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**The Role of Artificial Intelligence in Healthcare,
Finance, and Education**



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Abstract- Artificial Intelligence (AI) is a term that has been widely and frequently asserted in various aspects of life. With the latest rise of machine learning that is now touted as a subset of AI, motivation to leverage AI technology surged around the globe. Consequently, several studies exploring AI-based technologies are currently being conducted in numerous fields including, but not limited to, healthcare, finance, robotics, smartphone, and education. The survey is intended to provide an overview of the current applications of AI-based technologies in healthcare, finance, and education as well as to summarize any potential concerns and remaining issues related to these technologies. Among the plethora of AI-based technologies, the three representative fields were selected.

Key words: AI in Healthcare, Medical Diagnosis, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning, AI in Finance, FinTech, Fraud Detection, AI in Education, Intelligent Tutoring Systems, Personalized Learning

1. Introduction to AI Applications

Artificial Intelligence (AI) is a term that has been widely and frequently asserted in various aspects of life. With the latest rise of machine learning that is now touted as a subset of AI, motivation to leverage AI technology surged around the globe. Consequently, several studies exploring AI-based technologies are currently being conducted in numerous fields including, but not limited to, healthcare, finance, robotics, smartphone, and education [1]. AI is the capability of a machine to imitate intelligent human behavior. Broadly, AI encompasses machine learning that can be thought of as a subcomponent of AI. Machine learning is a technique that can enable a system to learn the knowledge from data and improve the performance of the system without the need for explicit programming.

The survey is intended to provide an overview of the current applications of AI-based technologies in healthcare, finance, and education as well as to summarize any potential concerns and remaining issues related to these technologies. Among the plethora of AI-based technologies, the three aforementioned representative fields were selected. For each of these fields, summary is made on some representative technologies in performance, data, system, expert system, and human-level intelligence. The summary of potential concerns and remaining issues related to these technologies includes considerations of ethics, interpretability, trust, safety, regulation, responsibility, transparency, human-computer interaction, and technology adoption.

2. AI in Healthcare

Artificial intelligence (AI) powers the digital age. Broadly defined as the imitation of human cognition by a machine,

recent interest in AI has been driven by advances in machine learning, in which computer algorithms learn from data without human direction. AI is increasingly incorporated into devices that consumers always keep with them. In health care, there is great hope that AI may enable better disease surveillance, facilitate early detection, allow for improved diagnosis, uncover novel treatments, and create an era of truly personalized medicine. There is also profound fear that it will overtake jobs and disrupt the physician–patient relationship. The wealth of data available in the form of clinical and pathological images, continuous biometric data, and internet of things (IoT) devices are ideally suited to power the deep learning computer algorithms that lead to AI-generated analysis and predictions. Consequently, there has been a substantial increase in AI research in medicine in recent years. AI can obviate repetitive tasks to clear the way for human-to-human bonding and the application of emotional intelligence and judgment in health care. Given the time limitations of a physician, as the time demands for rote tasks increase, the time for physicians to apply truly human skills decreases. By embracing AI, humans in health care can increase time spent on uniquely human skills: building relationships, exercising empathy, and using human judgment to guide and advise [2]. Accordingly, a number of studies on the use of AI-based technologies in health care are currently being conducted. The use of machine learning algorithms in medical image analysis has been expanded widely to most medical departments. AI-based medical image analysis tools are being commercialized by startups such as Vuno, Lunit, JLK Inspection, and Deepnoid by receiving approval from the Ministry of Food and Drug Safety. Various technology giants such as IBM, Google, Apple, and Samsung are competing to develop and commercialize devices and services that can assist in improving user health by acquiring health information from daily life using a combination of Internet of Things (IoT) technologies and wearable devices [1].

2.1. Transforming Patient Care

AI has the potential of automating patient-centric responsibilities that fill much of a healthcare provider's time. Patient care-related tasks and processes that enable and enforce patient care are already ripe for automation. These tasks are repetitive, interactive, or both. Scheduling, billing, and dealing with insurance companies generally fall into the routine administrative tasks automation category. AI-enabled chatbots can triage patients on the hotline, and Healthcare bots can simulate human-like conversations. AI-based customer support can expedite responses for non-patient-specific inquiries. Facilities, bed, and operating room scheduling can also help manage patients more efficiently, while cleaning and sterilization tasks could be managed with

AI. Reducing the administrative burden is an enabling step that will leave more time for actually providing patient care. One option for clinical care is AI-generated results, where a machine mimics a part of a human function and produces part of the clinician's result. Examples include diagnosis via imaging analysis, automatic identification of patients with COVID-19 based on lung X-ray analysis, and selection of appropriate patients for surgical procedures. [2] [3]

Lastly, patient-centric interactions or direct human-to-human interactions can be improved by AI. Patients and families forget information after receiving treatment and consent forms, leading to dissatisfaction and disputes. Evidence-based kaizen automation, implemented with process-mining technology, can assess the co-interactions of a patient, family, physician, and staff in an operating room surgery during the period of perioperative. Inpatient notes saved in a notebook can be difficult to access at the clinical site. AI with natural language processing can analyze large amounts of text data and summarize and visualize clinical notes. Rounding experience of medical students can include AI, where students acquire the digital capability of creating care outcomes based on mobile devices and learn real-time data extraction techniques to steer the rounding mission.

2.2. AI in Diagnostics

Healthcare systems have witnessed enormous advancements during the last decade, all thanks to contemporary technology. Today, virtually all healthcare systems have incorporated automated systems, data collection, and storage due to medical databases, the Internet of Things (IoT), and wearables. With the advent of modern data-rich healthcare systems, there has been substantial development in the field of Artificial Intelligence (AI) in healthcare. Machine Learning (ML) and Deep Learning (DL)-based AI tools have shown a huge impact on medical diagnosis in the healthcare system. They can correctly predict different categorizations in biomedical research data, health record encoding, EHR data analysis, and image data diagnosis of diseases or tumors [4]. Moreover, AI applications are extensively used in other fields of healthcare, including MMHG, biomedical knowledge representation and analysis, big data analytics in integrated databases, predictive modeling in EHR, gene discovery in personalized medicine, decision support in genome sequencing, and safety monitoring.

The recent COVID-19 pandemic reminds and raises awareness of rapid disease data accumulation due to its significant global devastation. It inspired the scientific community and the general public to innovate and use advanced technologies, gaining momentum in the last decade. This paper reviewed and presented the state-of-the-art application and development of AI-based ML and DL diagnostic tools that have been successfully leveraged in the fight against COVID-19 by different research communities and companies. Additionally, open challenges and directions in this field are discussed. On 31 December 2019, the World Health Organization (WHO) Country Office in Wuhan, China, was informed of an outbreak of pneumonia in Wuhan, Hubei Province, China, which has subsequently been reported as the coronavirus disease 2019 pandemic. Due to its high transmission ability and conflicting symptoms with other respiratory diseases, the early detection and treatment of the COVID-19 disease are imperative to contain its spread.

On 11 March 2020, WHO declared COVID-19 as a pandemic. By 5 May 2020, there were more than 3.6 million confirmed cases worldwide, and the cases were continuing to increase alarmingly. Additionally, because of the unavailability of the required number of kits and manpower to perform the tests, a low number of tests per positive case, other operations, and an insufficient number of hospitals, most of the countries were undergoing high positivity rates compared to the number of tests and case increases. The alarming increase of the COVID-19 pandemic raised awareness of the importance of rapid COVID-19 detection screening systems to isolate potential patients. Thus, unlike the common person, COVID-19 diagnostic tools are required for nonmedical persons to speed up the process.

2.3. Predictive Analytics in Healthcare

Predictive tools are automated and employ a wide array of sophisticated statistical techniques to predict future occurrences of events from historical and current data. Predictive analytics uses learning algorithms, statistical modeling techniques, and data mining technologies to draw inferences from the data and predict trends and behaviors. In the medical area, predictive analytics can change the face of patient care by forecasting infectious disease outbreaks, tailoring treatment plans, and employing hospital resources more effectively [12]. Predictive analytics is similar to forecasting but employs a wider array of algorithms and statistical techniques. Rather than predicting future occurrences of events, predictive analytics are used to provide a basis for insight that can be tested more rigorously. For example, predictive analytics is being applied to determine how to search texts, analyze sentiments, and measure health impacts. Across widely varying applications, predictive analytics require three key interrelated components: the analytics, the data, and the application. In most cases, these components need to be integrated to provide useful insight regarding the usage of health services, with users searching for possible interventions and for evidence to support them. Predictive analytics employs techniques such as machine learning, statistics, and data mining to analyze historical and current data and make predictions about future events or behaviors. In healthcare, predictive analytics can help forecast outbreaks of infectious diseases, tailor treatment plans, or allocate hospital resources more efficiently. Using predictive analytics, machine learning (ML) algorithms can forecast the patient's risk of longer hospital stays and various diseases. A machine learning algorithm is a set of statistical techniques that allow a computer to learn, analyze, and make predictions or decisions based on data, a key component of predictive analytics.

2.4. Ethical Considerations in Healthcare AI

While the excitement surrounding discoveries in hospitals, medical research facilities, and industries is great, so is the concern over the ethical and technical problems connected with these approaches [6]. There is a growing need for work ethics to match increasing use of AI in healthcare as a result of its cross-disciplinary nature. The requirement for AI systems that are sufficiently interpretable and transparent, as well as interdependent with responsible AI standard processes, architecture, data, training techniques, standards,

measures, and degree of autonomy, arises as smart healthcare products become more automated. The ethical necessity for AI decided conclusions to be in the same measure of convergent expert opinion in order to be held responsible arises as AI health technology assessment becomes more advanced. Machine learning, natural language processing, and cognitive computing are only a few of the processes used in AI healthcare applications. While the investment in digitalisation has risen because of the COVID-19 pandemic, AI development in delivery, patient-facing services, and data management in health services is apparently lagging in many jurisdictions.

On the one hand, the healthcare sector is lagging in front of the important AI advancement. While healthcare is one of the pioneering sectors to embrace ICT frameworks and solutions, it has often been stagnant due to regulation complexities, stakeholders' reluctance, and a naturally more opposed sector regarding pre-disclosure processes and risk aversion. At the same time, AI development is crucial to ensuring a higher quality, efficiency, and responsiveness to population needs, imperatively coupled with the post-pandemic recovery efforts transitioning towards a well-being economy. On the other hand, the H308-Healthcare AI scope requires a good understanding of the fine balance between the need for an open frame for AI to flourish, and the obligation of regulations and standards to bind AI systems within the psychological, legal, and ethical boundaries. AI systems enable increasingly automated societies and better control of these systems are of major concern, but undue restrictions can cause irretrievable opportunities.

3. AI in Finance

Artificial intelligence (AI) is a collection of algorithms that allows computers to carry out a variety of tasks that would ordinarily require human intelligence, such as perception, reasoning, learning, and problem solving. Financial businesses frequently involve multi-market application, business modeling, and service provision in several financial sectors. Among them are trade markets, crypto assets, fintech, insurtech, Internet finance, stock exchange, cryptocurrency, FX market, e-lending/loans, reconstruction financing, decentralized finance, payment markets, billing, remittance, cross-border transfer, mobile payments, and app-based payments. However, many online/mobile (payment) services are not originally funded by the finance sector but by technology and service companies. It is critical to take a multi-disciplinary approach to investigate multi-market activities and services by AI in finance. With the growth of financial businesses every day, there is a dramatic increase in the volume, velocity, variety, veracity, and value of finance data generated, acquired, and traded, data-driven modeling toward better understanding, explaining, and understanding of EcoFin phenomena and behaviors, financial pattern recognition, product basis/valuation pricing, dash-board analytics, and financial smart payment and service recommendations [7]. Today's huge finance data produced in various data formats and via diverse data sources, platforms, and channels in a distributed/multi-market fashion becomes a central/global concern, challenge, and opportunity of such a data economy.

Mainstream financial channels store and process data at source by data-wise federated analytics, designing algorithm/hyper-parameter-wise distributed ML model updating for multi-market multi-node finance modeling, employing federated learning at AI/ML application-layer to robustly model market pricing/forecasting in cross-market applications, and so on. Hybrid AI/ML cloud-and-edge smart modeling and reasoning is short of deep interpretation/plausibility and data-driven development in predictive knowledge realization. AI with other advanced computing methods is applied in finance, resulting in explanation and understanding opacity/uncertainty in EcoFin phenomena, overselling knee-point fluctuation/price clustering in crowding effect, broad financial technology implementation challenges, and black swan uncertainties in the market. AI models their respective EcoFin systems/data-generation processes physically, laterally, and at variable resolutions in a multi-domain, scale, and space manner. Multi-domain/cross-scale models capture free-phase common phenomenon/agenda and analysis/understanding of the overall complex EcoFin systems, unbounded by existing domain-limited/micro-scale modeling/view.

3.1. Algorithmic Trading

Algorithmic trading is a central application of Artificial Intelligence (AI) and has played a crucial role in finance. In the past, basic algorithmic trading was commonly employed in stock trading, and traders needed to rely on years of experience to devise an efficient trading algorithm. Recently, with the rapid growth of code-sharing communities, many resources for designing algorithms have become available for use. However, a comprehensively applicable design of the data science pipeline in comparison to specific asset classes across different exchanges in one system is still limited. It is rewarding to design a generally applicable data science pipeline, including pre-selecting pertinent parameters for data gathering, coding out backtests of different trading strategies, brief explanations of universal trading strategies, and evaluation of models involved, to request attention and use in academic research and application [8].

With aid from the open-source Python3 backtesting library, a relatively thorough and concise instruction on how to program trading strategies is provided. Four algorithms widely employed to trade stocks and crypto assets are arranged: classical algorithmic trading (moving average crossover of close prices and floating upper/lower bands of volume-weighted average price on close prices), sentiment analysis (interpreting and trading sentiments expressed on Twitter), and statistical arbitrage (take advantage of temporal mispricing with high-frequency trading strategy). To improve the compatibility of the source code across platforms and asset classes, it is advised to apply the library to code and analyze trading strategies. In terms of simple programming availability, the library is preferentially selected in this research.

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Artificial Intelligence (AI) systems have been used in various industries, including fraud detection in the financial services industry. Regulations such as the European Union's Artificial Intelligence Act and the monetary authority of Singapore's guidelines on AI and data analytics have been developed to

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ensure compliance frameworks succeed compliance approaches across the enterprise. The system and lifestyle framework addresses compliance with AI regulation in a service lifecycle approach and helps identify compliance gaps and formulate tailored solutions. The prototype CASE tool has aided compliance by surfacing and instantiating compliance requirements. Financial services is one industry where AI has found broad application due to vast amounts of available and collectable structured and unstructured data. AI has enabled services and applications previously not thought possible in this industry, significantly improving customer experiences and achieving higher operational efficiency. However, its involvement in broader and increasingly critical decisions has exposed gaps in the currently established compliance frameworks. Direct negative impact from negligence and poor oversight of high-stakes models has been seen and anticipated by the financial services industry, most notably with the 2021 collapse of hedge fund Archegos Capital with multi-billion-dollar loss to Nomura Holdings and Credit Suisse. The rise of explainer AI techniques has bumped ethical concerns about algorithmic discrimination in AI models in general usage, such as inadvertent discrimination against ethnic and demographic minorities by Amazon and Facebook recommendation engines [9]. Fraud causes substantial costs and losses for companies in the finance and insurance industries. As the digitization of these industries continues, the threat of fraud increases, while at the same time big sets of new data are generated that could be exploited for fraud detection. Companies have to cope with vast amounts of data and at the same time find beneficial fraud patterns. To deal with these issues, many companies in this sector have developed so-called fraud detection systems that match customer requests with rules to identify fraudulent cases [10]. However, data-oriented issues complicate the use of classic methods for fraud detection in finance and insurance companies. Typically, this task is solved by applying statistical and machine learning methods to develop predictive models. Nevertheless, applying these methods is hampered due to generic issues from the claim model point of view, transaction and claim data are often unstructured, and fraud data are highly unbalanced. A target claim can consist of a collection of input claims, which in turn can consist of a collection of multiple claims. Thus, a claim does not have a fixed length. Before a model can be trained, it has to be designed for analyzing data with such cumbersome structure.

3.3. Customer Service Automation

The field of AI is continuously being developed in healthcare, finance, and education as it benefits the society and different organizations. The healthcare industry is benefitting from machine learning that helps in diagnosing the disease and artificial intelligence is getting transformed into medicine applications, robot-assisted surgery, imaging diagnostics, flood diagnosis & prediction, and personal devices. AI decreases human error and is able to deal with huge data sets that can be handled through IT solutions [11].

The finance industry is mainly revolutionized by AI applications. Algorithms are being widely applied across the finance sector like trading, forecasting of prices, portfolio management and risk management, fraud detection,

reconciliation, text and sentiment analysis, accounting, compliance, customer relations, insurance, and credit scoring. AI is geared to cut costs and save time across sectors. A huge transformation is being brought in education through AI. AI will be able to assist students and make learning easier and engaging. Subject representation will be able to help students learn about their interests and understanding levels. Smart content is generated through technology so that AI tools assist in preparation of updated books, exercises, and assessments. Students need to be taught on how to evaluate sources of information, both in terms of legitimacy and location of material. AI is able to revamp the customer service automation with use of chatbots for massively programmed interactions. There will be a shift towards more personalized interactions with customers that entail a heavy lift for programming. AI driven services can be deployed that can receive training on actual sources of information through interacting with Human agents and even tapping in context from background material.

3.4. Regulatory Challenges in Finance

The financial system has long been characterized as one of the most heavily regulated parts of the economy. This is in recognition of the strong externalities arising from financial activities that make the regulation and supervision of financial institutions important for the stability of the wider economy 5. A fundamental, even philosophical, challenge for regulating finance is that stability is a property that is hard to establish for all parts taken together. Individual parts can be perfectly safe, but the system as a whole remains unsafe, a situation that has played out historically on many occasions. Fortunately, there is a wealth of experience in regulating the financial system, and the early warning signals of emerging problems in one part of the system are well known. Creation of new instruments or institutions in a certain country or market typically spreads to others, inducing dynamic equilibrium considerations. Emerging risks typically realize when the system is unprepared, leading to accidental impoverishment of agents before authorities realize their existence. It is also understood that everyone should look beyond the margins of regulation adopted or overseen by others to limit the emergence of regulatory black holes.

Nonetheless, AI will have consequences for the conduct of financial regulation and supervision 5. The private sector will increasingly adopt AI systems for the gathering and processing of incoming information and provisioning of risk metrics. This may change the behavior of private sector institutions, and how approaches to prudential regulation take mortality into consideration. If a number of institutions adopt the same engine and training data to the same knowledge and risk universe, they will likely do similar actions under similar stimuli, inducing contagion. The same underlying beliefs also lead to procyclical behavior. Reactions to sudden shocks will also tend to be similar, amplifying societal behaviour.

Supervisors will likewise have to address how AI will affect all aspects of financial regulation and supervision. Supervisors will likely end up outsourcing many analytics to a few large AI vendors. This will change the nature of the regulated/supervisor divide, blurring lines between the public and private sector, banking and technology, and domestic and international boundaries. It will also lead to a single

representation of the financial system, as regulated firms or supervisors begin consenting to a single language. This will not be value-neutral, and its implications for financial stability will need scrutiny.

4. AI in Education

Quality education is a basic right for every individual in a democratic world. With the advancement of technology, education has evolved from traditional blackboard teaching to chalk-less smart classrooms where non-standardized digital whiteboards present conference room setup. There have been paradigmatic shifts in knowledge delivery methods in the era of the internet, resulting in the emergence of different types of e-learning systems. To outsource the upcoming technological advancement, the emergence of artificial intelligence (AI) driven tools and technologies is expected to revolutionize the educational landscape, benefiting all stakeholders: students, educators, and education-related administrative staff.

AI can be described as "the computational science of descriptions, analyses and predictions of the dynamic behavior of systems exhibiting a degree of complexity typically CF a and beyond" which is achieved through computer programming, machine learning (ML) and deep learning (DL) algorithms trained with required datasets to enable computers to perform the tasks usually requiring human intelligence. In education, the addressable diversity in student abilities, feelings, behavior pattern and teacher idiosyncrasies make learning personalized for no two students even in the same classroom.

However COVID-19 resulted in a forced global online rush and changed the education landscape substantially, exposing challenges that need to be urgently tackled using proactive engagement of AI. Disruption in knowledge flow due to pandemic, masking the teacher's facial expression, making eye contact impossible, detaching students from smartphone usage for online assessments and development of self-driven learners are some of the new challenges in online educational systems.

4.1. Personalized Learning Experiences

AI-driven co-curricular activities represent a simulated yet rich milieu in which isolated online learning can occur. Via intelligent systems, a range of SLIs (Student Learning Interventions) can be deployed to excavate intelligent information about learners and their engagement in DL (Distance Learning). The products from these mining footprints can drive a highly personalized experience for every student regardless of how they normally engage with DL (i.e. watching videos, quizzes, notes, forum). The implementation of intelligent tutoring systems means that development of student profiles can happen automatically as behavioral data are logged across systems. The training materials are customized in order to permit instructors to draw upon a single curriculum while this content and its presentation are modified for individual users. Personalization can also occur at the content level, with smart online textbooks having extensive interactive interfaces that render student learning highly individualized both in terms of the delivery of materials as well as the feedback given.

Several forms of interaction were identified in initiatives to address this skill-set disconnect. For example, a learner interacts with material in many ways external to the formal educational event. Providing students with access to a range of these dimensions of interaction is a critical link in developing the overall quality of student experience. Currently, the intelligent co-curricular concept consists of five initiatives. National projects are making good progress on an intelligent podcasting tool, as well as personal education assistants. However, the patient responses to the initial recruitment of students have slowed progress. Workshop participants called for the augmentation of tutoring with personal, conversational education assistants. Global experiments with voice-activated, chat-style interfaces were highlighted, but they require an enterprise-level commitment to the platforms involved. A two-angle need to ensure scalable and effective engagement was identified. Improvement needs to be made to the granularity of understanding student needs. Learning systems that reinforce concepts in a personalized fashion with additional and different materials were emphasized as a critical enhancement.

4.2. AI-Powered Tutoring Systems

The introduction of artificial intelligence (AI) into education has opened new avenues for the design and support of learning experiences. An important development in this regard is the creation of AI-powered tutoring systems. These systems take as their primary design task the creation of adaptive tutorial dialogue models, such that for any given scenario in which it is important for a student to listen to a tutor explain something, a question-answering pair is automatically generated by the system. The effectiveness of such systems is especially important, as the success of the KNewBOTS effort hinges upon the ability of students to derive some benefit from the explanations provided by these tutoring systems. The utilitarian value of AI systems like KNewBOTS for education is therefore supported by a lot of research, which demonstrates that when subjected to scientific evaluation, such systems are efficacious.

There are many applications for AI in education, including assessment, educational and social robots, lifelong intelligent mentors, and more. AI is also being incorporated into traditional education tools, such as adaptive learning management systems, MOOCs, and big data analytics tools for higher education. It is important to remember that AI is not necessary or sufficient for any of these applications to fall under the category of AIED. For example, "simple" intelligent tools applied 40 years ago in the derivation of basic educational software using expert systems would not be included here. Today, there are hundreds of applications of AI in education, many of which only incorporate "simple" techniques without an intelligent component and therefore fall outside this category. AI-powered tutoring systems in particular take as their primary design task the problem of creating adaptive tutorial dialogue models.

4.3. Assessment and Feedback Automation

The increasing prevalence of authentic assessment methods means that there is a growing likelihood of the inclusion of

data from other sources in the work that students submit for feedback. Automating the provision of feedback complicates the privacy issues by changing the nature of the information involved. More people are involved in the loop and can potentially access this information, which raises potential privacy problems. AI-generated feedback is still confidential information; it needs to be treated with the same privacy considerations. This is particularly important for students in the long tail, whose feedback is much more likely to be unique to them than students and thus more likely to be identifiable to a specific student. The introduction of generative AI solutions poses a specific risk regarding reporting on implementations. Evaluating the effectiveness of these systems will involve investigating the data; this introduces additional privacy risks for those who are most identifiable in the dataset. Accountability for AI systems is where frameworks can be particularly powerful.

Automated assessment systems, which can analyze incoming submissions in real time and provide relevant feedback, can foster student learning by providing holistic concurrent assessments of performance. Instructors are starting to adopt these systems in specific subjects, such as engineering and health assessment. However, most prior research has focused on the model's performance and accuracy in detecting correct knowledge. There has been little exploration of how these systems could shape classroom instruction and pedagogical practices. For instance, high-level clustering of responses can generate deeper insights for student advising. Instructors should incorporate text-based assessment systems into classroom practice for holistic feedback and evaluations rather than numerical evaluation alone. It is necessary to apply the appropriate automated assessment system to a learning context and investigate its impact beyond model performance. Many ML-based approaches are being adopted for student advising, such as identifying at-risk students and early warning notifications. These can be adapted for classroom instruction. The first step is automatically classifying questions and answers. Identifying whether the questions asked are sufficiently challenging indicates the potential to gain much deeper insight into how students think about concepts. This has always been a challenge for large classes, where instructors cannot grade the written answers and have preferred multiple-choice questions alone. This is an opportunity for text-based assessment systems to work alongside instructors and provide holistic feedback and evaluations. Automated systems do not need to supplant or replace the human assessor; instead, it suffices for the automated system to recognize the acceptable answers so that the human grader only deals with those that the automated system is unsure of or identifies as incorrect.

4.4. Challenges in Educational AI Implementation

There are five major considerations for educational institutions that wish to integrate NLP tools into their operators, some of which may not be easy to address. First requires continual funding. Educational institutions must rely on public funding, which may become severely constrained every election cycle. To meet yearly revenue needs, all products need to maintain a minimum user count. If an agency's user count drops below this threshold, the agency's products will no longer be maintained; thus, they will need to pivot to another system or develop new ones. Second benefits

of contracts must be apparent enough. Institutions must undergo lengthy processes to procure software, and few educational institutions have confidence in promising-but-untested software. To offset agencies' reluctance in taking risks, they will require clear proof that an infusion of capital will directly result in substantial and tangible improvements. Both the risks of adopting new software and the concrete measurable benefits must be made evident. Third model robustness and AI accounting must be ensured. Addressing both challenges requires a substantial investment in engineers. Engineers must develop and rapidly iterate on NLP systems that are kept robust and accountable. This could either draw the engineers away from other projects or require onboarding from offended institutions. Addressing either of these paths will take substantial time, capital, and resources. Fourth must be in-line with agency's missions. Newly minted NLP tools must be maintained in a consistent and predictable environment. Moreover, educational agencies must strive to keep their products with respect to recent developments in NLP models. High capital investments in NLP infrastructure may quickly become wasted if the tech crashes. Lastly prioritization of applicable versus exploratory inquiries. Model evaluation is straightforward; must agencies also try to investigate innovative or higher-order uses of these newer models? If the answer is yes, agencies must find a way to work them in without sacrificing helpful headway elsewhere.

5. Comparative Analysis of AI Impact

This comparative analysis examines the impact of AI development on occupations in the fields of education, healthcare, and finance in the U.S. through machine learning. Recent advancements in Artificial Intelligence (AI), especially generative AI and its language capabilities, are revolutionizing many sectors. Nevertheless, the labor market dynamics that AI brings are not yet completely understood. A fundamental question is how AI changes job postings. Two complementary methodologies are proposed to investigate this question. First, the state-of-the-art ability-to-task and task-to-occupation mapping is improved to investigate the impact of AI on occupations across considerable occupations and time periods. The average AI impact is measured through the distribution of occupation AI impact. Second, data on tasks is extracted from job postings to investigate how job postings change through a large self-trained domain adaptive generative model. Advertising tasks are first classified, and their share is measured to analyze how job postings change regarding automation in response to AI development at different time periods.

The main findings of this research are that compared to the national average, education and healthcare occupations have higher AI impact; finance has an average AI effect. AI has a great impact on the pharmaceutical sector, which is the most AI-affected subfield in finance. AI implementation also drives occupations to focus on conducting and managing tasks. However, the tasks of writing requests, checking, and user training become less frequently highlighted. A novel pipeline that combines task types extraction and items share evolution across time is proposed to study the change of this task composition. The results show that management, conducting, and development tasks cover a larger share over time, reflecting the irreplaceable nature of these tasks [19].

Meanwhile, advertising tasks suffer from a substantial decline through automation, which is related to prompt engineering. This study lays a foundation for future research on the AI task development process.

5.1. Healthcare vs. Finance vs. Education

Healthcare, finance, and education have been three promising domains that can leverage the benefits of AI and machine learning (ML) techniques and tools. They have much at stake, as there has been much intense local research, as well as applications in which AI and ML are expected to fuel significant transformation. New tools are being developed pushing AI and ML capabilities beyond previous frontiers: methodologies that are being made widely available leading to new and smarter solutions. However, the doubts and fears concerning their likely effects have also been prevalent in those domains, just as in many others. There is a desire to exploit them, and, to some extent, there is a wish to resist them, both of which are likely to lead to significant conflicts and disruptions.

Healthcare is all about saving lives, but "safety in life" and "safety of lives" are both highly active, complex, and uncertain systems. Data-driven analyses and predictions are often crude, inaccurate, and misleading. There are difficulties in adapting and adopting software tools that usually require strong IT literacy and computational experiences. Unpredictable development cost and R&D expense usually surpass the benefits of less obtainable but more valuable outcomes than attention- and trust-seeking and cheap short-term but self-destructive returns, which are damaging to systematic social stability. AI applications often appear a black box, making people's lives safer and good life better, or creating over-reliance and mislead minds.

Finance is not just about managing flows of money, but "safety of income". It is a tightly constructed complex and uncertain system. Financial analyses typically involve data amounting to terabytes online and gigabytes offline, as well as distributed networks often across political jurisdictions with different regulations and legal restraints, which are challenging to deal with. New software tools often are not user-friendly enough, requiring strong IT literacy. Deep learning-based methodologies frequently yield black-box results that cannot be well interpreted by humans, which are difficult to trust for money. Regulation is often behind the fast pace of development. AI and algorithms are creating enormous impacts either to be positive as assistants or negative as manipulators.

Education is not merely about grading scores for students/candidates, and "safety in education" is not just about test preparation. Teaching and learning are highly sensitive, complex, and uncertain processes. Class performance outcomes are improved by cognition processes from quiz scores to grades. They are also influenced by many stochastic variables, i.e., teaching materials, methods, and styles, but too many or questionable collected data are damaging to student- and school-created social stability. AI and ML techniques and tools requiring proper and a huge amount of data are among the best, but serving the low-cost large margin market, i.e., test preparation, the greatest issue is how to adopt them. Sophisticated models are either black boxes that are unable to interpret foreign results and thus

cannot be trusted, or so complicated that they are sensitive to suits of pre-defined hyperparameters leading unpredictable and misleading outcomes.

5.2. Long-term Implications of AI Adoption

The advancement of AI and its applications are expected to positively impact several industries, including healthcare, finance, and education. In these industries, AI is expected to improve service delivery while also potentially widens the gap between developed and developing nations. Although the full scope of the positive and negative impacts of AI at the global level is yet to be determined, the continuous development of AI apps will unquestionably have unforeseen long-term effects. However, there is a current lack of research on the social, ethical, legal, psychological, and environmental effects of extensive AI adoption in these industries. Consider the healthcare industry, which functions as a cornerstone of society in support of the public. New AI applications in healthcare have disrupted the field, proving capable of diagnosing diseases, both common and rare, at levels surpassing human doctors. AI apps are streamlining the healthcare process by making disease treatments more time-efficient and competent. On the other hand, there is a fear of job destruction brought about by AI. Medical jobs that have taken years of complex training require no such preparation for AI. Additionally, AI's potential access to personal life and intimate data raises uncertainties about how it will be stored and used. In finance, particular AI technologies can analyze vast datasets in a short amount of time, assess user preferences, behaviors, and unfavorable tendencies, identify fraudulent transactions, suggest stocks to invest in while also analyzing trends, and reiterate on previously successful bet types. Conscious or subconscious fear of job displacement may arise from their observable superiority to humans. Financial monitoring systems powered by AI could be accessible to illegal organizations attempting to obscure criminal life with poorly recorded bank transactions. Furthermore, the presence of AI agents would allow illegal organizations to exploit trades and policies within their networks immediately after uploading.

6. Future Trends in AI

Advances in Artificial Intelligence (AI) are leading to a transformation of the current education systems, new opportunities for education and training, and new socio-economic parameters as part of an overall strategy for sustainability and inclusiveness. Adopting AI will require legislative and policy changes to ensure no one is left behind. World governments recognize the gifts of AI but pose a threat to jobs and even humanity. Research communities must address the fundamental science of AI applications for education, environmental understanding, healthcare, and sense of well-being and security. Schools will need to teach children how to use AI and keep them safe in an AI world. With the rapid advancement of Artificial Intelligence (AI) technologies, it is essential to narrow the gap between the research community and industry in the field of AI. Discussions surround the demographic and industry adoption of AI and how both the public and private sectors are investing heavily in AI, including natural language

processing, self-driving vehicles, computer vision, and making use of big data. AI for education refers to the application of artificial intelligence technologies to benefit learning, assessment, and education. This report illustrates recent trends and major challenges in six areas: Research, Industry, Education, Educational Ecosystem, Policies and Regulations, and Equity.

Firstly, data science education will need to be prioritized due to the explosion of AI, machine learning, big data, etc. High stakes machine learning applications demand a workforce trained in probability, statistics, numerical analysis, algorithms, computer ethics, philosophy of AI, and more, drawing on neuro-psychological research, teaching epistemic tools for scrutinizing knowledge claims, bias identification, and data equity/politics. Secondly, it is important to promote interdisciplinary AI education. AI is inherently interdisciplinary, so efforts will need to be made to embed AI ethics within history and the humanities. Data and statistical literacy will need to be taught in mathematics courses. The formation of new fields such as computational biology illustrate the need to create domain-specific courses for students in STEM.

6.1. Emerging Technologies

The advent of artificial intelligence (AI) in the healthcare sector is gaining momentum as a key technology that can transform the healthcare industry and facilitate the emergence of next-gen healthcare services [1]. AI systems analyze large sets of data to develop algorithms and identify patterns that lead to predictions or recommendations for further actions. These services are mostly categorized as rule-based systems or based on the learning processes classified as supervised, semi-supervised, reinforcement, or unsupervised methods. Health care is a critical domain in which AI has been a subject of research for decades, especially in regard to applications such as financial investment, risk assessment, credit scoring, fraud detection, and various algorithm-based services in the capital market. AI techniques have been applied to various healthcare fields including smart health care, preventative health systems, and diagnosis/information exchange applications. In addition, algorithms and systems developed in non-health-care fields can also be applied to the health care area.

The AI-based transformation of the healthcare sector will include competitive negotiations, next-gen health insurance system and service, financial investment, and M&A prediction or investment risk assessment. In these areas of application, text-based learning models, signal processing methods, and dynamic pricing systems may be applicable, and these methods might be closely related to the AI financial insurance systems. Furthermore, since the healthcare sector has less liquidity and slower movements in markets compared to other sectors, AI-based forecasting and decision-support algorithms about market movement, investment opportunities, and related risks will need to be explored. AI techniques have been used in healthcare for more than 30 years, and related tools such as intelligent medical imaging tests, chatbots/virtual health assistants, and robotic and AI-based surgery systems are in service today.

6.2. Policy and Regulation Developments

AI policy development across healthcare, finance, and education sectors remained high-profile again this quarter. Several healthcare AI policy papers refocused debates by highlighting ethical and regulatory challenges in deploying new technologies. This included concerns about AI use in mental health, physician-assisted suicide, and reproduction, as well as the challenge of ensuring safety and effectiveness of AI in federally subsidized programs. In finance, consensus opinions began presenting practical recommendations for the responsible development and use of generative AI products. The SEC opted to delay drafting an AI-centric data security regulation. Education AI policy gained renewed attention around model governance, privacy and safety considerations for children, and approaches for AI talent. Viewpoints and editorials across all sectors began pushing discourse toward highlighting positive uses of generative AI and public interests raised by biases and unintentional social or economic harm. This quarter's normal development of high-profile policy events likely prevented bolder or more nuanced risk discussions, alongside concerns about AI chipped public trust in science.

Five new healthcare AI policy papers were published this quarter. Both the FDA and HHS published position statements refocusing discourse toward the ethical and regulatory challenges of deploying new AI technologies to maximize public benefit. This included considerations about AI use in mental health, physician-assisted suicide, and reproduction, along with the challenge of ensuring safety and effectiveness of AI-powered devices, products, and services in programs federally subsidized under Medicare or Medicaid. Additionally, preprint policy ideas to better address AI discrimination in medicine were shared, reviewing existing efforts through health equity, algorithmic discrimination, and more generally, systems approach.

7. Conclusion

The application of artificial intelligence (AI) within education, finance, and healthcare has been a source of exploration for researchers around the world. For education, AI technologies can be used to assist student learning and evaluate instructors, allowing students to engage in a new type of learning environment. Additionally, the automatic feedback loop of AIED enrichment tools can help teachers identify strengths, weaknesses, and misalignment. However, there are important design and implementation issues such as a lack of educational content diversity, high initial and maintenance costs, a shortage of skilled personnel, and concerns about privacy and safety. Further longitudinal studies across diverse settings with more various populations are necessary to understand technology adoption more comprehensively.

In finance, AI technologies, specifically ML algorithms, have been identified as a source of efficiency gains over traditional mathematical-based models. In addition to transaction cost savings, AI algorithms have been used in both private and commercial settings to mine costly currency and equity trading data. Being able to analyze multiple variables and discover novel patterns makes AI approaches, specifically neural network-based architectures, advantageous to banks.

In healthcare, AI-based systems are being adopted for tasks like medical image analysis and diagnostics, and recently also for administrative tasks. There have been AI-based solutions that automate the invoicing process to improve efficiency, or virtual assistants that draft health records and automatically generate medical reports. However, research also shows that from a data governance and ethical perspective, administrative applications come with their own risks and pitfalls. AI solutions that interface with doctors' workflows raise concerns about trust, accountability, and liability regarding the decisions made by the AI system and their impact on clinicians' decision-making capacity. In contrast, AI solutions that are fully automated raise fears concerning a lack of accountability and the loss of jobs.

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