DELIVERING HEALTH INTELLIGENCE FOR HEALTHCARE SERVICES

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***Abstract*— The systems barrier for clinical information interoperability and standards has now evolved from a technology barrier to a semantic barrier. The processes to gather clinical data and to build clinical information and knowledge cannot be fully implemented, owing to semantic dissonances and limited data normalization. According to [1], "Just over a half of entered codes were appropriate for a given scenario and about a quarter were omitted." This is a significant data and financial gap for healthcare provision. Huge amount of addition to the financial cost, lack of data integration and loss of information affects the ability to maintain standards in clinical care delivery and patient outcomes.**

This paper proposes that the solution to these issues is an augmented network of clinical note taking, where coding is automatically generated by an AI system as clinicians write their clinical notes. The system (AI-KEN) offers enhanced web support that is integrated to local clinical systems, whereby clinical notes are prompted by suggested predictive text options in real time. The anticipated benefits include reducing financial loss for acute services, support for clinical standard maintenance and enhanced advancements for clinical practice and research in real time.

Keywords—artificial intelligence, healthcare, clinical decision support systems

1 THE CHALLENGE

Clinical note-taking has become an imperative element of quality health care delivery [2]. The quality and risk management component of clinical note-taking has been recognised by most jurisdictions globally, where policy and regulatory requirements direct clinicians to record medical interventions, prescriptions and diagnoses for patient safety. In addition to service provision, clinical note-taking is also fundamental in coding healthcare transactions, such as treatment costs, appointment scheduling or health billing (Adams et al. 2002). These in turn have direct impact on payment or reimbursement from government and insurance companies.

The challenge now arising is the absence of interoperability of these coded clinical notes, both between and within organisations. Interoperability dissonance occurs where different institutions, or different departments within a given institution, choose to self-select which coding standard they intend to apply for their area (often from globally recognised taxonomy systems such as ICD9, ICD10, ICD11, Snomed or LOINC), giving rise to a variance in practice. In addition to this variation, a further complication is manifested where local versions of a particular coding standard can be created and utilised.

It has been theorized that a continuum of practice variation creates a systems barrier for clinical information interoperability and standards (West et al, 2018). There have been suggestions that either blockchain or cloud-based solutions will bridge this gap. This paper argues that the

barrier to interoperability for clinical note-taking is no longer merely a systems or technological barrier, and that the evolution of clinical coding has brought about a semantic barrier, whereby the processes to gather clinical data and build a robust information and knowledge platform cannot be fully realised because of semantic dissonances and an absence of data normalization. It is proposed that the introduction of an artificial intelligence knowledge empowered network (AI-KEN) would address this limitation, remove the interoperability gap and beyond that support enhanced clinical risk management.

2 THE CURRENT ENVIRONMENT

Clinicians' notes can be comprehensive, including details on patients' demographic data, symptoms, diseases, treatment plans and procedures care pathways, medications management, and psychological social and environmental situations. Elements of this information are coded using clinical coding taxonomies or classification systems, such as:

• International Classification of Diseases Codes (ICD) [2]. The ICD is a core function of the WHO, and its taxonomy frequently plays a significant role in public and private health care provision by converting clinical notes into designated related groups (DRGs), which are essential billing codes for service quantification. Version 11 is scheduled for 2022 [1](Lancet, 2018).

• SNOMED [3]: This taxonomy has a substantive clinical focus, facilitating the coding of body part terms, synonyms and definitions used in clinical documentation and reporting including treatment procedures, plans and pathways and medications. • LOINC [4]: This is a coding standard, which focuses on laboratory tests, measures and observations. To maintain consistency and a standardised approach in clinical note taking, clinical institutions direct their staff to apply these coding taxonomies to specified datasets including diagnostic data, medical actions, nursing actions, medications, morbidities and also the type and seniority of clinical staff required for each of these information management items. However the absence of interoperability, owing to the conflation of dissonant data semantics, allows the generation of significant healthcare and financial deficits; for example:

There are 25% gaps and some errors in clinicians' recording of clinical notes [1]. This can result in more than 25% loss in revenue per year to each clinical institution. For example, a large hospital with a budget of €200 million, this may be a loss of €45 million per year. In the healthcare industry as a whole this can result in billions of loss in euro per year.

Such classification errors may potentially result in patients receiving a lower quality of treatment, higher incidence of adverse reactions and possibly lead to patient fatalities and subsequent legal litigation issues. For example Johns Hopkins Hospital research has calculated that more than 250,000 deaths per year are due to medical error in the US, making it the third leading cause of death (BMJ, May 3, 2016).

In practice, clinical notes recorded by clinicians have to be converted into DRG (designated related group) codes, which allows the hospital to get paid either by government funds or private insurers. These are financial codes put against distinct pieces of clinical work carried out. Regardless of whether the clinical records are stored in paper or electronically, a large percentage of this conversion has to be done manually; it can take up to three months before the hospital can reconcile this activity and be paid (i.e. the treatment received, the costs incurred in carrying out the service and how much the acute service is owed. This delay in data processing directly impacts hospital income and financial planning.

Clinicians are expected to constantly keep up to date with best practice huge e.g. on the latest procedures, research, new medications and new ways of achieving better clinical outcomes. This is an expanding area for clinical practice and information management [5].

The use of taxonomies for clinical note taking can also evolve (as with dialects of language) over time. These 'clinical dialects' can also vary across geographic regions, cultures and clinical settings. The evolving 'clinical dialects' are created by local clinicians and/or administrative processes owing to different interpretations of clinical terms, their meanings, and synonyms, and various financial coding considerations. This may affect treatment planning and care pathways, leading to variations in practice across geographical areas. Alternatively variations in clinical dialects or dissonance in note-taking can arise from differences in the scientific background of the data producers, different styles of reporting and writing, different aims of the documents and the different motivations by the document producers [6]

3 THE ARTIFICIAL INTELLIGENCE-KNOWLEDGE EMPOWERED NETWORK (AI-KEN) SOLUTION

AI, which includes machine learning, neural networks and genetic algorithms, is currently being applied across healthcare and most notably so in diagnostic analytics (MRI and CT) as well as in oncology (Simon et al., 2019). This paper proposes that an AI solution, using AI-KEN can be applied to derive semantic pattern matches which will address the semantic dissonance in clinical information that is spread across diverse systems and approaches. The substantive benefit of this proposal is that clinicians can continue to utilise clinical terminology, without resorting to the limitations of circumscribed coding lists, and that AI-KEN as an agnostic service will automatically code to their organisations system/systems of choice. This real-time approach will significantly improve coding, billing and clinical risk management.

The AI-KEN solution steps are to:

• Upload a base line of existing clinical notes e.g. 10,000 clinical records into a data warehouse and map with AI pattern techniques to produce patterns from clinical notes.

• As further clinical notes are added, AI-KEN prompts the data upload with predictive text, in an intuitive and user-friendly approach • Where predictive text is not offered, AI-KEN stores and retrieves the additional information to inform future cases

• Text patterns with less frequency of usage is then faded out, becoming lower in the prompt list over time until no longer suggested, following evolutionary patterns in nature.

• As the algorithms continue to learn and improve, the AI patterns will describe the most frequently chosen options whilst continuing to support the coding of even the most rare clinical conditions.

In this approach, normalized ontologies languages are engaged to disseminate the knowledge (such as OWL - Semantic Web Standards, as proposed by W3C). The usage of the semantic platform will improve the quality of data in a recursive way. The predictive analytics are undertaken by servers located on data centers which process the large quantity of raw data and deliver trained models using PMML language [7]. This analysis is distributed on the cloud to a domain of intelligent agents that use the knowledge to retrieve the information and send it to the network nodes that process it. The main objectives of using multi-agents are the modularity, scalability, fault tolerance and specialization of the various components.

4 FUNCTIONAL ARCHITECTURE OVERVIEW

The multi-agent architecture is composed of three layers, in accordance with [8].

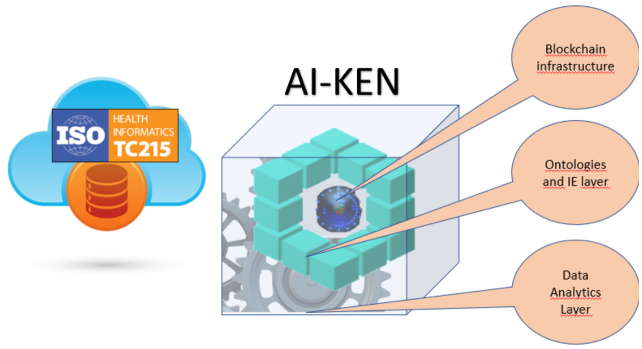

Figure 1- AI-KEN Multi-Layer Architecture

1- Blockchain Infrastructure, Data sharing and interoperability;

2- Ontologies certification and Information Extraction;

3- Data analytics and knowledge construction.

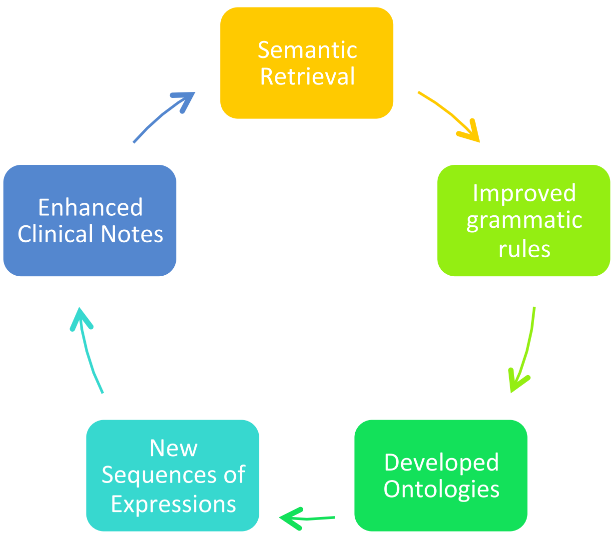

Figure 2- AI-KEN development and enhancing IE

AI-KEN is evolved by extracting semantic expressions from different sources and constructing information by normalizing terms, then relating those to ontologies that describe concepts, constraints and relationships. The extracted information is then available to be archived on information hubs using open source mapping, accessed by decision support, expert and recommendation systems, which are applicable for clinical, research and financial usage.

A deeper analytical layer shares system ontology and normalizes the data annotation with the ontologies. Each new concept that can be created by any node is ranked by the rest of the network and a final score assigned, facilitating the validation of ontologies across the network. This ontology share is similar to blockchain authentication and message validation, having the features of privacy, confidentiality, non-repudiation and fault tolerance.

An additional web service and user interface mechanism feeds agnostically into any existing clinical system or can be offered as a stand-alone approach to existing clinical note taking formats. A team of AI-KEN experts is available to guide any text that that has not been patterned, supporting continuous learning and quality improvement. The normalized ontologies and grammar rules can also be shared through this web service and can be used by clinical applications to assist with clinical notes. Thus AI KEN becomes an augmented network of clinical information, where clinicians can see and code patients in real time, with support from a central team of experts, together informing the neural net.

In order to evolve AI-KEN exponentially, it is proposed that case loading should commence with specific identified pathologies initially. The semantic intelligence system will parse semantic expressions of clinical notes and to relate them with a normalized ontology. Following this, the strategies, principles and methods for the initial pathologies are expanded on an organic basis over time, where repeating patterns are applied, with minor adjustments per pathology or diagnosis. As the systems evolves an intelligent platform is built to extract in real time all the data related with clinical findings, diagnosis, treatment plans, prescriptions, drugs administrations, adverse reactions, clinical exams and morbidities and established relationships with normalized ontologies. The normalized ontologies, the grammar rules and the intelligent agents can be shared on the web and can also be used by clinical applications to help the clinicians write clinical notes according with the guidelines.

5 THE BENEFITS OF DELIVERING HEALTH INTELLIGENCE FOR HEALTHCARE SERVICES

Clinical Benefits

• Normalizing clinical note taking:

• Provides the probability on treatment outcomes, including less common treatment approaches;

• Supports input feeds from advanced testing and machine learning statistics, e.g. genomics testing, proteomics testing, metabolic testing and bionomics testing;

• Enhances the latest and best clinical methods and research, in real time;

• Risk mitigation for adverse reactions and contraindications.

Cost Control Benefits

• Real time coding of cases improves billing times, reimbursement times and financial planning;

• Improved coding quality, which is directly aligned to provider revenue and income

• Risk mitigation for litigation against clinical error, adverse reactions and contraindications;

• Audit trail of mapping clinical investigation, through clinical coding and into costing;

• Enhanced service activity oversight and analytics – for planning and cost containment.

6 CONCLUSIONS AND FUTURE DEVELOPMENT

This proposal argues that AI-KEN has the potential to integrate data from different data sources, normalize that data in accordance with declared transformation rules promoted by intelligent agents and can share the data across a network using blockchain to preserve the integrity, confidentiality and privacy of clinical data. The second layer of functional architecture integrates the data and transforms it into information with validated ontologies. Lastly the third layer transforms the information into knowledge using data analytics models. The authors propose that AI-KEN will be the solution for knowledge construction and the basis for medical good practices development, drugs development and public health policies. While this paper discusses the application of AI-KEN to a use-case in healthcare, these same principles, approaches, architecture and technology developed with AI-KEN can be readily adopted to multiple industry sectors that require technical industry texts linked to industry standardised codes. Examples of other applicable sectors for a framework of semantic intelligence continual improvement include: taxation, accounting, legal, engineering, manufacturing, banking, general finance and carbon markets.

REFERENCES

[1] J. Horsky, E. A. Drucker, and H. Z. Ramelson, 'Accuracy and Completeness of Clinical Coding Using ICD-10 for Ambulatory Visits', AMIA Annu Symp Proc, vol. 2017, pp. 912–920, Apr. 2018.

[2] 'WHO | International Classification of Diseases, 11th Revision (ICD-11)', WHO. [Online]. Available: http://www.who.int/classifications/icd/en/. [Accessed: 14-Jul-2019].

[3] 'SNOMED Home page', SNOMED. [Online]. Available: /. [Accessed: 14-Jul-2019].

[4] 'LOINC Table, Reports, and Users' Guide — LOINC'. [Online], Available: https://loinc.org/downloads/loinc-table/. [Accessed: 14-Jul-2019].

[5] T. Moe, 'Healthcare's Problem: Sacrificing Patients for Paperwork', eFileCabinet, 17-Feb-2016. .

[6] A. Mathioudakis, I. Rousalova, A. A. Gagnat, N. Saad, and G. Hardavella, 'How to keep good clinical records', Breathe, vol. 12, no. 4, p. 369, Dec. 2016.

[7] PMML, 'PMML 4.3 - General Structure'. [Online]. Available: http://dmg.org/pmml/v4-3/GeneralStructure.html. [Accessed: 30-Jun-2019].

[8] L. Palazzo, M. Tossi, A. Dragoni, A. Claudi, D. Gianluca, and P. Sernani, 'A Multi-Agent Architecture for Health Information Systems', ResearchGate. [Online]. Available: https://www.researchgate.net/publication/256553299_A_Multi-Agent_Architecture_for_Health_Information_Systems. [Accessed: 30-Jun2019].