TELEHEALTH AND MEDICINE TODAY

OPINIONS, PERSPECTIVES, AND COMMENTARY

Closing the Loop in AI, EMR, and Provider Partnerships: The Key to Improved Population Health Management?

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Keywords: artificial intelligence, coronary artery disease, osteoporosis, population health

Abstract

The capabilities of and interest in artificial intelligence (AI) in healthcare, and more specifically, population health, have grown exponentially over the past decade. The vast volume of digital data or 'big data' in the form of images generated by an aging population, with an ever-increasing demand for imaging, amassed by radiology departments, provides ample opportunity for AI application and has allowed radiology to become a service line leader of AI in the medical field. The screening and detection capabilities of AI make it a valuable tool in population health management, as organizations work to shift their services to early identification and intervention, especially as it relates to chronic disease. In this paper, the clinical, technological, and operational workflows that were developed and integrated within each other to support the adoption of AI algorithms aimed at detecting subclinical osteoporosis and coronary artery disease are described. The benefits of AI are reviewed and weighed against potential drawbacks within the context of population health management and risk contract arrangements. Mitigation tactics are discussed as well as the anticipated outcomes in terms of cost-avoidance, physician use of evidence-based clinical pathways, and reduction in major patient events (e.g. stroke and hip fracture). The plan for data collection and analysis is also described for program evaluation.

Received: July 12, 2022; Accepted: July 27, 2022; Published: October 10, 2022

The capabilities of artificial intelligence (AI), a term first coined in 1955 to describe the 'science and engineering of making intelligent machines', have grown exponentially over the past decade in the medical community (1). There are now many ways to categorize AI: by its functionality, its stage of intelligence, and by the process by which it learns and produces results. AI technology ranges from the developmental of more simple expert systems to highly complex deep learning; however, it is important to distinguish these and other forms of AI from creatively applied statistical modeling when considering this topic. Interest in the use of AI in health care has also risen dramatically. The number of FDA-approved AI medical devices approved each year since 2013 has increased tenfold, while AI computational power has vastly outpaced Moore's Law – doubling every three and a half months (2–13). Research involving AI has followed, with the topic demonstrating a greater than 45% publication growth rate between 2014 and 2019 (11). The vast volume of digital data or 'big data' in the form of images generated by an aging population, with an ever-increasing demand for imaging, amassed by radiology departments, is especially fertile soil for AI applications and has allowed radiology to become a service line leader of AI in the medical field (14). As of early 2020, greater than 70% of all FDA-approved AI devices and algorithms in health care are radiology-specific tools. While these tools offer a wide range of diagnostic, explorative, quantitative, and repetitive functions, the following discusses AI in the context of its use as a secondary screening tool embedded in computed tomography (CT) scans and its integration into clinical care delivery.

AI in a Value Setting

If there is skepticism to be had of AI in the medical setting, it may revolve around the question the true value it brings to the patient or physician. According to Thrall et al., 'Adding value includes the discovery of new knowledge and extraction of more and better information from imaging examinations to achieve better outcomes for patients at a lower cost (14). For radiologists, adding value includes establishment of more efficient work processes and improved job satisfaction'. This goal mandates that the benefit derived from applied AI must exceed the cost of execution that it reduces provider burden rather than add to it, and it provides clinically impactful results. Many applications of AI perform to most of these standards: performing pre-analyses to prioritize review, improving image quality, detecting findings not visible to the naked eye, and generally helping to combat the impact of observer fatigue in image review; all represent ways in which AI benefits the patient, radiologist, or both. However, there are many examples of AI that have failed to meet this imperative: when the cost of AI is too high to facilitate a return on investment (ROI), when it does not incorporate neatly into clinical workflows and creates barriers for clinicians, or it fails to provide clinically meaningful and accurate results. Many well-meaning traditional screenings have not stood up to such scrutiny, and recommendations surrounding their use have been modified as their value has been debated among experts. To avoid these pitfalls, it is noted that the most successful applications of AI are when they are executed in partnership with the clinician (15).

Widespread adoption of AI is often limited by its required financial investment, lack of immediate cost savings, or ability to generate revenue, especially in a fee-for-service (FFS) model, as the ROI associated with many AI programs is not favorable in the short term. However, the downstream savings associated with early intervention make AI a valuable tool in value-based reimbursement models (9, 16). Under these models, the health organization that the patient is empaneled to is afforded a set amount of money by the payor to care for the patient on a yearly basis, a value that may increase or decrease depending on the illness burden of that patient. The health organizations are responsible for the cost of care to the patient, which both mandates and incentivizes organizations to proactively engage in prevention and early intervention to keep medical costs down, as they are liable for any costs that exceed the payor payment. Likewise, any savings between the allotted payment and total cost of care is kept as profit by the health organization. The clinical benefit of AI is not debatable in either a risk-based or FFS context; however, it is the associated shift toward population health management that is necessary in risk-based models that create the business case for adoption (17). The following elements make a compelling case for the implementation of AI.

Early Identification

Early identification or diagnosis of chronic disease facilitates interventions aimed at slowing, stopping, or even reversing disease progression. Interventions may include lifestyle modifications, use of pharmaceuticals, or a combination of these. Implementation of such may lead to both cost avoidance and improved clinical outcomes associated with a reduction in critical clinical events (e.g. myocardial infarction and hip fracture). This reduction in critical events leads to lower rates of hospitalizations, invasive procedures, need for post-acute care, and ongoing management associated with prolonged disability. It is estimated that the use of AI can reduce annual US healthcare costs by 150 billion by 2026 by facilitating a more proactive versus reactive approach (18). In many cases, and in our context specifically, AI is able to identify subclinical disease that would otherwise go undetected or require much greater resources to capture: in one validation study, Nanox reported that 32% of patients with a coronary artery calcium (CAC) score of 400 or greater and 57% of patients with CAC between 100 and 300 went undetected by the radiologists but were captured by their AI algorithm (19). For one partnered organization, 36% of the patients captured by their algorithm were identified as new follow-up opportunities. Additionally, when subclinical disease is identified through AI, the degree to which the algorithm can detail the progression is often valuable in forecasting how it may present itself clinically. This information can be used in conjunction with patient-specific history, risk factors, and signs or symptoms to create a more customizable treatment plan that provides more targeted, and therefore effective, intervention at the patient level. This highly informed treatment plan has the capability to slow, or even in some cases even reverse, disease progression. Subramanian et al. detail multiple examples of AI-driven precision medicine, facilitating early intervention to slow or reverse chronic diseases, including cystic fibrosis, diabetes, oncology, and heart disease (20).

Illness Burden Capture

Health systems engaged in risk-based reimbursement models rely on thorough and accurate diagnostic coding by clinicians to ensure that they are allotted an appropriate 'per member' payment for the population they care for. The use of AI allows for the opportunity to improve disease burden capture, specifically related to Hierarchical Condition Category (HCC) coding. Given that the purpose of AI in this context is increased identification of patients with specific disease states, this increase will easily translate into a higher rate of HCC capture. This, in turn, will allow providers to be compensated for the care that these patients require, which is required for a health system to be successful in their risk arrangements.

Right Care, Right Place (Level of Service)

Additionally, by identifying the disease at an earlier stage, preventative treatment more likely can be provided in a primary care setting, avoiding more costly specialist

Citation: Telehealth and Medicine Today 2022, **7**: 370 - http://dx.doi.org/10.30953/tmt.v7.370

consultations and visits. While a patient may eventually require referral to a specialist, the majority of patients who undergo imaging with AI screening capabilities with positive findings are in an earlier disease state that is able to be addressed by their primary care physician (PCP). The use of AI may also in some cases negate the need for diagnostics that would typically be ordered by a specialist, and results are able to trigger a clinical pathway that would previously have required a specialist to initiate.

Burnout Mitigation

On a similar note, the management of chronic disease is increasingly monopolizing provider time, and the ability of AI to effortlessly identify disease and integrate with the electronic medical record (EMR) to provide the PCP with appropriate recommendations or suggested next steps could be seen as a physician burnout mitigation tactic (21). Burnout may be characterized by poor mood, reduced productivity, job dissatisfaction, and may impact quality of care (22). Time and effort spent in the EMR are known to contributing factors to burnout, as it has been reported that physicians spend 2 h in the EMR for every 1 h of patient care (23). By automating several clinical and logistical steps required in medical management, the AI allows the provider to dedicate more time to further customization of the treatment plan and patient engagement. This may lead to increased provider satisfaction and retention, as providers are equipped with additional tools to aid them. The reduction in need for specialist referral may also contribute to reduced burnout in specialty service lines, as they are able to dedicate more time to those patients requiring a higher level of care and expertise.

It should not be overlooked that these benefits are derived through a minimally invasive or burdensome process, in consideration of patient and provider time, cost, and inconvenience, as the only disruption to standard workflow (Fig. 1) is represented in the review and verification of image series by the radiologist, which is estimated to be <1 min per study. This lack of indirect costs further adds to the value the AI provides.

Drawbacks of AI

While the benefits of AI have been clearly outlined, there are several factors inherent to AI that prohibit it from reaching its potential in most settings, the foremost being the vast resources required to implement an AI program. Despite 90% of hospital systems reporting that they have an AI strategy, only 7% report that it is fully operational, 6% report that they have 10 or more use cases implemented: of these respondents, 44% cite lack of resources and difficulty identifying best processes as their largest challenges (24). An operational consideration is the sheer volume of patients with a ‘new’ problem that is appropriate for intervention that is created from deploying the AI. This new reservoir of patients can strain primary care practices already at capacity. In many cases, including our use case, the patient may be undergoing imaging for purposes other than the AI target, and there is not a team ready to field the new diagnosis based on the AI results and respond to them. This can create a bottleneck of information flowing to PCPs, as they grapple with high volumes of unsolicited information about their patients. Most primary care departments do not have infrastructure in place to react this information, and many findings and their potential benefits go unrealized because of this. These barriers are similar to sentiments expressed by responders in a study performed by Strohm where the barriers to AI adoption and implementation were explored (25). This problem

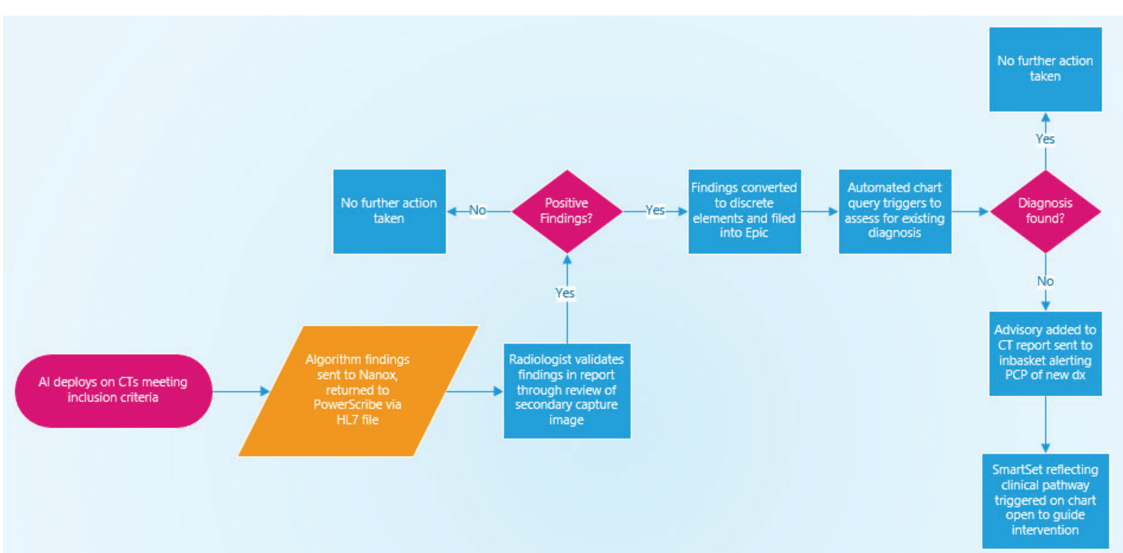

Fig. 1. Technical and operational workflow following algorithm deployment.

is also reflected in studies that demonstrate that up to 50–81% of patients with incidentally identified fragility fractures do not undergo follow-up or treatment, which is of specific interest in our use case (2, 3).

Likewise, providers may feel uncomfortable or unqualified to appropriately interpret the results or findings generated by AI, triggering an influx of specialty consults. Additionally, the information provided by the AI may at times not particularly relevant or actionable. Patients may already have a documented diagnosis of the disease identified and are undergoing treatment, or they may have a terminal condition that would negate any benefit associated with treating the newly identified disease. In these cases, there is no additional value derived from funneling the information to the patient's provider.

Another potential drawback that must be grappled with is the significant evidence of inherent bias within AI. This bias may originate from the type or source of data inputted to mature the algorithm, resulting in inaccurate data analysis and output (9). This is especially important when considering AI-based decision support systems, as there is risk of un- or under-represented populations being subject to recommendations that do not consider their unique characteristics. When this occurs, both bias and health risks are compounded, potentially leading to increased disparities in health outcomes (9, 10).

Finally, while the value of AI in a value-based model is detailed above, there is still cost and deployment to consider. Depending on licensing agreements, the use of AI programs may be subject to a 'per patient' fee, which may inspire health organizations to ration such care and only utilize it for specific populations. This may lead to further health disparities among populations, especially the uninsured.

Why Explore AI?

The converging forces of the exponential growth of chronic disease, the imperative to shift to population health management in risk arrangements, and the ever-growing accessibility of AI technology create the perfect opportunity for growth for our organization. Osteoporosis and coronary artery disease (CAD) together represent a significant portion of the patients that we care for, and both offer opportunity for early intervention through secondary screening measures facilitated by AI.

Vertebral fragility fractures are the hallmark of osteoporosis and are considered highly indicative of future major fracture, and medical and behavioral interventions have been shown to reduce hip and other fracture rates by 40–70% in patients with osteoporosis; given that the hospitalization rate is greater than 40% with a 12-month mortality rate of nearly 20% and $4.5 billion price tag of care, it is not difficult to see the value in preventative measures for this population (2, 4). Likewise, early detection in CAD is equally associated with improved outcomes, which has been identified as the foremost risk factor in the development of adverse cardiac events, and once detectable has an average progression rate of 25 ± 65 Agatston units per year (5). Cardiovascular disease (CVD) is the costliest diagnostic group in medicine, with total direct cost in the United States estimated at $226.2 billion, with hospital and emergency department admissions accounting for just under half of that (26, 27). Pharmaceutical intervention for CAD is associated with a 51% decrease in individual spending related to the diagnosis, and systematic reviews have shown secondary prevention programs to be cost effective (5, 6). Burden-based treatment selection methods, yielding a younger population than risk-based methods, have also been shown to result in favorable quality-adjusted life years gained without increase in treatment population (7). Greater than 25% of patients with a major CVD event had no previous symptoms, and aggressive treatment of CAD has been shown to reduce major CVD events by up to 45% (8, 28).

With the previously mentioned potential drawbacks in mind, our organization has set out to implement AI functionality to address these conditions in a way that is sustainable while attempting to ensure that the full benefit of the AI is realized. The administrative and logistical needs around AI are significant, and our process attempts to reduce this burden for both providers and the interdisciplinary health team. The potential barriers or issues previously discussed were carefully considered throughout each step of our program design, and all key stakeholders were consulted, including the AI provider (Nanox), radiology, primary health, cardiology, bone health, orthopedics, and population health. The collaboration allowed for multiple perspectives that helped to ensure that all potential downstream ripple effects caused by AI deployment were identified and planned for in a way that was conducive to both provider workflows and resource limitations.

Technical and Clinical Context

Spectrum Health West Michigan (SHWM) consists of 10 hospitals and 28 outpatient radiology centers. A total of 300,000+ risk-contract patients are attributed to the health system, approximately half of which are insured by the Priority Health, the integrated Payor. SHWM's operational goals include greater than 50% revenue resulting from risk contracts by 2028 and are fully engaged in bidirectional risk arrangements with a variety of payors. Greater than 80 radiologists (direct employment and contracted) are responsible for reading approximately 60,000 chest and thoracic CTs per year. An initial partnership with Nanox AI resulted in a promising internal pilot study that spoke to both the accuracy of the algorithm (greater than 95% agreement in CAD algorithm) and the volume of newly identified patients as having CAD that could be expected should the use of the algorithm be adopted throughout the system, approximately 1,400 patients yearly from the CAD algorithm alone. The Nanox technology uses a combination of convolutional and recurrent neural network technology and machine learning to detect and measure or quantify spinal compression fractures and CAC. Because the licensing agreement with Nanox allows for unlimited use of the algorithm without incurring additional 'per patient' costs, the algorithm is deployed universally on all scans meeting inclusion criteria. This census application helps to mitigate the risk of selection bias, as deployment is agnostic to insurance status and other demographics apart from age.

Technical and Clinical Infrastructure

Implementation of the AI required collaboration from multiple teams across the health system. Nanox worked closely with the information services (IS) team responsible for standing up the on-site server that supported the algorithm and allowed for two-way communication with the vendor cloud. Another team worked to integrate the AI findings into the PowerScribe report and send the radiologist validated findings back to Nanox for their own internal agreement review. These validated findings, which consisted of the CAC severity level for the CAD algorithm and the fracture location, percent height loss, and Hounsfield units (HU) findings for the osteoporosis algorithm, were then extracted from PowerScribe and sent as discrete fields into Epic Chronicles. If findings were positive for either algorithm, this triggered an automated chart query to determine if the patient already had an existing diagnosis of CAD or osteoporosis. Diagnostic criteria for CAD consisted of inclusion in the system CAD registry and mention of osteoporosis in the problem list for osteoporosis. If the patient's chart met criteria for an existing diagnosis, then no further action was taken; however, if no existing diagnosis was found, then a best practice advisory alert (BPA) was triggered to the patient's PCP alerting them of the findings and providing relevant recommendations that were specific to the severity of the results. These recommendations are based on the accepted clinical pathways for CAD and osteoporosis that were developed through collaboration by multiple clinical team members and based on best available evidence, providing detail on both the clinical and logistical elements of intervention. Included in these pathways is the utilization of the Multi-Ethnic Study of Atherosclerosis (MESA) and the Fracture Risk Assessment Tool (FRAX) for CAD and osteoporosis, respectively: these tools help to mitigate the risk of bias in both the algorithm and the interpretation of results and help ensure that each patient's unique characteristics and history are considered when developing a treatment plan.

The pathways were also developed with careful consideration of current available resources (e.g. referral criteria for specialty services informed by current capacity of those service lines to field new patients) to help ensure that the pathway was sustainable from a system perspective, and that it facilitated a positive patient experience. Following review of the findings and recommendations, the PCP would then be able to determine next best steps for each patient individually, being informed not just by the AI findings and clinical pathway, but by their intimate knowledge of the patient's risk factors and health goals. We believe this process allows for the ideal level of control by the PCP, providing clinical decision support (CDS) and autonomy to allow for individual patient differences and clinical autonomy.

From a billing and reimbursement perspective, no additional charges or codes will be utilized with the algorithms at time of go-live. Due to our risk arrangements, the financial benefit of this program for our organization is in the future cost savings associated with reduction in complications from chronic disease, not direct billing. However, Nanox has recently sought and gained approval from the American Medical Association (AMA) for the issuance of a new CPT, 'Cat III-Assistive Augmented Intelligence Analysis', which allows for tracking and establishes a reimbursement pathway for the algorithms' use. Once the use of these codes is better explored, Spectrum Health will seek to implement them to assist in risk-adjustment for our risk-contracted patients.

Challenges and Barriers

Given the wide scope of technical, clinical, and operational elements involved with this project, multiple challenges were encountered throughout the planning and implementation phases. From a technical standpoint, this work involved multiple IS teams that reported to different uplines, with different prioritization methods, and had different workflows and organizational cadences (e.g. some were organized as Agile Release Trains, and others worked in Waterfall); this created dependencies and risks that were often outside the scope of control of different teams and required a significant amount of cross-team communication and collaboration. There were also multiple clinical perspectives that had to be considered when creating the clinical pathways that would activate upon positive findings, as well as the method by which PCPs were notified of the results. Differing opinions between specialty and primary care providers reflected the degree to which they believed CDS was necessary and what the most effective means of notification to the PCP would be. It was recognized that 'BPA fatigue' among providers threatened the effectiveness of CDS that was offered, and this challenged the team to develop a provider notification that was delivered at the right time in the right way. Additionally, the risk categories upon which Nanox had built their findings (low risk 0–99, moderate risk 100–399, high risk 400+) did not correspond to the SHWM clinical pathway, which separated patients who had no CAC detected versus those with a score of 1+. This required additional workflow modification to allow these patients that did represent the SHWM-defined low risk category to be delineated from those with no CAC detected.

During the design process for the AI clinical integration, concerns were raised regarding the possibility that additional screening that occurs will, indeed, lower the cost of care or instead may increase the cost of care through additional testing the findings generate. We worked to mitigate the risk of increased non-value add testing by embedding guideline-directed recommendations into our BPA and guidelines, which incorporate evaluation of functional status, clinical and lab data, to limit additional testing only to those patients who would meet strict guideline directed care.

Anticipated Outcomes

We believe that this structure of AI implementation will result in myriad positive outcomes for both patients and our organization alike. Based on our own pilot and multiple published studies, we anticipate that the widespread screening for CAD and osteoporosis in this context will result in a significant volume of patients identified as having subclinical chronic disease. The ability to identify these patients will lead to the opportunity to provide early intervention, thus reducing the number of critical events that result in hospitalization, reduced quality of life, and mortality. It is the hope that this program and others like it in the future will have the ability to shift the curve of the trajectory of these patients enough that it reshapes the associated service lines, with more provider time spent on early intervention and catastrophic event prevention than on post-event care. If the acuity level of patients requiring specialist intervention is diminished, it will also hopefully expand the number of patients who are appropriate for e-consults by specialty service lines versus those requiring in-person consultation, which is costlier and requires greater resources by the organization. The reduction in critical events will not only improve the health of our community and reduce the financial strain on patients but will also significantly impact the ability for the organization to be successful in its risk contracts. If we can reduce inpatient admissions, the need for invasive procedures, and post-event care, this will greatly reduce per-member per-month (PMPM) costs of attributed patients, allowing for a beneficial margin in the context of overall rising costs.

Also contributing to reduced costs in this model is the use of clinical pathways to guide PCP interventions on newly diagnosed patients. A common concern among organizational leaders regarding secondary screening is that there will be an onslaught of diagnostics and specialty consultations that result from unsolicited new findings: the use of clinical pathways combats this by providing PCPs with the tools to manage the condition in the primary care space and provides guidance regarding the appropriate and best use of additional diagnostics and more expensive interventions. While these may be necessary in some patients with more advanced disease states, their use still represents a savings to the system in that those patients are likely the most at risk for catastrophic events, and their use will likely prevent those potential events.

A secondary benefit to this model is the anticipated increased patient and provider satisfaction that we hope to achieve. We believe we are both reducing the administrative burden and mitigating the risk of non-relevant information overload to PCPs by the automated filtering out of patients who are already undergoing treatment for the identified chronic disease, which reduces the manpower required to implement the full AI model as well as reduces the ‘noise’ a provider is exposed to. By providing recommendations but not automating them allows the PCP access to best practice around the findings but grants them the control they should have when it comes to implementing those recommendations. This prevents patients from being subjected to a ‘one size fits all’ approach and allows for personalization of treatment based on both provider and patient input. Additionally, while there may be a concern that patients will have little appreciation for being diagnosed a disease that they had not gone looking for, our pilot findings revealed that the majority were grateful for the information and appreciated that the providers were taking steps toward early identification and intervention. The deployment of the AI not only facilitated the potential avoidance of a catastrophic event but also reduced the need for the diagnostics that would have been required to identify the disease in the future.

Next Steps – Deployment and Data Collection

Following finalization of the above plans, our next steps will be to see the technological build come to fruition and deployed. We will also begin training the radiologists through a combination of onsite training/support, virtual assistance, and digital references. The new clinical workflows will be dispersed through primary care via standard communication processes, including hierarchical dissemination, newsletters, and huddles.

To evaluate the clinical and financial impact of this AI use case and model, following full deployment, we plan to collect several leading, intermediate, and lagging metrics (Table 1). The integration of AI findings as discrete elements in the EMR facilitates the ability to pull this information

Citation: Telehealth and Medicine Today 2022, **7**: 370 - http://dx.doi.org/10.30953/tmt.v7.370

into reporting and track their correlation with outcomes over time. Metrics to be monitored are as follows:

These data points will allow us to characterize the patients most impacted by the model, the breadth or scope of the model, the impact to clinical workflows, and the operational and financial impact. The ability to assess the volumes of patients impacted by the AI will allow us to plan for future resource allocation and the impact to operational workflows. The intermediate clinical metrics will also provide valuable information as to whether the deployment of the AI and associated clinical pathways resulted in concrete improvement in a patient's health, which will surely be top of mind for the patient and their provider following identification. The tracking of HCC capture, specialty utilization, and PMPM metrics will provide visibility into short-term financial benefit around the model, while, incidence tracking of catastrophic events, inpatient utilization, and mortality, will provide insight into both the long-term financial and clinical impact. Dashboard and patient-level report builds have been initiated to allow for quick reference of the trends of the above-mentioned metrics.

Table 1. Metrics to be collected for program evaluation

Capture of all patients undergoing AI-utilizing imaging:
- Patient demographics
- Volume of total scans
- Volume of scans assessing coronary calcium
- Volume of scans assessing spinal fractures
- Volume of scans with positive results – total
- Volume of scans with positive results – CAC
- Volume of scans with positive results – spinal fractures
- Primary diagnosis/reason for imaging order

Capture of patients with *positive* findings on scan:
- Referrals to preventative cardiology
- Referrals to endocrinology
- Referrals to bone health specialist
- A1c (average) – trend over time
- LDL (average) – trend over time
- Bone density (HU, average) – trend over time
- Volume of additional diagnostics ordered
- Volume of interventional procedures – CAC patients only

Capture rate and volumes for the following HCCs:
- HCC 85: pulmonary hypertension
- HCC 111: emphysema
- HCC 112: bronchiectasis
- HCC 108: aortic atherosclerosis/aortic ectasia
- HCC 169: vertebral fracture

Pharmacy PMPM:
- PMPM revenue
- PMPM cost
- Volume of hip fractures
- Volume of repeat spine fractures
- Volume of myocardial infarctions
- Volume of cerebrovascular accidents
- Specialty service utilization costs
- Inpatient utilization costs
- Mortality rate

A1c: hemoglobin A1C or HbA1c; CAC: coronary artery calcification: HCC: Hierarchical Condition Category: HU: Hounsfield unit; LDL: low-density lipoprotein; PMPM: per member per month.

Conclusions

In this paper, we describe an easy, routine way to identify CAD and osteoporosis, in many patients prior to clinical events or symptoms. The process on the surface appears simple and straightforward, with a computer analysis of an already completed chest CT; however, as one reads through the technology involved and grasps the operational requirements involved, it becomes clear that it is anything but.

The planning, deployment, and implementation of the AI technology has been both time and resource-intensive. However, we believe the preparation work done prior to implementation to be the operational equivalent of the ounce of prevention that we hope we are delivering to our patients. During each step of the process and workflow build, we tried to identify and capitalize on every opportunity available to add value to the patient and provider, working to truly integrate the AI solution and close the intersecting loops of technology and people. Working upstream, both operationally and clinically, will help us achieve the outcomes that we hope for, both for our organization and community, including promoting well-being and justice in health care. In working through this process, we have been writing the foundational playbook for future AI implementation within our organization, so we are prepared to systematically inspect, adapt, and adopt new technologies that serve our vision and mission.

Funding Statement

Work by authors was supported within salaried positions at Spectrum Health.

Financial and non-Financial Relationships and Activities

Nanox technology was acquired at the market value with funding provided internally through cardiovascular services department at Spectrum Health.

Authors' contributions

Alexis Kurek is the primary and corresponding author, including literature review, article design, and manuscript preparation and revisions. David Langholz provided content expertise, including initial pilot information and background having served as primary investigator on that project. In addition, Dr Langholz assisted with revisions and editing. Aiesha Ahmed provided guidance on paper content, journal selection, and editing/revisions.

Acknowledgments

None

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