ARTIFICIAL INTELLIGENCE TECHNOLOGY

AT

A.T. STILL UNIVERSITY

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ARTIFICIAL INTELLIGENCE TECHNOLOGY - A.T. STILL UNIVERSITY

Artificial intelligence (AI) is a tool that is poised to change our ability to educate our students, turn data into knowledge, deliver healthcare, operate efficiently and effectively within our university, and support interactions among faculty, staff, and strategic partners. AI is already used in many areas of healthcare, yet goes unrecognized by its end users.

This white paper examines many ways AI is currently or can potentially be used to support healthcare delivery, education, and business; but it is important to remind the reader that technology should not become an end in itself. Rather, AI should be viewed as one more tool to carry out the existing A.T. Still University (ATSU) mission, vision, and goals. Further, the use of AI should be considered only under circumstances where it can improve outcomes or help the University remain preeminent.

For individual readers interested in additional information about specific areas of AI, we have included appendices with this white paper. The appendices are as follows:

With any new technology, one must choose how best to approach adoption, for example, as an innovator, early adopter, early or later majority, or laggard.[1] On the one hand, early adoption can help promote ATSU as a forward-thinking leader in healthcare. On the other hand, waiting to adopt only well-established AI technologies would mean fewer failed projects, less wasted productivity, and unproductive expenditures. The “sweet spot” exists when investment in AI technology advances the University mission if it is successful but teaches us better ways to advance the mission if it fails.

As emphasized by the AI task force in this white paper, the most important investments in AI should be in areas related to how our graduates will use the technology in their professional lives after graduation. The AI technologies that students need to learn will vary across our academic programs. Similar to understanding how electronic healthcare records operate, the detailed mechanics of AI applications may not be important to teach our students. What will be important is providing our students a structured, ethical, and technical framework to understand how AI is used to support their clinical activities and lifelong learning after they graduate.

Change requires two components to be successful: (1) it takes innovative and forward-thinking ideas, and (2) it takes administrative support to effect change. The AI task force believes that now is the appropriate time to develop an institutional culture that monitors the everyday uses of AI in healthcare and ensures that our educational programs proactively prepare our students to use those technologies to effectively care for their patients.

Because the various categories of AI technology are at different levels of development, it is important to understand how those differences can be leveraged or avoided in a healthcare education setting. By far, the most common areas of AI currently available for end-user healthcare providers include biomedical *image processing*, *natural language processing*, and *clinical decision support systems*.[2] Examples of image processing include pattern recognition in radiology, pathology, dermatology, dentistry, and cardiology. Image patterns can be used to assist with making a diagnosis or manufacturing 3-dimensional patient products like prosthetics or dental restorations.[3] Natural language processing is not only ubiquitous in the chatbots on many websites but is also seamlessly integrated in most word processing applications, including the software used for this paper. Chatbot technology is currently used for asynchronous, 24/7 web-based support and customer service.[4] Speech recognition, predictive text, spelling and grammar, and many other facets of this technology assist healthcare workers with their writing and review of clinical notes.[5] This process can work in reverse with systems that digest enormous volumes of written data to extrapolate information, find patterns, and collate connected data.[6] Various clinical decision support systems are currently available as apps or websites that allow users to input known data and retrieve information such as differential diagnoses, drug interactions, and healthcare recommendations.[7] In fact, these systems are increasingly common in the drive to improve user experience that most users do not realize when they are interacting with AI as opposed to sophisticated user interface elements. For example, many health-related apps provide recommendations on diet and exercise based on the individual user's subjective data input and objective metrics, such as sleep time and quality, pulse rate, blood pressure, and respiratory rate.[8] These advanced examples of AI are only a small sample of the numerous ways that it is gaining traction in healthcare. However, most other forms of healthcare-related AI are still in their development stage.[9] Technology is progressing in society organically, and it is no surprise that our staff, students, and patients are affecting it and being affected by it. In order to establish specific recommendations for ATSU, it is important to focus on what the Institution must do to prepare for these new opportunities offered by AI and what resources within ATSU need to be implemented for its incorporation.

The ATSU workforce can be segmented into three distinct, but overlapping, areas: clinical, didactic, and administrative. Preparation for integration of AI technology must be carefully considered for each area, and considerations of cost, timeline, relevancy, and crossover must be addressed.

Clinical

ATSU directs eight internal clinics and numerous external community partnerships where students and residents hone their skills in direct patient care under the instruction of attending faculty. ATSU already uses a number of technologies in the clinical setting that incorporate AI technology. For example, each dental clinic, including the orthodontics clinic, uses software to capture and manipulate 3-dimensional computed tomography scans and optical scans of the mouth and head. These scans can be overlaid and manipulated to produce a preview of the intended outcome of the dental procedure before initiating any invasive treatment. Additionally, dentists at ATSU currently use AI technology to design and fabricate dental prosthetic devices, such as crowns, bridges, surgical guides, and even dentures. The Gutensohn Clinic in Kirksville and the Osteopathic Medicine Center and AFA (Audiology Foundation of America) Balance and Hearing Institute in Mesa currently do not use any “whole” AI systems although it is likely AI is covertly integrated into many commonly used healthcare practices, such as smart watches, electronic assistants, and various apps. As an institution, there is a broad range and unequal distribution of AI utilization in clinical usage.

Distinctively, ATSU places students in community health center clinics across the country as an integrated part of their clinical education, but some facets of technology and AI integration may be difficult to promote universally because of heterogeneity of the work sites. For example, the various electronic health records (EHRs) used throughout the United States have unique graphic user interfaces, embedded applications, and non-standardized features. Patient record ownership, data sharing permissions, and patient data portability are also crucial factors that significantly limit AI application, scope, and interoperability in EHR management across sites.[10] ATSU’s investments in robust EHRs across the clinical spectrum may eliminate some of these discrepancies while using baked in AI algorithms to enhance health outcomes, improve efficiencies, mine data for research, and aid in didactic development.

Determining the answer about which of ATSU’s application skills can be enhanced by using mature AI programs for different clinical situations must be broken down into specific categories with examples and recommendations. Detection tools (radiology, lab results/films) versus decision-making programs are some of the most advanced AI technologies included in applications currently used in healthcare and are in a constant state of development.[2] The goal for these applications is to reduce the routine, monotonous tasks that humans do not need to do or do not do well consistently. As these programs continue to improve, the output will result in less variability in common, mundane tasks that are susceptible to human error. The relationship of cost to error is significant and dramatically affects the bottom line across the healthcare spectrum. Achieving consistency saves money throughout the clinical workflow - triage, procedures, and retrospective analysis. Battles fought for EHRs and portability of medical information will, hopefully, end with a unified, generalizable system that allows programs to cross multiple arenas of the healthcare continuum. ATSU must start evaluating the landscape of EHRs and strategic partnerships that can leverage AI to benefit our internal clinics and community partnerships.

Didactic

The didactic education of healthcare providers is changing rapidly. Current events such as lockdowns and quarantines affect our ability to congregate and learn in person, but research has shown the effectiveness of asynchronous learning and technology-assisted education. Additionally, the past decade saw an explosion of technology integration into education while the pedagogy evolved to incorporate asymmetric learning, student-centered approaches, and competency-based assessments.[11] ATSU's utilization of technology in the classroom is varied and diverse as is the approach to teaching among our instructors in different degree programs. However, a concerted effort to identify best practices and incorporate effective technology is an active component of the ATSU mission. That said, AI technology offers a multitude of opportunities to increase our ability to educate students. The main challenges of such opportunities are the maturity of the software programs and lack of long-term data supporting AI-based education.

The most developed forms of AI in education software focus on intelligent tutoring systems, dialog-based tutoring systems, and natural language processing; whereby students achieve mastery in a topic at their own pace and can seek tertiary help from teachers who monitor the progress of each student.[12] Coursework specific to healthcare education is still limited in this area of AI in education. However, opportunities abound for strategic partnerships with companies that can integrate our analog coursework into their digital systems and return a fully functional digital education tool. Risks, benefits, and costs will drive these partnerships, and ATSU will need to proceed cautiously.

Personalized education that has a greater emphasis on online experiences and learning will require collaboration both within the University and with AI partner organizations. As such, ATSU Information Technology will need to expand its influence to ensure that we have a balanced approach to complexity, student-centered, and faculty-centered programs. One possible example of this expanded role would be to include input from the Teaching and Learning Center and Information Technology in the basic strategic plans of each college within the University such that their advice can be programmed into the acquisition, implementation, and training of all end users. An additional concern involves the timing of educational milestones for students, where a shift to online learning can mean a major shift in when knowledge is acquired for our learners. Students today are restricted to a course timeline that dictates assessments at given intervals and stratifies students based on knowledge gains assessed through grades. AI-based learning platforms are designed for learning the totality of the given content.[12] Stratifying students based on academic achievement with this style of learning is irrelevant because all students who complete the module have learned *all* of the content as defined by the algorithm. Thus, students can follow individualized academic journeys at their own pace, and in-class time can be converted to integration of the learned concepts and pursuit of a deeper understanding of material through mentorship by faculty. This major shift toward individualized learning pathways will be difficult for those students who were classically trained; therefore, the use of AI will be vital to the engagement and, ultimately, success of the student. Although implementing individualized learning pathways across all programs would mean a complete re-analysis of the financial model used to fund a tuition-driven university, this aspect may only be moderately impacted using AI. Balancing AI capabilities with University needs will require careful analysis and a deep understanding of the relationship between technology and learning.

Administrative

Although the administration of healthcare education and healthcare facilities is related, it has distinctive differences. As indicated previously, the EHR is the primary target for numerous AI-based applications in healthcare facilities.[13] Using unsupervised machine learning and natural language processing, enhanced EHRs are able to use intelligent data capture software that automatically learns to identify, classify, and extract patient-related information from documentation.[5] This data is then indexed and incorporated into patient records for clinical and administrative applications. Essentially, AI applications create a new medical record that integrates all relevant data.[14,15] Healthcare administration is slowly integrating AI in the most common areas of business organization, such as human resources, supply chains, billing/accounting, and legal.[16] Numerous opportunities exist to use AI-integrated software to maximize efficiency in the mechanics of normal business operations. In many ways, this integration is currently happening inconspicuously at ATSU. From Human Relations (HR) management software with built-in AI for resumes to travel management software that reads your receipts to insurance company software that automates billing, AI is already a part of our University’s daily activities.[17–20]

RECOMMENDATIONS

One question to consider is how ATSU will procure this new technology. Currently, some academic institutions on the cutting edge of AI integration are the primary developers of applications that use AI tools to assist content creation and delivery. Other institutions opt to partner with AI technology companies that use existing in-house content to create applications specific to an institution’s needs, such as accounting and educational resources. Various companies are competing to build the AI algorithms and applications for our huge data sets. However, companies need the data and the problem to solve. For institutions that do not have the infrastructure, content, or time to build something from scratch, there are companies that sell off-the-shelf software that includes content from other institutions.[21] Numerous risks and benefits can be identified from these diverse options for a university-wide approach for integration of this technology. Vast data sets are required for these applications, and having that data organized and ready for any integration process will be a vital component of ATSU's information technology strategic plan. Aligning and unifying data for use in potential future solutions is beyond the scope of this discussion but remains a challenge that will eventually need to be addressed.

It is too early to determine what all of this means for any given program within the University, and it is unclear what the most successful uses of AI in healthcare will be a decade from now. The AI task force recommends a more measured approach to ensure our University and our students remain on the forefront of this new technology. It is in this spirit that we offer the following three recommendations:

1. Periodic faculty development programs should be provided to keep the faculty abreast of evolving uses of AI in their respective disciplines. These programs should not be strictly focused on technical aspects of AI. They should also include ethical aspects of AI and issues of socioeconomic accessibility, and they should focus on areas where AI is most likely to help ATSU achieve its core mission. Therefore, the task force would create an implementation strategy appropriate for each school based on the unique needs of the school and the current use of AI within each program. The task force believes that with a vigilant faculty and a supportive administration ATSU will naturally evolve into an institution with an appropriate and forward-thinking set of AI-containing curricula for our various academic programs.

2. A small amount of funding should be designated to support specific pilot projects that use AI to advance the University mission. While researching this white paper, it was clear that AI projects need massive infrastructure support of a size that is unlikely to be available at ATSU or similarly sized institutions. Rather, such projects are likely to be carried out using a cloud support service like Amazon Web Services, IBM Watson, or smaller start-ups. Pilot projects provide a mechanism for ATSU to learn about the readiness of AI to support a specific aspect of our mission and about the costs and technical aspects of using cloud-based AI support partners. This experience will pave the way to plan and budget for AI from a business perspective, especially as AI becomes more seamlessly integrated into University management. An analogy for this recommendation arises from previous University experiences related to piloting an electronic library for ASDOH in preparation for our current geographically agnostic

library support for the entire University. Being able to plan for a return on investment will require this type of time-extended rollout and careful attention to University needs.

Although AI products can be expensive, resource-intensive, and cumbersome to implement on an institutional level, teaching students about AI is inexpensive, realistic, and necessary to prepare them for their future careers. Because ATSU students will likely work with AI products during their careers, understanding AI-related ethical dilemmas, legal issues, workforce diversity, and roles and recognizing the need for an AI-minded team approach will inculcate foundational principles for our students.

3. AI subject matter experts at ATSU should develop a core curriculum related to AI ethics, workforce, and team building; and faculty in each program will be able to add discussion of discipline-specific AI products for their students. Developing an AI curriculum will likely be challenging. Multiple curriculum developers and faculty from each program will need to be identified. Currently, it is unknown if faculty have enough AI-related knowledge to develop a robust curriculum for each program. Some level of oversight is recommended for this process to ensure that the AI curriculum is appropriately launched for each program. Such oversight may be charged to the appropriate curriculum committees of each school. In addition to having the knowledge base to teach AI, faculty also need the will to incorporate it into their programs.[22] Educating faculty about basic AI principles can help them see the value of this technology. By allowing faculty the autonomy to decide how AI modules are integrated into their programs (e.g., as an assessment, through applications), we can increase enthusiasm for the topic among faculty and students alike.[22]

Although the three recommendations of the AI task force are quite broad, they address an ill-defined, emerging technology from an early vantage point in the evolution of AI. If ATSU remains focused on its mission and continues to nurture a culture that welcomes evolutionary change, we will continue to be a leader during this period of AI incorporation into every aspect of healthcare education and delivery.

One of the major challenges when providing specific recommendations for the incorporation of AI at ATSU is the breadth of AI platforms vying for space in the healthcare landscape. Every day, companies develop new algorithms for use in healthcare. However, those programs are in various stages of testing, implementation, adoption and, in many cases, disuse. Much like the Internet of the early 1990s, this field is in its infancy. Further, recommending a specific platform for incorporation into the ATSU infrastructure is beyond the scope of this report. Instead, this white paper focuses on the various ways that we as a University and as leaders in healthcare education can establish fertile ground for long-term integration of AI into our educational and institutional workflow. This paper steers us toward what we need to do to prepare culturally, academically, and technologically. It also highlights what we must do from a support-service and infrastructure investment perspective to be ready. AI will come with or without us.

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APPENDIX A: BASIC CONCEPTS IN AI

Uninitiated individuals sometimes confuse AI with the general use of computers. As such, it is important to emphasize and distinguish between computer technology as a whole and AI (see Figure 2). For example, telemedicine refers to the practice of caring for patients remotely when the provider and patient are not physically present with each other. Although telemedicine uses technology, it may or may not use AI to enhance the delivery of care. When the ATSU community was asked to provide their list existing uses of AI at ATSU, it was common to receive a list of computer technologies that do not involve any aspect of AI. Throughout this white paper and its appendices, we have focused on technologies that build models based on existing data to accomplish intelligent tasks because this white paper is about artificial intelligence. That said, there are many non-AI technologies that will also continue to provide opportunities for ATSU to conduct its business and provide its learner with improved learning opportunities. Although artificial intelligence (AI) research dates to the 1950s, experts often begin discussion of the topic by noting the lack of a common definition for AI or specificity about its applications.[1] This appendix will introduce some terminology commonly used in the AI literature.

As a starting point, AI systems are characterized as systems that engage in human-like behaviors.[2] AI is a computer performing a task that normally requires human intelligence and human thought processes. AI should not be thought of as an intelligent machine replacing a human but as an intelligent machine that enhances a human's work.

Artificial Intelligence in Current Practice

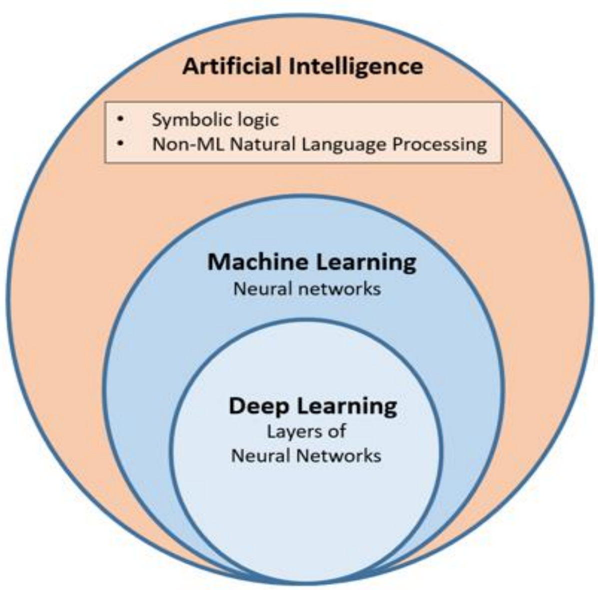

Figure 1. Artificial Intelligence Terminology. (ML = Machine Learning)

When people talk about AI, they are often actually referring to an advanced type of machine learning known as deep machine learning. The relationship between deep learning and the broader field of AI can be shown with a Venn diagram (Figure 1).

However, there are also examples of AI that do not involve machine learning. For example, machine learning is not involved when natural language processing and symbolic logic are used to solve problems. As an example, A.T. Still Memorial Library is subscribed to a resource called Micromedex that is by the IBM Watson AI infrastructure.[3] Micromedex uses natural language processing to help with user queries.

Traditional computer programs are designed to take input data and execute a defined task with defined parameters. The program generally includes knowledge about the best way to perform the task. These model parameters typically have meaning for the humans who develop the models. Those of us who use the programs trust that the models were designed and programmed correctly. For example, a spreadsheet takes a collection of numbers and a knowledge of arithmetic operations and produces results with models (formulas) provided by the user. We trust the spreadsheet to add the cells correctly. This traditional computer program workflow is illustrated on the left side of Figure 2.

Computer-based machine learning uses a different workflow illustrated on the right side of Figure 2. The model is not constrained by prior human understanding. For tasks involving AI, the computer attempts to develop a model (or mapping) based on a set of data and a solution to a problem. Ideally, the model will get us from the data to the solution. The algorithm is not limited by human understanding and becomes "smarter" because it can analyze millions of data points iteratively.

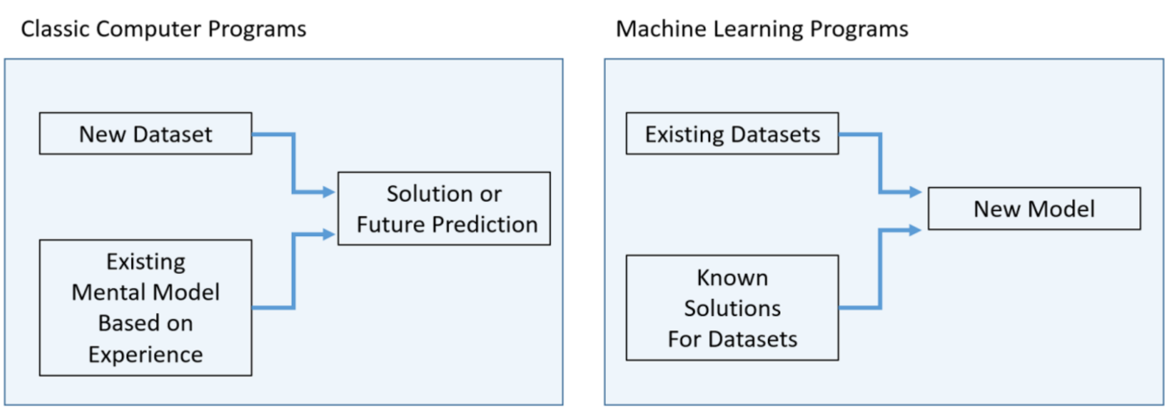

Figure 2. Traditional Computer Programs Versus Machine Learning Program

At this juncture, we want to highlight a specific point. When experts say that machine learning uses "neural networks," (see Figure 1) they do not mean, and we should not be fooled into thinking, that the process is anything like the human brain. It is not, but this terminology has been around long enough that we are unlikely to see it change. However, we are just as unlikely to learn anything of value about reality from machine learning model structures, as we are to learn anything of value about our conscious perception from studying detailed wiring diagrams of individual neurons.

A technical description of how machine learning works is beyond the scope of this appendix, but a brief look at the general process of creating a machine learning system in the context of learning theory is appropriate. Learning theorists often highlight the difference between naive learners and expert learners when both are confronted with a novel task.[4] Specifically, experts possess a well-developed model of how things work that allows them to process new data. As long as the task is similar to existing knowledge, experts will make use of their experience.

Naive learners have much cruder models about how things work because they lack the knowledge base and have fewer examples of successful or failed predictions. To use a medical example, attending physicians are often more willing to treat a patient or send the patient home because their confidence in diagnosis is more certain and based on a wealth of experience. A physician-in-training may have the same suspicions as the attending but is much more likely to perform additional diagnostic testing before feeling comfortable with a diagnosis. As the trainee gains experience, the distance between "dismiss without further tests" and "treat without further tests" narrows.[5]

As illustrated in Figure 3, the process used in machine learning is quite similar.

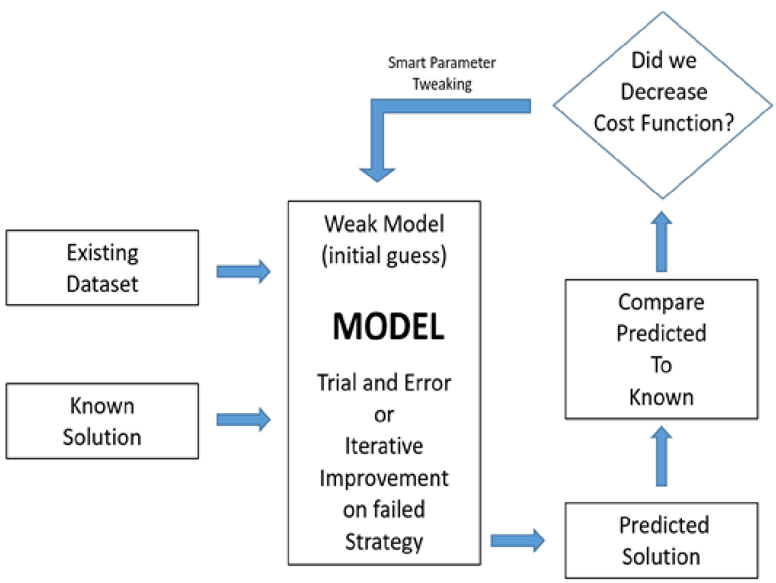

Figure 3. Conceptual Framework for the Process of Machine Learning

With machine learning, the AI program is provided with a set of existing data that is associated with known outcomes. This dataset is generally called the training dataset. The program develops an initial guess for the predicted outcome for each item in the training set and compares its guess to the known reality. Initially, the computer program is naive and is likely to have a large error term. It then randomly tries a second time with the same training set and looks to see whether it did better or worse. If it performed better, it tweaks its model in one direction; if it performed worse, it tweaks its model in a different direction. During subsequent cycles, it “learns” the best solution.

Because the data and outcomes are known to the computer program, it can continue refining the model from the training dataset until outcomes are 100% accurate. This process is equivalent to memorizing answers for a test and does not necessarily mean that “learning” has taken place. For this reason, a portion of the training set is often held back to see how the model performs with new data of the same type, and to see whether it chooses the simplest model with near maximal performance. Finally, the model is used on a test dataset of more new data (of the same type) to see how machine learning algorithm performs in the real world. Depending on the task, AI deep machine learning models have accuracies above 90% on test datasets. However, that means 10% or more of the answers in a classification task may be wrong. Importantly, it is these wrong answers that will need to be acknowledged and accounted for as AI is used more and more in healthcare and healthcare education.

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APPENDIX B: AI IN HEALTHCARE EDUCATION PEDAGOGY

The modern concept of artificial intelligence (AI) began in the 1950s and has roots in the cryptographic algorithm deciphering used during World War II. However, it is only in the last two decades that the computational power of computers has evolved to allow practical examination of AI in specific domains like healthcare education. Clinical decision-making is largely based on probabilities of input and output, so it follows that AI research is most advanced in this area. In conjunction with the growth of "big-data" repositories, the exponential growth of computing power, the connectivity that allows instant information flow, and new human–machine interfaces like virtual reality, new roles for AI in healthcare are becoming possible.

A systematic review of the AI literature suggests that AI in education has gained traction in the areas of learning support and the assessment of student learning.[1] Importantly, these uses of AI are more germane to the didactic part of our curricula than to undergraduate or postgraduate clinical training.[1]

As A T Still University of Health Sciences (ATSU) considers the role of AI in its future, there are two critical questions that require analysis. The first is, "What will our students need to know about using AI to be the best educated clinicians we can produce?" The second is, "How will AI affect the pedagogy of delivering healthcare education?" It is the latter question that we address in this appendix.

Rules-Based AI Educational Applications and Intelligent Learning Systems (ITS)

Current AI products on the market focus heavily on learning support functions. These products can be student-facing, teacher-facing, or both. Current AI tutoring systems are produced with a catalog of discipline-specific knowledge base and a corresponding set of inference rules. This approach works well for discipline-specific demonstrations of knowledge;[2] however, AI tutoring systems are less successful with development of critical thinking skills or application of ethical principles. These latter elements are foundational elements of adult higher education learning[2] found in ATSU's programs Therefore, it is imperative that ATSU administrators, faculty, and students understand the limitations of AI educational products and set expectations accordingly.

With regard to institutionally built AI systems, best practices in instructional design need consideration. Specifically, all stakeholders (e.g., students, staff, faculty, and administrators) should be involved and have input into the processes and outcomes. Additionally, the content and features of any AI product should be accessible for all users.[3] Deaf, hard of hearing, blind, and other individuals with accessibility challenges should be considered when developing or purchasing an AI educational application.

With respect to effectiveness, there is a modest amount of literature investigating AI educational applications that identify and supplement knowledge gaps in didactic education. A meta-analysis of intelligent tutoring systems (ITS) in a variety of educational settings (not necessarily healthcare) concluded that ITS could effectively increase student test scores relative to no tutoring or to other types of tutoring, including human tutoring.[4] The authors added that the results were better with local rather than standardized tests.[4] Using ITS that provide personalized feedback and just-in-time tutoring may be helpful during the didactic portions of healthcare-related courses.

Traditionally, AI products that support learning, such as ITS, are labor-intensive to develop. Considering the numerous courses needed for a graduate or professional degree, it would require extensive programming resources in terms of time and personnel to provide support for all ATSU curricula. Fortunately, research has been focused on reducing this time from 200 hours per course to about 40 hours per course; it is currently around 30 minutes per course.[5] Because course development is now so much faster, this newer process provides faculty with control, and they no longer have to rely on programmers.[6] Perhaps we will reach a practical level of resource requirements as AI products mature. AI products to support learning may then become a reality at ATSU.

Rules-based scenarios are developed by faculty, programmers, and other stakeholders instead of being driven by data as in machine learning. These rules-based applications also have the potential to collect data from student responses, which can then be analyzed by other AI applications. This process might include developing predictive learning models to identify gaps in student knowledge that need remediation. Outcomes from other AI products, such as ITS, could also be leveraged as data sources for predictive models. With this kind of AI product-stacking, the various products must be able to recognize each other and work seamlessly together, but they are still subject to the inherent limitations of their respective product categories. The AI systems that are specifically built with one layer providing input for the subsequent layer are an example of deep learning AI educational applications.[2]

Rules-based AI applications could also be used in university operations for education of faculty and staff. These products can enhance the delivery of training and identify knowledge gaps in institutional policies. Although an individual institution may be unable to build or invest in an AI product, teaching healthcare professional students about the current and future state of AI in their respective disciplines is an important piece of the AI movement. Healthcare workers of the future will likely need knowledge of topics and skills related to AI. Specifically, they will need to understand aggregation and analysis of data to personalize healthcare and learning; proper use of decision support systems; management of robots used in hospitals and homes; and basic medical informatics concepts.

Machine-Based Learning AI Educational Applications

In contrast to rules-based knowledge and inference systems used for ITS, machine-based learning is used for early warning systems and predictive modeling tasks.[2] Machine-based learning systems are trained and validated on large data sets and are used to predict a variety of outcomes, such as student dropout probability.[2,7] However, diversity in the data elements must be carefully considered. For example, developing predictive models on data sets that exclude students by race, gender, ability, or other data elements can lead to unintentional bias in outcomes. Therefore, the data sets used to train AI applications need to be both diverse and inclusive.[3] Such considerations are central to accomplishing ATSU's core professional attributes.

Another consideration for these systems is determining the correct size of the data set. Murphy[2] suggests that millions of data records may be needed to ensure the validity of an AI predictive model. Few academic institutions, including ATSU, will have that many records. Pooling data sets across academic institutions is a potential solution; however, non-standardized record-keeping and information systems, along with unique and diverse student populations, may be barriers to effective predictive modeling using this approach.

Automatic writing evaluation tools, which are also a subset of machine-based learning, may be useful for Faculty.[2] However, such AI products are only as effective as the topics and scenarios their algorithms address. The more numerous the potential outcomes, the more time and resource-intensive development required to effectively employ AI.[5] Additionally, there is more potential for failure of the system and subsequent frustration of the student and faculty members if the system lacks effectiveness. A mandated system with heavy institutional investment—whether self-built or purchased—will go unused if faculty expectations are not met. With current AI learning support systems, faulty should still be available to students, providing human support as needed.[8] AI learning support systems do not necessarily have the ability to measure or read student feedback, such as stress or frustration, but teachers are better able to respond and adjust support as needed.[9]

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APPENDIX C: AI IN ACADEMIC LIBRARY RESOURCES

Although libraries are historically slow to adopt new technologies, generally relying on a wait-and-see approach in response to user trends,[1] the A.T. Still Memorial Library proactively pursues resource enhancements, engages in professional development, and explores trial software opportunities to stay abreast of new technologies to better support students, clinicians, faculty, and staff alike. Two core skills of contemporary medical and academic librarians are query creation and resource evaluation. As departments adopt and integrate AI into their various specialties, our librarians will be positioned to provide query support and facilitate transferable search skills development.

Because they are primarily research specialists, librarian support will be limited by their access to technologies supported by artificial intelligence (AI) and the connection of those technologies to the research process as a whole. Therefore, librarians will be more familiar with and better equipped to support research-focused AI technologies, such as Semantic Scholar's open access search engine or IBM Watson, which is available through the library's Micromedex subscription.[2] The incorporation of AI into libraries is an evolving area with exciting but limited applications. As new partnerships and resources develop among library vendors and as more trial opportunities become available, the scope of support will likely increase as new tools are adopted.

LibGuides

The library's position at the intersection of students, staff, and resources support is ideal for pooling AI at ATSU. LibGuides is a useful tool for sharing information about AI applications because it helps manage relevant resources for access by a wide variety of audiences. This resource offers the flexibility of a collaboration space with hidden and public content sharing options while maintaining security through a managed login. LibGuides is already a familiar tool to librarians, faculty, and students. Initially, this tool could be used to create links, directions, and program-specific content.

ASITC and ITS

As we expand the use of AI at ATSU, technology experts from the Academic Support and Information Technology Committee (ASITC) and Information Technology Services (ITS) will need to be involved for coordination of trial scheduling, licensing, implementation, maintenance, and reevaluation cycles. As new stand-alone tools and custom learning tools interoperability products are adopted to connect users with AI-backed resources through the Canvas learning management system, these technologies will need to be registered through completion of an application overview for security evaluation and inventory management. ITS will also need to determine the appropriate escalation routing of incident tickets for those who need troubleshooting support.

Teaching & Learning Center (TLC)

Instructional design experts from the TLC will be ideal contacts for faculty training as needed for support of AI integration in didactic sessions. Collaboration between curriculum developers, subject matter experts, and the TLC will facilitate faculty awareness and consistent instructional deployment across programs.

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APPENDIX D: APPLICATIONS OF AI IN MEDICINE AND ALLIED HEALTH

In today's changing landscape of healthcare systems, physicians and other allied healthcare providers will need to meet increasingly complex challenges. For instance, they will need to be able to extract meaningful information from large amounts of data in medical records; focus on the aging population, including treatment of the chronicity and multimorbidity of illness; use bidirectional models of management for inpatient and outpatient care, such as telehealth and community-based care; and keep abreast of emerging advancements in biomedical knowledge and technology.[1] When applied to healthcare, artificial intelligence (AI) has the ability to analyze complicated medical data. It can be gathered, evaluated, processed, and provided to the end user or healthcare provider. The process of data mining exchanges raw data into useful patient information. Aggregated clinical data can assist healthcare providers with diagnosis and treatment options. Consistently focusing on patient-centered care and empowering patients with information to make the best treatment decisions for themselves is of utmost importance.

The future of AI is difficult to comprehend, especially with accelerating changes in healthcare. The urgent need to reduce costs, create value-based care models, and focus on a more personalized patient care experience continues to transform the healthcare industry. This transformation also cultivates improvements in clinical processes. AI can process images and patient health records more expeditiously and with greater accuracy than humans are capable of, lessening the provider's workload, reducing misdiagnosis, and empowering clinical staff to be more efficient and provide more value. Our human minds do not have the ability to find patterns and anomalies in massive data sets because of their sheer size and complex intricacies. A computer's strength comes from its ability to analyze large volumes of data reliably, efficiently, and accurately without fatigue. The decision to adopt and securely implement AI across healthcare systems is crucial. These efforts will use enormous volumes of data in the most positive ways to benefit patient outcomes.

To date, AI has had an enormous impact on healthcare. The literature is full of examples from all disciplines. Although it has been identified as an innovative force, how will AI benefit patients and providers? Evaluating and learning from exceptionally large amounts of data is what machine learning and deep learning accomplish to support better clinical insight for allied healthcare providers. Leveraging technology to detect patterns from these algorithms creates the potential for data-driven clinical decision support (CDS) at the right moment during patient care. Several areas, outlined below, must be considered to determine where and how AI will transform and change the science and delivery of healthcare.

Transforming Clinical Decision-Making Through the Use of AI

AI can use predictive analytics and CDS tools to provide insight into problems long before providers might otherwise recognize the need to act.[2] For instance, AI can alert providers about conditions like seizures or sepsis and identify dangerous medication interactions that normally require intensive analysis of highly complex data sets.[3] CDS tools integrated into electronic health records (EHR) streamline workflows and take advantage of existing data sets. However, creating intuitive, user friendly, and effective protocols for alarms, alerts, and decision-making pathways can be more challenging.[4] Leveraging AI for CDS, risk scoring, and early alerts is one of the most promising areas of development for data analysis in healthcare.[2,3]

Basic principles of CDS tools used for applications in patient care are listed below[2,5]:

- Detecting infection in highly personalized cancer therapies
- Decreasing sepsis mortality rates
- Reducing unnecessary lab utilization
- Helping nurses deliver complete and accurate phone screenings for patients seeking advice or appointments
- Providing information to patients with head injuries while evaluating the severity of the injury
- Combining a CDS with genetic testing data to determine drug-drug and drug-gene interactions and reduce hospital readmissions in high-risk patients
- Completing drug dosing calculations
- Accessing drug formulary guidelines
- Using severity indexes for specific illnesses
- Tailoring order sets or templates for specific diseases
- Identifying reportable conditions based on EHR inputs
- Using time-triggered reminders for medication delivery or dosage changes
- Identifying necessary preventative care screenings or care gaps (e.g., mammograms, colonoscopies, flu shots)
- Accessing filtered reference information or educational materials

A collaborative team that includes physicians, nurses, other healthcare providers, administrators, and technology users can effectively implement CDS tools. Analysis of that data can then be used to flag medical conditions, such as osteoporosis, diabetes, hypertension, pneumonia, and heart failure.

Data rich environments like the intensive care unit and emergency department are ideal for obtaining big data information and knowledge. Further, using AI-based CDS tools will become increasingly important to identify deterioration in a patient's health status, identify sepsis, or predict complications that may improve outcomes and decrease costs related to hospital-acquired condition penalties.[6] Aggregating data is not something that humans do well—especially with large volumes of data.

Creating Better Patient Outcomes and Elevating the Patient Experience

AI can improve healthcare by fostering preventative medicine.[7] Promotion of well-being, prevention of disease and illness, and early intervention for positive outcomes are the goals of safe, secure, productive, and efficient healthcare. AI can assist in these endeavors by determining patient risks for hospital-acquired conditions, identifying patients for recommended medical therapies, and improving the likelihood of suggested patient adherence for desired outcomes. Remote patient monitoring can be helpful for a variety of reasons, including identifying whether patients follow prescribed drug regimens or abuse opioids. AI can create a more personalized virtual encounter for better patient experiences and increase engagement for improved outcomes.

Information provided by AI and advanced analytics can provide a more holistic view of patient health to better meet patient needs. Further, AI tools have the ability to examine an individual's clinical and socioeconomic factors, which may be beneficial for identifying nonclinical challenges a patient may be encountering. These tools allow the provider to deliver treatment beyond what they typically have time for in a busy practice. Because they are better informed, providers can address key challenges using these personalized insights from the analytics.

Mechanisms for real-time feedback position AI as an essential element for achievement of the quintuple aim of healthcare: better patient outcomes, better population health, lower costs, increased clinician well-being, and prioritized health equity and inclusiveness.[8,9] Machine learning techniques can predict risks for future health events and behavioral tendencies. For instance, reviewing data activity patterns, peripheral physiology, and current behaviors and experiences of individuals related to mood and emotion enable a provider to offer suggestions for personalized lifestyle modifications. In the future, smart devices may become critical for monitoring patients. According to mobile marketing statistics,[10] there are 7.7 billion people in the global population, and just over four in 10 people currently have a smartphone. Gathering appropriate health information from these devices in the home, school, community, or employment settings decreases dependence on healthcare facilities. Because smartphone manufacturers continue to price their products lower to attract first-time users, they are increasing access for individuals in underrepresented communities. Thus, including intelligent algorithms in these devices can reduce the cognitive burden of providers while ensuring that patients receive care in as timely a manner as possible.[11]

Patients are becoming more aware that advanced technological applications improve their care in environments outside the hospital or clinic. This improved care will continue with increased use of these applications, such as smartwatches and Fitbits, remote monitoring tools, and virtual assistants. Sensor devices are also helpful for collecting health data. From step trackers to wearables that monitor heartbeat around the clock, a large amount of health-related data is collected from smartphones.[11] These recent advancements allow passive collection of real-time data without disruption of daily lives. This data also informs individuals about their risk profiles and enables healthcare providers and patients to make more informed care decisions.

Collection and analysis of data provide a unique perspective into the lives of individuals and communities, especially when issues of population health are addressed. Data is central to AI effectiveness. Technologies such as Blockchain work in parallel with AI, so the data is securely shared before AI extracts insights from it. By extracting these actionable insights from large and varied amounts of data, efficiency and productivity are increased from repetitive tasks and processes. However, ensuring the trustworthiness of the data is of extreme importance.

With this information, providers can strategize and discover key areas of patient care that require improvement. Coupling devices, such as wearable healthcare technology, with advances in AI may allow shifts in the healthcare paradigm toward a more precise, economical, integrated, and equitable care delivery system.[12]

Radiology Tools—Looking at the Next Generation

Medical imaging allows a disease to be revealed before it is physically identified. For diseases like cancer, the earlier the diagnosis, the more likely the patient will survive.[13,14] Early diagnosis saves lives and alleviates pain and suffering, but it also reduces healthcare costs.[13] However, there is an invisible side to medical imaging. Although human eyes may not see small changes, they still exist, and a computer has the ability to identify hidden patterns that may represent these small changes.

Magnetic resonance imaging (MRI) machines, computed tomography scanners, ultrasound, and x-rays offer noninvasive visibility of the human body to identify tumors, masses, and diseased areas. Currently, a diagnosis still requires analysis of a tissue sample obtained through biopsy of these radiologic findings, and the resulting information determines how providers treat the patient. The use of AI enables “virtual biopsies” and is advancing the innovative field of radiomics.[15] Using data mining techniques, this emerging field extracts information from patterns in the clinical images and uses image-based algorithms to characterize the phenotypes and genetic properties of tumors.

The synergistic development of computers and imaging techniques has increased and expedited the use of AI in radiologic imaging tasks, such as risk assessment, identification, diagnosis, prognosis, therapy response, and risk occurrence. Clinical applications for AI are consistently improving. Using MRI, deep learning models can discriminate between benign and malignant lesions and identify various histological subtypes of cancer.[16,17]

During the current pandemic, AI has had a vital role in the analysis of thoracic images. These images have been useful in the assessment of lung nodules, tuberculosis findings, various pneumonias including COVID-19 detection, and estimation of diffuse lung diseases. Chest radiography and chest computed radiography are also promising tools for the application of AI techniques. For instance, AI has been extremely valuable in the interpretation of breast and lung cancers.[16,17] Transport-based morphometry has been able to identify osteoarthritis by examining MRIs of knee cartilage. In fact, this method was 86% accurate at identifying changes in the MRIs three years before the diagnosis of osteoarthritis through analysis of pattern changes and interrelationships of pixels in the images.[18]

Medical imaging is extremely important in healthcare, yet the majority of care decisions are based on a pathology result. If the goal is a quick and accurate diagnosis, digital pathology and AI have the ability to drill down to the pixel level on extremely large digital images and identify nuances that may escape the human eye. Medical image focused subspecialties, such as radiology, cardiology, pathology, dermatology, and ophthalmology, already use these tools.[19,20] As identified by deep learning neural networks, these AI tools perform as well as or better than board-certified specialists on cognitive tasks, such as detecting diabetic retinopathy[21] in retinal fundus photographs or classifying skin cancer based on images of skin lesions[22]; specifically, the computer performed at 92% and the board-certified physicians at 88%.

Experts believe that images from smartphones will be an important supplement to clinical quality imaging.[19,20] Dermatology, radiology, and ophthalmology have already used this tool. With smartphones collecting images of the body and wound changes, additional value can be added to patient care. Using smartphones to identify and share information can also benefit primary care providers during consultations with specialists because of distance or shortages of specialists in underrepresented areas.

Reducing the Burden of EHR Use and Making It a Reliable Risk Predictor

There is a wealth of information in the EHR. Yet challenges remain with extracting and analyzing this data. For instance, analysis must be accurate and efficient. Reliability is key for data quality and integrity issues, and multiple data formats may cause decreased interoperability from multiple inputs and incomplete records. These considerations make it extremely difficult to understand issues of risk stratification, predictive unbiased analytics, CDS, and data security.

Routine processes are time-consuming for anyone, and automating routine processes through use of AI saves time and is more efficient. For example, natural language processing can be used to assist with voice recognition and dictation.[23] Virtual assistants have become the new medical assistant because they are able to connect patients and providers through secure video conferencing software on a tablet, smartphone, or computer. A healthcare virtual assistant is able to accompany the provider into the exam room and provide live charting directly into the EHR in real time. During telehealth experiences, these assistants are able to connect to the current phone system and can make or receive calls as if they were sitting in the clinic office. They can also schedule and confirm appointments, complete insurance verifications, and perform administrative and back office tasks. Additional duties can include referrals, authorizations, prescription refills, medical records management, medical billing insurance verifications, and eligibility.[24] To provide physicians with more time for patient care, Google has designed a virtual clinician called Dr. Liz.[25] This system listens to a doctor-patient conversation, disambiguates the voices, follows the consultation, and gives suggestions to the provider. It also transcribes the conversation so everyone has a complete record, and then it fills out and navigates the EHR. It is of utmost importance that the most accurate data is fed into the EHR system so the machine learning application can provide the best suggestions to physicians or researchers.[25] This process also saves time and money.

Another benefit of AI is related to multidrug resistant organisms. They affect patient care in the hospital setting and claim thousands of lives every year. Fortunately, the use of AI algorithms within the EHR can identify infection patterns, and patients who are at risk can be identified and highlighted before they begin to show symptoms. These AI tools are vital for alerting healthcare providers and enhancing their accuracy of care.

Google's Cloud Healthcare API (application programming interface) includes CDS offerings and other AI solutions.[26] The AI used in this tool analyzes data from EHR through machine learning techniques to provide data-driven support and help healthcare providers make better clinical decisions.[4,25] The world of AI has changed dramatically since the debut of IBM Watson in 2011. Watson is currently applying its skills to everything from developing personalized health plans to interpreting genetic testing results and identifying early signs of disease.[27]

Leveraging technology creates opportunities for impactful interventions at precise intervals in patient care. Described as an "emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person,"[7] precision medicine allows healthcare providers and researchers to accurately predict the precise treatment and prevention strategies that will work for an individual based on their unique biochemical makeup. Precise analytics has unlimited possibilities. Many are affected by diseases with genetic components, such as Alzheimer's, diabetes, autism, and cancer. Finding individualized treatments for these debilitating and sometimes fatal conditions remains a top priority for the American healthcare system in the 21st century.

Brain-Computer Interfaces

Brain-computer interfaces use direct communication between an enhanced or wired brain and an external device.[28] Integrating AI with these interfaces may replace underlying experiences for patients with neurological diseases or those who have lost this ability because of trauma. Decoding neural activation using communication technology allows patients to communicate using a device like a tablet or smartphone. Through these interfaces, the lives of those with amyotrophic lateral sclerosis (ALS), stroke, locked-in syndrome, or spinal cord injuries can be drastically improved. To help individuals with ALS, Microsoft developed Eye Control for Windows 10,[29] which is an eye tracking technology that allows people with disabilities to type with their eyes so they can continue to function, communicate, and remain independent.

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APPENDIX E: APPLICATIONS OF AI IN DENTISTRY

Artificial intelligence (AI) in dentistry is developing rapidly with varying levels of advancement and integration into modern practice. The most developed use of AI technology in dentistry is related to rapid prototyping using computer aided design and computer aided manufacturing (CAD/CAM).[1] With the introduction of this technology in 1985, methods of fabrication of dental restorations transitioned from a hands-on, technical, and artistic process to that of a mechanical process largely controlled by computers. Today, many prosthetics including dentures, partial dentures, and other various fixed and removable oral appliances are designed and manufactured by machines in addition to most dental crowns and indirect fillings.[1] These CAD/CAM computer systems use AI algorithms to predict design characteristics and render 3-dimensional images that can be easily manipulated by human technicians on a computer screen. Once a design is finalized, it can be produced by machines that use either additive or subtractive techniques.[1] This technology-driven work flow enhances precision but requires training technicians and dentists using expensive and ever-advancing technologies to create these complex prosthetics; it is no longer limited to highly trained artisans using conventional, time-tested techniques.[2]

Another common area of dentistry where AI technology has made a significant impact is in dental radiology. Like medical radiology, algorithms identify normal anatomy and flag areas of potential pathology in both 2-dimensional and 3-dimensional radiologic images.[3,4] Using these basic functions, dentists can identify and label cephalometric landmarks, segment out bone and teeth from soft tissue, identify possible carious lesions and craniofacial pathology, and convert radiologic images into optical images that can be printed.[5,6] Radiological pattern recognition is the basis for AI algorithms designed to interpret data and provide useful feedback. With the superimposition of 3D radiographic images, facial soft tissue, and scans of the dentition, a virtual patient can be created which can be used for planning interdisciplinary treatment and teaching dental students and residents.[7] These tools currently have significant impacts in prosthodontics, oral rehabilitation, implant dentistry, oral and maxillofacial surgery, orthodontics, and plastic surgery.[6]

Although AI in dentistry is most common in CAD/CAM workflows and radiology interpretation, the development of clinical decision support systems (CDSS) for dentistry continues to evolve rapidly.[8] These systems are designed to provide expert support for dental health professionals by reviewing patient-specific data and providing suggestions based on probabilities. However, many of these algorithms are still in the early phases of development.[9] In a study by Kim[10], daily toothbrushing frequency, duration, technique, use of dental floss, professional cleanings, diet, nutrition, and exercise were analyzed with an AI modelling algorithm that predicted future dental pain with 80% accuracy. Xie[11] used an AI model based on machine learning and artificial neural networks to predict the necessity of extractions to achieve ideal orthodontic treatment. The model's accuracy increased even more with additional training on larger data sets.[11]

Because of its ability to superimpose sequential images and analyze minute changes, AI is particularly well adapted as a tool for diagnosis, classification, and follow-up of progressive disease processes like periodontal disease and bruxism.[7,12] In the field of endodontics, artificial neural networks have been used to accurately measure the working lengths of teeth during endodontic therapy, identifying apical lesions, and serving as a valuable second opinion to providers in clinical situations.[13,14] In the field of orthodontics, AI algorithms analyze and plan tooth movements, predict tooth size and jaw relationships, and even recommend extractions to facilitate an idealized treatment outcome.[11,15,16] AI systems are also looking at large data sets to predict risk of decay, periodontal disease, and orofacial pain, as well as aid in forensic identification of skeletal remains using age estimates based on tooth development and soft tissue reconstruction.[6,10,12,17]

Outside of clinical dentistry, AI is used to read electronic dental health records, assist with insurance claims and fraud detection, aid in the education and training of dental students, and support research applications investigating relationships in large data sets.[6] In one study, machine learning was used to mine a large amount of restorative data to determine life span differences among dental restorative materials.[8] Data mining of digital dental records can also be used to analyze variations among dentists when diagnosing caries.[17]

These examples show that AI can be used in dentistry to help clinicians make appropriate diagnoses and predictions through the analysis of large amounts of data thus improving the ability to help patients understand their dental problems and enabling the healthcare provider to make better clinical decisions. The following table shows some uses of artificial intelligence technology in dentistry.

Dental Specialty	Application of Artificial Intelligence in Dentistry
Orthodontics	- Predicting the sizes of unerupted canines and premolars - Decision if extractions are necessary prior to orthodontic treatment - Clinical approach to impacted maxillary canines - Cephalometric diagnosis - Predicting mandibular morphology in skeletal class I, II, and III - Skeletal patterns classifications
General Dentistry and Prosthodontics	- Modeling the longevity of dental restorations - Computer color matching - Removable partial denture design - Predicting color change after tooth whitening - Design and fabrication of fixed and removable oral prosthetics - Clinical decision support systems for dental treatment
Orofacial Pain	- Analysis of TMD using MRI - TMD clinical decision making - Differentiation of subgroups of temporomandibular internal derangements

Endodontics	- Locating the minor apical foramen - Analysis of 3-D images for endodontic pathology
Dental Radiology	- Detection of caries and other oral pathology - Labelling and analysis of images
Dental Surgery	- Oral cancer prognosis based on clinical pathologic and genomic markers - Analysis of hypernasality in patients treated for oral and oral pharyngeal cancer - Oral cancer risk assessment - Periodontal analysis and risk assessment

Challenges and Future Perspectives

AI in dentistry can help analyze data, build prosthetics, and offer suggestions to help with disease risk mitigation and treatment techniques. However problems with missing, incomplete, and non-standardized data in dental health records limit the use of AI in the dental office.[18] This challenge can be addressed by requiring uniformity of dental terminology and data standards to facilitate data aggregation for analysis, learning, and quality improvement purposes.[19] AI can also reduce the gap between dentistry and medicine, so there is better understanding of general disease patterns and their influences on oral health. In the future, we can expect AI to continue to affect every aspect of dentistry; possibly being able to analyze a patient's demographics, medical history, and dental history to assist the clinician with comprehensive diagnoses and treatment planning.[6] Moving forward, bridging the gap between basic science and large-scale population health applications will be the challenge.

A.T. Still University is already invested in the application and allocation of AI technology throughout the preclinical and clinical education of our dental students. Maintaining this trajectory will inevitably result in the continued exceptional level of dental education our school is known for. Recommendations for continued development in AI infrastructure within the dental school should be determined by a group of technology focused faculty members tasked to look for innovative ways to use AI in the education of tomorrow's dentists.

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APPENDIX F: APPLICATIONS OF AI IN POPULATION HEALTH

Although ATSU students will likely see artificial intelligence (AI) in individual-level health-related applications at some point in their careers, they may not be as aware of the presence of population-level AI. While healthcare refers to individual-level care between a provider and a patient, population-level care involves the community or population itself as the patient to be treated. Population-level or public health care is not limited to providing resources and programs only for underrepresented populations. Instead, population-level interventions are meant to promote conditions in which everyone can be healthy.[1]

AI applications in population health have been studied for usefulness in several scenarios. For instance, AI systems that rapidly evaluate social media posts during disasters have the potential to provide organizations with timely information to assess status, share with collaborators, and determine necessary decisions when information might otherwise be limited.[2] AI has also been suggested as a tool to deliver personalized health education interventions in response to social media posts that indicate risky or unhealthy behavior.[3]

Data analysis is another potential application for AI in population health. Public health surveillance systems are data rich and can be immense. Currently, analyzing and preparing data reports for dissemination can be a lengthy (e.g., yearslong) process. AI could be used to accelerate this analysis or mine previously unused population-level data to provide better insight into public health problems.[3]

Natural language processing is useful for identifying risk patterns in data and can be used by health plans to more accurately identify population health issues for complete risk identification. Using AI to identify gaps and opportunities for improvement may assist in the coordination of retrospective and prospective analysis tasks. Analyzing these patterns may be important for predicting whether a patient will return for treatment of the same condition within a specific period of time. This could also lead to more proactive outreach from the healthcare provider to patients that ensures they stay on a healthy journey to wellness.

Addressing shortages of healthcare providers remains a serious problem in our country. AI could mitigate the impacts of this deficit in underrepresented areas. For example, AI imaging tools can assist providers in underrepresented communities through screening of chest x-rays for signs of pneumonia, tuberculosis, or COVID-19; retinal fundus photographs; and skin lesion images. These tools often achieve levels of accuracy comparable to board-certified physicians.[4,5] Such applications could also be used for evaluating lesions, rashes, and other pathologies; and they could be made available to these providers to reduce the need for a trained diagnostic radiologist on site. This application of AI in population health could be greatly beneficial because imaging tools are used in a variety of disciplines, such as cardiology, pathology, dermatology, and ophthalmology.[6]

However, AI algorithms are almost certainly a concern for potential bias. Therefore, to avoid bias, algorithms should be based on data from diverse populations and consider different environmental factors.[7] Surveillance systems also need to address all populations, including the health status of many underserved and underrepresented populations, such as incarcerated individuals or those living in long-term care settings.

Basing population-level policy and programming decisions on an incomplete data set or biased algorithms can propagate disparities.[3] Although research has investigated the use of AI in public health, funding and the workforce have been identified as barriers.[3] Because ATSU is educating not only future healthcare providers but also future public health professionals, we have the opportunity to enlighten our students about the future of AI at the population level.

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APPENDIX G: AI IN UNIVERSITY AND BUSINESS OPERATIONS

Businesses are using artificial intelligence (AI) algorithms to enhance workflows, reduce errors, and transfer repetitive, data-intensive tasks from human workers.[1] Pilot projects are the most common method that companies use to test AI-assisted workflows; larger-scale deployments are much less common.[2] The current challenge is sifting through the media hype and industry journals to find products that enhance workflows at a reasonable cost and have some staying power. When considered from the business perspective of educating students and managing healthcare clinics, these technologies are in their infancy but are quickly adapting to the needs of our marketplace.

Business Operations

Incorporating AI into business operations has the potential to increase productivity dramatically over the next decade. Every component of a management system is subject to algorithms designed to minimize routine, mundane tasks and to deliver insights from large data sets, such as purchasing, inventory management, quality assessment, human relations, facilities maintenance, and marketing.[3]

Process automation is the most common type of AI technology used, mainly for back-office business applications. It uses robotic process automation (RPA) to input and consume information from vast data sets.[2] For example, updating customer information, replacing lost credit cards, reconciling billing and shipping information, and reading legal documents for contextual information are RPA functions currently used in business. Many of these RPA tools were built to specifically handle a given task, but the underlying architecture makes them versatile for use in any business operation, including a university or healthcare center.

Cognitive insights are the next major application of AI technology in business.[2] Through basic analytics, cognitive insights can enhance a user's ability to understand large quantities of data and make predictions about the future. Some examples of this use of AI are recommended movies on Netflix, curated content on Pandora specific to your tastes, and targeted advertisements. Beyond making predictions, these machine learning algorithms can also detect credit card fraud, analyze safety data, and create precise actuarial models. Unlike traditional data analytics, which have limited capabilities, these machine learning algorithms improve over time and with more data input.

Cognitive engagement is another common form of AI used in business practice today.[2] Virtual chatbots are ubiquitous on websites. They are getting more sophisticated and are able to solve many straightforward problems without human intervention. Using natural language processing (NLP), intelligent agents can work 24/7 and provide a range of helpful solutions from password resets to technical support. Although there are numerous instances of a company's intelligent agents failing with external customers, internal use is quickly gaining acceptance with employees who have questions about human relations, employee benefits, or information technology (IT) services. The business of healthcare also uses intelligent agents to act as an intermediary between patients and healthcare facilities, offer advice based on simple symptoms, and analyze biometric data.[4]

At A.T. Still University (ATSU), we are currently using an application called Chrome River for automated travel expense reporting. Since hundreds of companies use this product, the system has gathered enough data to learn assumptions that save time and reduce error. For example, the program can use optical character recognition to read a scanned receipt that indicates purchase of a salad and is time-stamped at 11:46 AM. The program knows this specific combination generally indicates a lunch receipt and will automatically populate the appropriate field with the total expense on the receipt. Another in-house example is our use of UltiPro software for human relations, payroll, and hiring. It has embedded AI algorithms to review candidate applications, survey employee engagement, and even analyze employee emotions, motivations, and drivers for workplace satisfaction based on survey results.

AI in business operations is making steady progress toward widespread use. Although limited to specific functions at this time, the software will quickly become more robust and interconnected, and ATSU will have to prepare to use these applications on a larger scale. We will also see opportunities for implementation throughout our business operations environment.

Healthcare Operations

Using AI in healthcare operations could dramatically improve productivity, reduce costs, and change the composition of the healthcare workforce. There will be an estimated shortage of 54,100 to 139,000 physicians by 2033,[5] so changes to the healthcare workforce are inevitable and will involve using technology to do more with less. AI is in the early stages of development and implementation for use with back-office healthcare operations and should improve data accuracy, reduce payment and insurance errors or fraud, and enhance auditing processes.[6] A currently available and frequently used tool that enhances workflows for administrative documentation, such as the creation of transcripts and patient-case summaries, is NLP . Many parts of this white paper were produced using dictation software that listens to speech and formats with appropriate punctuation. Although not perfect, this software is widely used and continues to improve.

AI use in the health insurance industry is also in its infancy. Initial use cases leverage existing algorithms to check for fraud, ensure clinical pathways adhere to guidelines, and customize insurance plans for situations, such as patients with chronic diseases.[7] However, claims management is the primary area where AI algorithms are being developed to reliably identify and correct errors in medical billing, potentially saving health insurers and healthcare facilities time and money. Currently, this area is the central focus of AI applications in the health insurance industry since it has the potential to dramatically impact cost savings throughout US and worldwide markets. In a focused analysis of a single health insurer in Germany, nearly 70% of claims were flagged as unusual, and approximately 10% were erroneous or required investigation.[7] The company generally has over 700,000 claims per year, which means several hundred human employees must individually investigate and correct claims to ensure accurate payment and eliminate fraud.[7] Even modest input from AI algorithms to reduce and correct routine errors would significantly improve the fidelity of information and allow human employees to focus on relevant patient-specific claims.[7]

Billions of health insurance claims are filed in the United States each year, totaling over $3.5 trillion in expenditures.[8] A conservative estimate suggests 3% of all health insurance claims are fraudulent, although some estimate it as high as 10%, resulting in healthcare payments of nearly $300 billion.[8] Health insurance fraud causes lost revenue for insurance companies, increases patient healthcare premiums, and consumes time, money, and human capital to investigate and prosecute these crimes.

Some examples of insurance fraud include the following[9]:

- Billing for services that were never rendered
- Billing for more expensive services than were actually provided
- Performing medically unnecessary services
- Misrepresenting noncovered treatments as medically necessary covered treatments
- Falsifying a patient's diagnosis to justify tests, surgeries, or other procedures that are not medically necessary
- Unbundling
- Billing a patient more than the required copayment
- Accepting kickbacks for patient referrals
- Waiving patient copayments or deductibles for medical or dental care
- Overbilling the benefit plan

The use of AI in health insurance claims management software is currently being developed and implemented throughout the industry. In 2017, Aetna began development of a proprietary application, called Auto-adjudication of Complex Provider Contracts, that uses existing algorithms and NLP to automatically resolve insurance claims. This application works at the health insurer level and the provider level, allowing reallocation of workforce, time, and resources.[8,10]

Although widespread use of AI in healthcare business operations is currently limited, the breadth of development across the healthcare spectrum indicates that this technology is poised to make a considerable impact. ATSU will need to closely monitor the technology as it develops and be ready to introduce applicable components into our operational infrastructure at the optimal time.

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APPENDIX H: ETHICAL AND BUDGETARY ISSUES OF ARTIFICIAL INTELLIGENCE

Ethical Considerations

Privacy, transparency, and avoidance of biases in artificial intelligence (AI) applications are important concerns and should be a part of any AI curriculum or strategic partnership. A lack of transparency about how patient or student data is used in conjunction with the AI can lead to privacy problems and ethical questions. Human biases can also be unintentionally coded into the algorithms. Therefore, any strategic partnership that A.T. Still University (ATSU) forms to develop or trial an AI application will require expertise to identify and mitigate potential privacy issues and biases. Educating our students about the ethical issues of AI and AI processes will benefit them as future healthcare workers.[1]

Job Loss and Job Creation

AI is meant to aid physicians, not replace them. A common concern of increased use of AI is the loss of jobs when automated processes are turned over to a machine. In many cases, automation reduces the need for outsourced (overseas) workers.[2] According to World Economic Forum statistics on the impact of AI, over 75 million human jobs will be replaced by AI by 2022. [3] However, 133 million jobs will be created, refuting the misconception that AI will make more people jobless.[3]

There are only 4.45 skilled healthcare professionals per 1000 people globally, and the World Health Organization estimates a shortage of 13 million healthcare workers by 2035.[4] Although a common belief is that AI will replace healthcare jobs, it will actually improve the efficiency of delivery of care, decrease the cost of healthcare delivery, and increase job opportunities.[5]

From a clinical perspective, AI cannot replace empathy. Having empathy, showing compassion, and building trust are crucial components of patient–provider interactions, especially during life-altering situations. Technology cannot replace these human factors that are integral to the delivery of proper healthcare. Finally, medical diagnosis and care are not linear. Complex diagnoses require critical analysis and are multifactorial. Even though AI can support these processes, it cannot replace competent professionals.

Information Technology Infrastructure

From an information technology (IT) perspective, AI will usher in a new era of clinical quality and exciting breakthroughs in patient care by powering a new generation of tools and systems that make clinicians more aware of nuances, more efficient when delivering care, and more likely to get ahead of developing problems. Therefore, available IT resources must be able to reliably deploy and maintain conventional machine learning tools. Ultimately, the widespread implementation of AI will enable healthcare organizations to address these challenges as the healthcare industry continues to transform.

At its foundation, AI is driven by data and is computationally intensive. ATSU can prepare for a successful AI future by planning now for the infrastructure to meet these challenges. As such, ATSU and Information Technology Services (ITS) should focus on several core infrastructure areas to support AI within the University. Machine learning typically uses large data sets for model training and testing. Because these data sets can sometimes require considerable amounts of storage, expansion of our data warehousing capabilities is the first infrastructure area to focus on. Our data warehousing must evolve to support not only AI but also easy and secure access to data stores by individuals or organizations that need the data. A second focus area is related to network bandwidth. Large data sets require a lot of bandwidth. To ensure timely consumption of data by AI models, the network infrastructure at ATSU must evolve to support high-speed transfers of data for both on-campus and off-campus AI initiatives. Another focus area requires scaling of computational resources at ATSU for the training of AI models and the end use of models performing inference analysis of new data. Scaling of computational power requires specialized servers for machine learning, typically hardware processing cores with graphics processing units and tensor processing units that substantially decrease model training times and provide much quicker results than existing AI models. Scaling of computational power may also include off-campus resources. Online providers of AI services are expanding at an exponential rate and facilitate scaling of AI processing power through the use of cloud services in a pay-as-you-go model. Examples of these services include well established providers, such as Amazon Web Services, Microsoft Azure Cognitive Services, and Google AI; but more niche-style AI services are becoming more common in response to specific AI application needs.

Timing for Adoption

As technologies emerge, University leadership must decide on the optimal timing for investing resources in these technologies. History teaches us that such decisions are complex. Inevitably, some choices will be made too early or too late. The University ecosystem is a community of individuals with different talents and needs, and there will be early adopters and late adopters of these technologies. Fortunately, this heterogeneity reduces possible consequences of mistimed technology adoption, and other resource needs may be useful for determining the best timing. One of our University standards is to produce lifelong learners, so we should trust that our students will be able to adapt to new uses of AI that evolve over careers that will last much longer than our current ability to predict future capabilities of AI.

Budgeting for AI

From a business point of view, many of the AI opportunities for the University will be implemented as services. Since different segments of the University will have different needs, even for a single service, we will have to decide how to manage which services are chosen and how those services are budgeted within the University budget system. To effectively meet University needs, such decisions should be made by a team that understands individual needs and the technology services available.

This type of interaction is not unprecedented in the current University workflow. The Academic Technologies committee is one example of the necessary interactions between various strategic stakeholders to make good decisions. The committee includes representatives from each of the major teaching programs, library support services, academic technologies support services, and IT. This diverse team balances the needs of the end user with the need for understanding of the technology itself. As technology is acquired, including AI, and as more services are outsourced even if they lack a one-size-fits-all structure, it may be necessary for ATSU's financial officer to critically examine current funding structures for such services and determine whether we have an optimal structure for budgeting and finance.

As a common starting point, AI applications being considered for use in didactic courses should be discussed with ITS and the Academic Support and Information Technology Committee. Together, these groups can determine the next best steps based on the intended scope of the application. New technologies will also need to be evaluated for security, technical maintenance planning, and licensing purposes. To help the University inventory and track academic programmatic use of newly adopted AI, an ATSU Security Application Overview report will need to be completed for each new AI program and shared with ITS. Tracking the adoption of AI at clinical sites would also be necessary, and completion of an ATSU Security Application Overview report would be beneficial for those instances that require ATSU affiliate logins or network hosting.

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