: dynamic, partially unknown environments not originally robot-friendly; a broad variety of situations with rich semantics to understand and interpret; human interactions requiring fine yet socially acceptable control strategies; natural and multi-modal communication requiring common-sense knowledge and divergent mental models. Collaboration of researchers and practitioners from across a variety of fields to integrate and share their data, knowledge, understandings and experiences is essential to meeting these challenges [58]. Cross-functional AI teams made up of diverse participants lead to greater innovations, more collaborations and better outcomes [94].

## 7.7. Ethics/Trustworthiness

Artificial intelligence (AI) technology continues to advance by leaps and bounds and is quickly becoming a potential disrupter and essential enabler for nearly every company in every industry. At this stage, one of the barriers to widespread AI deployment is no longer the technology itself, but a set of human issues from ethics and governance to human values and trust [95].

AI has a tremendous impact on how we do things and how we relate to one another. For example, children are growing up with AI assistants in their homes (Google Assistant, Siri and Alexa) and some observers might say they are an extension of co-parenting. As voice and facial recognition continue to evolve, machine learning algorithms are getting smarter. More and more industries are being influenced by AI, and our society as we know it is transforming [96].

Although AI promises enormous benefits for economic growth, social development, human well-being and safety improvement, the low-level of explainability, data biases, data security, data privacy, and ethical problems of AI-based technology pose significant risks for users, developers, humanity, and societies [97].

Ethics of AI studies the ethical principles, rules, guidelines, policies, and regulations about issues of transparency, data security and privacy, autonomy, intentionality and responsibility, human bias, accountability, ethical standards, human rights laws, automation and job replacement, accessibility, democracy and civil rights which form the foundation for Ethical AI [97].

AI reasoning needs to address societal values, moral and ethical considerations; weigh the respective priorities of values held by different stakeholders in various multicultural contexts; explain its reasoning; and guarantee transparency [98].

Facing this challenge, AI bioethics provides guidelines for AI technology so the world will be benefited by new intelligence. AI engineers and designers are the ones who give AI the ability to discern so that it will avoid any deviated activities causing unintended harm such as negative impacts on humans and society. Human experts are essential and necessary to design, program, and operate AI to prevent unpredictable errors from occurring [99].

Accountability, value alignment, explainability, fairness, and user data rights are 5 main areas of focus for Ethics in AI that must be embedded in the design and development process from the very beginning of AI creation [100].

In the healthcare industry, AI has potential promise for better medical diagnosis and treatment, but human experts are still needed to avoid misclassification of unknown diseases and to oversee treatments because AI is not omnipotent to solve all problems. Vigilant watch of AI's function is needed through the ‘physician-in-the-loop’ process [101].

As AI expands into almost every aspect of modern life, the risks of misbehaving AI increase exponentially—to a point where those risks can literally become a matter of life and death. Real-world examples of AI gone awry include systems that discriminate against people based on their race, age, or gender and social media systems that inadvertently spread rumors and disinformation or prey on a young girl’s esteem and image vulnerabilities [102].

AI ethics needs to understand the computational techniques it deploys and have a critical understanding of the datasets it operates on, how data is collected, and the social organizations and the biases that those datasets may represent. It is the responsibility of anyone who works with AI technology to understand the ethical, legal and moral issues involved [103].

Potential consequences include everything from lawsuits, regulatory fines, and angry customers to embarrassment, reputation damage, and destruction of shareholder value. To better address the challenges related to AI ethics and governance—it helps to use the ‘Trustworthy AI’ framework which introduces six key dimensions of the design, development, deployment, and operational phases of AI system implementation. Being fair/impartial, robust/reliable, protecting privacy, safe/secure, responsible/accountable, and transparent/explainable are all factors impacting AI governance and regulatory compliance and that define ‘Trustworthy AI’ [102].

AI’s profound and far-reaching potential for transformation concerns the engineering of systems that establishes a new, ethical balance between human and artificial autonomy, which promotes AI solutions that are good for humanity and the environment [104].

AI has a lot of benefits when it comes to societal, individual or cultural development. But any mistake in either the development or in the working phase of the AI system can be disastrous, especially when human lives are involved. Understanding what really makes an Artificial Intelligence system trustworthy is key [105].

For the community to accept intelligent AI and trust the firm behind it, they need to feel that their opinions are valued, that their point of view of what is “right” and “moral” has been accounted for, that they are being treated respectfully and with dignity, and that their view is being integrated into the solution. The concept of social license to operate, where a firm openly works with the communities that will be affected by its actions to gain their trust and acceptance, offers an approach for crafting AI solutions that are acceptable to all stakeholders [106].

One author calls for a “New Enlightenment“ which encompasses a broad dialogue to establish new philosophical and ethical foundations that sustain an economy, a society, a culture and regulations adapted to the new scientific/technological environment with the objective of maximizing growth and wellbeing [107].

The need for ethical considerations in the development of intelligent interactive systems is becoming one of the main influential areas of research in the last few years [108] and has led to several initiatives relating to ethics and trustworthiness, including the IEEE initiative on Ethics of Autonomous Systems [109], the Foundation for Responsible Robotics [110], and the Partnership on AI [111].

Responsible Artificial Intelligence is about human responsibility for the development of intelligent systems along fundamental human principles and values, to ensure human flourishing and wellbeing in a sustainable world [98].

## 8. Critical Success Factors for AI Maturity and Transformation

What are the keys to becoming a transformational organization in this new era of AI technology? From a compilation of the numerous models, the authors envision a new transformational path to guide your organization and workplace.

In a systematic literature review of Information Systems publications, researchers found 150 articles on maturity models with 3 commonalities: 1) Followed a stage of growth modeling approach with 4 or 5 levels or stages; 2) most designed a linear, unidirectional path from lower maturity to higher maturity; 3) all used dimensions to assess maturity (also called benchmark variables, process areas, capability) [112].

The Business IT alignment (BITA) maturity model [113] was recommended as one of the most accepted and most cited models for assessing Business-IT alignment among academics and practitioners. Similarly, the Analytics Maturity Model [114] with a measurable scoring system is also well recognized [112].

In their overview of Artificial Intelligence Maturity Models, scientists found that the use of a bottom-up design approach, descriptive characteristics, a maturity grid and continuous representation with five levels are the current trend in AI maturity model development [10]. In the AI Maturity Model (AIMM), four dimensions were used: 1) people (all who work to create artificial intelligence technologies within the organization); 2) organization (characteristics and resources that might influence AI process such as firm size, managerial structure, decision-making and communication); 3) data (amount and structure of the data to getting AI systems to work); and 4) AI functions (tools and technologies to scale AI) [115].

The critical success factors to becoming transformational gleaned from an overview of recent research included data, analytics, technology and tools, intelligent automation, governance, people, and organization [10] and have been incorporated into the presented "AI Transformational Maturity Model" as the construct "critical success factors". In this model, these 7 critical success factors are the dimensions that impact the extent and timing of technology adoption and where in the process the capabilities of an organization lie on the path to the transformational level. Each level is described in detail and builds upon completion of the previous one in a step-like progression (see Figure 5 for more details).

It appears from the literature that organizations still require an improvement in their AI capabilities and in strengthening their AI maturity and maturity models help in the evolution of organizations using AI by explaining the concepts, factors critical to success and characteristics needed [10]. The significance of organizational maturity suggests that technological capabilities such as technology infrastructure, data structure and human capital are critical for determining if an organization adopts AI and takes the path to become truly transformational.

Despite the benefits of AI, some organizations are still far from applying AI to their businesses or their value chain [116]. Some have adopted AI technologies in their business but are still at an early stage, with limited benefits achieved [117] [118]. In a survey of the pharmaceutical industry, for example, AI maturity overall was assessed at the beginner level by 75–100% of the highest rated respondents [119]. In a recent paper, the author believed that AI applications have the potential to cut annual US healthcare costs by 150 billion USD in 2026, if the healthcare model changes from a reactive to a proactive approach, focusing on health management rather than disease treatment [120].

AI functions are immature due to the substantial unrealized potential of AI tools and technology to further improve competitive positioning [116]. In other words, the implementation of AI needs to be organization-wide, fully integrated into the culture and DNA of the company, otherwise, it will achieve only a fraction of the value and benefits promised [121]

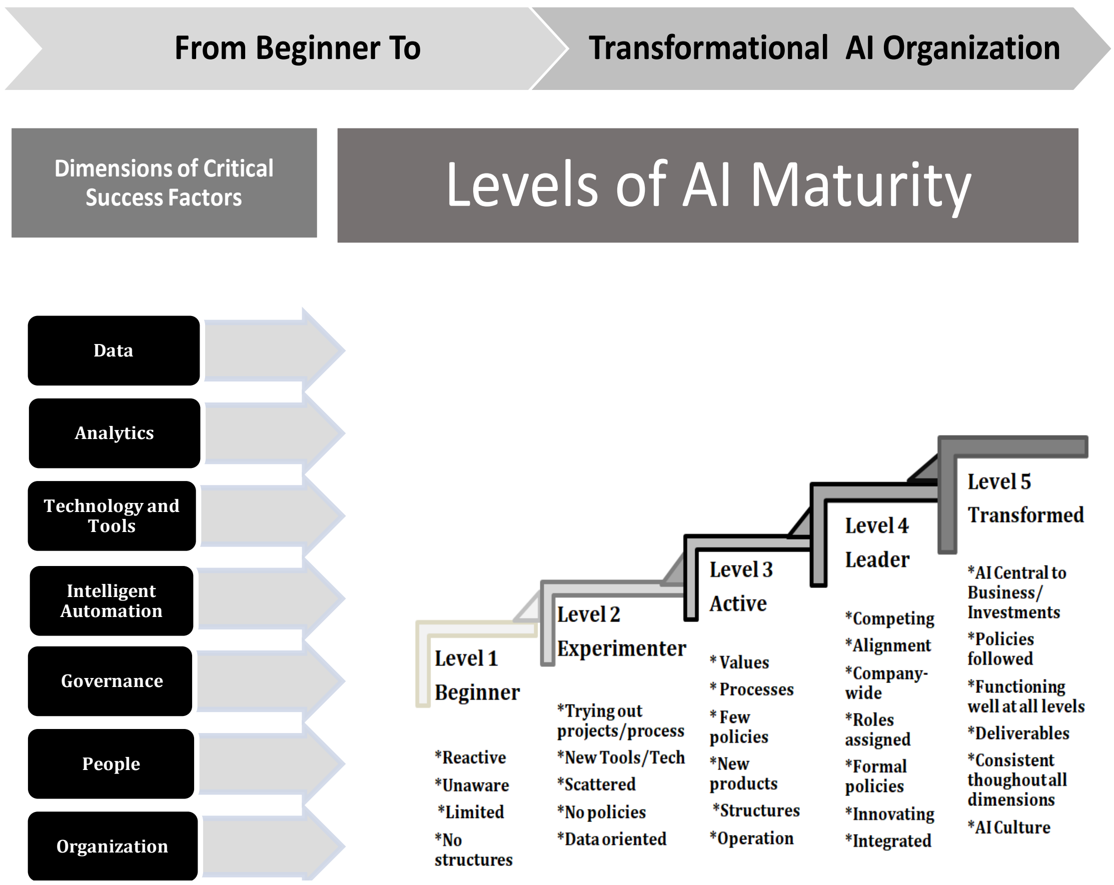


Figure 5. AI Transformational Maturity Model

## 9. CONCLUSIONS

In this paper outlining the Framework for Artificial Intelligence, the authors analyzed the triggers for AI development as well as the influencers to AI adoption. There is no doubt that current triggers such as speed, cost, accuracy, diversity/inclusion, competitiveness, personalization, the need for cross-disciplinary collaboration and ethics/trust will continue into the foreseeable future. The present factors such as the coronavirus pandemic of 2019, climate change, customer needs, or resources may fluctuate or change in the future, but there will always be influencers that encourage wider AI adoption and those that discourage AI deployment in organizations.

In this comprehensive look at the past, present and future applications in key industry sectors, a better and more comprehensive model for AI emerges. Organizational leaders have tools such as the AI Transformational Maturity Model presented in this paper, to use as a guide, and perhaps, an impetus to attain the full array of advantages that transformational AI can bring.

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