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ELECTRONIC HEALTH RECORDS – WHAT DOES THE FUTURE LOOK LIKE?

Andy Kramer, FLMI
VP, U/W Risk & Innovation
M Financial

Paulo Pinho, MD
Chief Medical & Strategy Officer
Discern Health

Executive Summary *This is the final article in a series on Electronic Health Records. The first article introduced Electronic Health Records, while the second article introduced data standards and the work underway to define data standards for life underwriting. The third article addressed the nuances of structured and unstructured data and how each can be leveraged to make underwriting more efficient. This article pulls all of this together to describe in greater details how data standards will change underwriting in the next decade, driving efficiency, effectiveness and flexibility through the entire life insurance value chain. This article also provides an update on the ACORD project to define data standards for Electronic Health Records.*

Introduction

In the June 2023 edition of *ON THE RISK*, the authors described the evolution of health care data sources and formats currently used in life insurance underwriting. In a follow-up article in the December 2023 edition of *ON THE RISK*, the authors described the importance of data standards and introduce work underway to define data standards for Electronic Medical Records and their use in life underwriting. Earlier in this edition of *ON THE RISK*, the authors described the current evolution and adoption of Electronic Health Records (EHR) in life underwriting. This article concludes the series by describing the second phase of the EHR Data Standards and the underwriting optimization they will enable.

The 1990s ushered in automated underwriting engines and set the groundwork for their rapid adoption. Carriers began providing underwriters with desktop computers and switching from paper files to imaging, with the expectation that new decision engines coupled with a novel file display would drive efficiency and consistent underwriting decisions. While gains in consistency were made, particularly in cases that were standard or better, results of efficiency improvements were mixed. Clerical processes like mail matching benefited from automation, but underwriter efficiency improvements proved elusive. This was due to the intense labor required to translate information from PDF files into structured data and underwriting workbench synopses that could be fed into the decision engines. Since the early 2000s, many carriers have implemented efficiency initiatives that use internal clerical staff to facilitate data entry. Low complexity data entry was sent offshore, and even some technical underwriting interpretation and data entry to attending physician statement (APS) summary services were outsourced.

As mentioned in the December article, new Artificial Intelligence (AI) tools continue to drive improved efficiency, especially with recent landmark gains in generative AI solutions. Their outputs are able to feed the decision engines by structuring unstructured data. However, clinical data standards should be the foundation of this structuring because of their ability to provide consensus-led and consistent data presentation through the entire life insurance value chain. These benefits are similar to those realized in other domains of health data utilization, be it in the payer, provider or public health spaces.

Figure 1. Simple PDF Review Only, No Decision Engine.

Figure 2. PDF and Structured Data Easily Extracted From EHR.

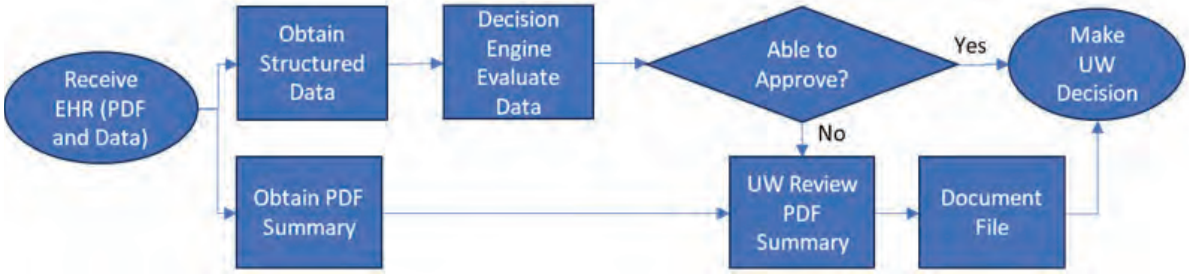


Figure 1 depicts a simplistic underwriting process where the APSs are routed to an APS summary service. When a PDF summary of the medical records is returned, an underwriter receives a CliffsNotes version of the comprehensive medical record in flat file format. Because it lacks a table of contents or hyperlinks, an underwriter's review of the PDF is similar to an APS review—a chronological reading, then documenting the file in the underwriting workbench and finalizing the underwriting decision. The APS summary serves to greatly reduce the medical record page count, but ultimately the process is still heavily dependent on manual underwriter review.

Figure 2 shows an example of a carrier receiving both a PDF EHR summary and structured data capable of being fed into a decision engine. The PDF summary contains a table of contents with hyperlinks to the documents' relevant sections. These documents can be quickly triaged in the process of traditional underwriting, and the underwriter can turn their attention directly to high-severity problems to determine the risk class more easily.

The structured data received is effectively the XML or JSON feeding a style sheet that generates the APS. It contains standard vocabularies and their translations (e.g., SNOMED codes, ICD-9/ICD-10 codes and others that comprise standard health care vocabularies and terminologies) which can be fed into a decision engine to drive automation. While not every decision engine can currently accept and act on these, most carriers and reinsurers have decision engines in development that are geared to do so.

Structured data is well suited for use in these engines, but nuances from the unstructured data (narrative text) may not have structured representation and cannot always be extracted and translated into structured data. In Figure 2, the decision engine identified the relevant medical conditions, resolving those it can. Unresolved conditions get routed to the underwriter for resolution. That underwriter, armed with the APS summary (or possibly the full EHR source documents if necessary), can then action this critical narrative data. While many of the EHR presentation solutions offer this type of PDF summary and the underlying XML or JSON code, few carriers are able to process the data in the stepwise fashion as described above.

Moreover, this approach presents challenges including the vast number of health care concepts and, more critically, their interactions, as well as the rapidly evolving pace of medical change. There are over 340,000 SNOMED codes and 70,000 ICD-10 codes, which are updated at least twice per year with new codes added and old codes removed. A significant resource commitment is required to maintain these codes and, more importantly, to understand their associations.

As a simple example, assume Part 2 of an application indicates the applicant had a skin lesion and was referred to a dermatologist. A generic "skin lesion" diagnosis code in the primary care EHR triggers the rules engine to pause and look for a more specific code from the dermatologist. Without one, the case gets referred to the underwriter, who then reviews the APS summary or the source documents seeking a consult note from the dermatologist, the pathology report or reference to the final diagnosis. This information is used to conclusively determine the pathology of the lesion and its overall risk to underwriting. For

Figure 3. APS Structured Data Output From EHR.

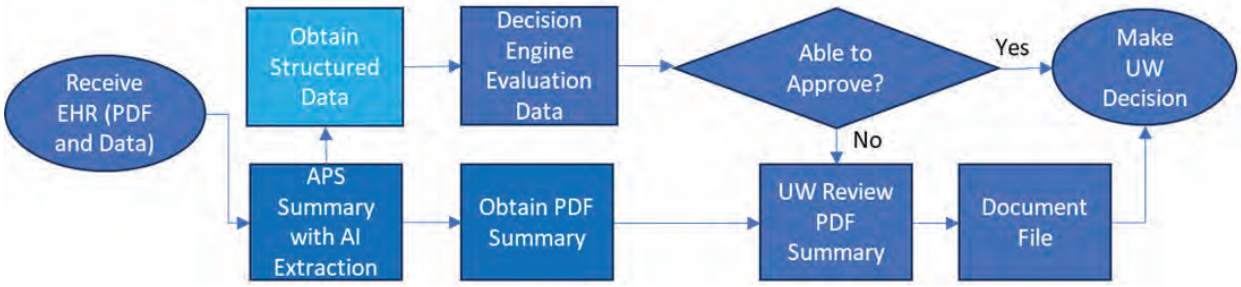
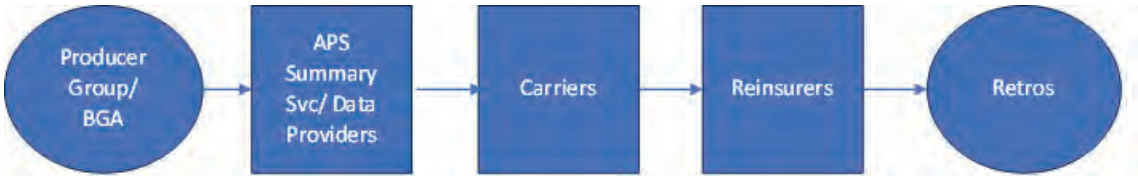


Figure 4. APS Summary Initiated by Producer and Passed to Reinsurers/Retros.



example, a basal cell carcinoma can be documented in the underwriting workbench, leading to manual resolution and ultimate approval.

This process spares the underwriter from the need to review the full medical file, requiring only a resolution to those issues flagged by the decision engine. The APS summary table of contents or index allows them to hone in on the specific diagnosis in question. The decision engine accesses and acts on significant structured data from the Rx, diagnosis (Dx) and laboratory results, but the rich details in the narratives within the records are not accessible without human interaction or additional tools.

Figure 3 displays a slightly more sophisticated approach where the APS summary has a structured data output appended to it. The output contains both the structured data from the EHR JSON or XML, and also unstructured data (file narrative) which through Optical Character Recognition (OCR), Natural Language Processing (NLP) and other Artificial Intelligence (AI) services has been converted to structured data by a vendor. AI has definitively evolved in leaps and bounds over the course of the last year. The one caveat these authors provide is that there is always the possibility of bias and certainly probabilism in these AI algorithms. What has been structured from the unstructured does not represent what was determined by the medical provider at the point of care. The need for audit of random samples to ascertain accuracy is critical, specifically with those concepts that involve feature negation or attribution.

Using Figure 3, assume an APS summary service employing AI interpreted the general practitioner notes referring to the basal cell carcinoma into a structured format that can drive decision engine review. In this case, the disclosed skin lesion issue would be resolved automatically, and the case approved without review by the underwriter, significantly increasing the auto approval rate and reducing the number of cases referred to an underwriter. This substantially improves an underwriter's efficiency and the consistency of offers by eliminating subjective judgment and human error.

ACORD Electronic Health Record Risk Factor Data Standards

The objective of the ACORD Electronic Health Records Risk Factor Data Standards (also called EHR Gen 2) project is to define the risk factors for medical conditions with the greatest prevalence and impact on mortality. Particular attention is given to structured data elements that can be used to quantify the risk and ideally enable an automated decision with the decision engine. This will not only benefit the carrier, increasing the percentage of cases that receive an automatic decision and creating a data structure that will allow efficient and consistent analysis of the underwritten cases. It will also create a standardized format for industry-wide use and interoperability.

At the heart of the concept of interoperability (a foundation to EHR evolution in the health care delivery space), data can be transmitted in a consistent format through the entire life insurance value chain as indicated in Figure 4. This offers significant automation and consistency improvements over the traditional method of sending PDFs that needed to be reviewed by a person.

A future state could involve producer organizations obtaining the medical records, having them summarized by a third party, and providing the PDF summary along with the structured summary data to one or more carriers to efficiently decide on and deliver tentative offers. Once the application is subsequently submitted, it could be automatically approved. If there are medical issues or jumbo limit concerns with the case that require a facultative reinsurance review, that same data feed could be sent to the reinsurers and retrocessionaires, enabling them to greatly automate their facultative triage process. The above example is not an overnight phenomenon and requires industry-wide collaboration, but certainly represents what's possible. Recall that it took almost a decade to get imaging adopted and implemented, with the support of industry and carrier level champions and reliance on change management. This effort will likely require a similar time frame.

The EHR Gen 2 team is composed of representatives from:

- 6 carriers
- 8 reinsurers
- 5 medical data providers
- 3 APS summary services

Representatives on the team include five medical directors, innovation/strategy leaders, enterprise data architects, underwriters and other subject matter experts.

Status of the ACORD EHR Project

Currently, the team has refined the scope and identified a priority list of 200 medical conditions that impact both life and long-term care/disability products. To date, it has defined the risk factors for about 40% of these top 200 medical conditions. Early on, it was decided to avoid mapping medical conditions to SNOMED and ICD-10 codes as part of the data standard. While SNOMED and ICD-10 codes are frequently found in electronic medical records and contain a significant amount of detail critical to risk stratification, the effort to maintain them will be too great as ACORD is a member-supported organization that depends on volunteers. Moreover, the nuanced detail they provide, highlighting disease severity, laterality and acuity, can generate a host of risk profiles that individual carriers and reinsurers can use as differentiators. The maintenance of these mappings is best left to carriers, reinsurers, data providers and rules engine providers where the costs of maintenance can be recovered.

The team has decided to use the Clinical Classification Software Refined (CCSR) codes as our primary taxonomy for major medical conditions. This taxonomy aggregates ICD-10 codes into 530 clinical categories across 22 body systems, making maintenance more manageable than managing the numerous ICD-10 and SNOMED codes. Additionally, there are current mappings maintained between CCSR and ICD-10, and between ICD-10 and SNOMED, making it easy to group both SNOMED and ICD-10 across similar disease concepts.

An example that the team is working on is Type 1 diabetes. We have identified three CCSR codes for this condition:

- END004 Diabetes mellitus, Type 1.
- END002 Diabetes mellitus without complications.
- END003 Diabetes mellitus with complications.

For simplicity's sake, the risk factors identified for Type 1 diabetes are:

1. Duration of the condition (current date minus date of onset/diagnosis).
2. Degree of control as measured by the hemoglobin A1C.
3. Medication prescribed, and the dosage required for control.

Complications include build, hypertension, chronic kidney disease, neuropathy and more. We have identified the CCSR codes for these conditions.

Figure 5 (next page) contains the current relational structure of these vocabulary and terminology concepts stratifying Type 1 diabetes risk. This will undoubtedly continue to evolve over time, but it is a strong start. The team is finding instances where the CCSR code list does not contain a reference to a condition/risk factor pertinent to underwriting decisions. To solve for this, ACORD members voted to append a local code concept to the CCSR classification. This will help drive interoperability within the industry, as this taxonomy ultimately becomes the primary life underwriting taxonomy for medical conditions. Two examples for Type 1 diabetes that did not have a specific CCSR category include complications of diabetic ketoacidosis and diabetic coma. The reader can see that these concepts were given ACORD CCSR codes of END100 and END101.

Figure 5. Relational Structure of Vocabulary and Terminology for Type 1 Diabetes Risk.

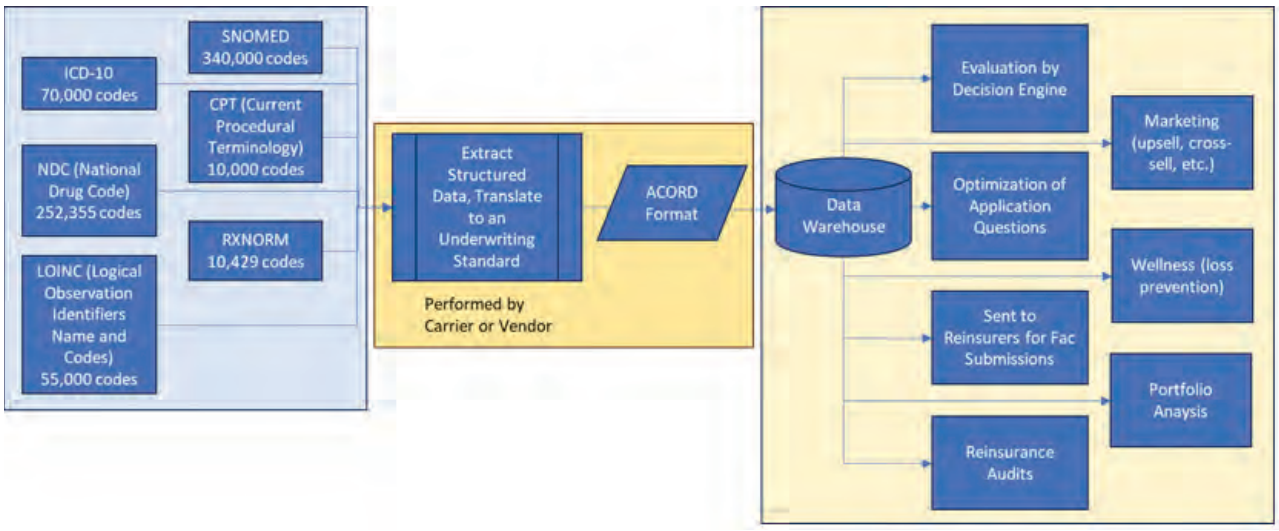
Impairment Category	Condition	CCSR Category	CCSR Category Description	Risk Factors	Risk Factor CCSR Category	Risk Factor CCSR Category Description	Severity	Value	NGDS Mapping
Endocrine	Diabetes Type 1	END004	Diabetes mellitus, Type 1						medicalCondition. {typeCode, description}
		END002	Diabetes mellitus w/o complication						medicalCondition. {typeCode, description}
		END003	Diabetes mellitus with complication						medicalCondition. {typeCode, description}
				Duration			Current date – date of onset	Years	medicalCondition. duration.startDate
							Current age- age of	Years	
				Degree of control			Elevation of A1C	A1C	
							Average A1C		
							Fasting Blood Glucose		
							Proteinuria		
							Albuminuria		
				Treatment/ Dosage			Medication	Medication name	medicalCondition.medication. {genericName, brandName}
							Dosage	Medication dosage	medicalCondition.medication. dosage.{unitCode, number}
				Eyes/ Retinopathy	EYE005	Retinal and Vitreous conditions			medicalCondition. {typeCode, description}
				Diabetic ketoacidosis	END100	Diabetic ketoacidosis			medicalCondition. {typeCode, description}
				Diabetic Coma	END101	Diabetic Coma			
				Build	END009	Obesity			
				Hypertension	CIR007	Essential Hypertension			
				Renal Involvement	GEN003	Chronic Kidney disease			
				Neuropathy	NVS015	Polyneuropathies			
				Eyes/ Retinopathy	EYE005	Retinal and Vitreous conditions			
				Peripheral Vascular disease	CIR026	Peripheral and visceral vascular disease			

Future State Process

EHR data sources, including Electronic Medical Records, Patient Portal Records, Prescription Drug (Rx) Reports and Medical Claims Data (Dx Reports), for the most part are currently used in a PDF format. Many vendors in this space also can provide the data in the native code, which includes vocabularies like SNOMED, RXNORM, ICD-10 and others. This data is provided in multiple standards like C-CDA, FHIR and HL7 which are represented in formats like XML and JSON. Today, based on the ubiquity of PDF as the format of transmission, most carriers have underwriters or APS summary services review, annotate and summarize the PDFs. In the future, to meet the needs of evolving times and changing formats, carriers and APS summary services will need to advance their capabilities to consume and translate these raw data formats into a normalized structure that can be used by decision engines. Figure 6 (next page) shows how this will occur, and where this data can be used to drive additional benefits to the carrier, the insured and supporting reinsurers.

Given the impressive list of variables and their associations, it may not be easy or cost-effective for each carrier to develop and maintain this translation capability. These health care data standards are very dynamic and quickly evolving. Many are updated at least twice a year, with some codes getting removed and others added. Evolving disease trends like COVID-19 and the rapid evolution of personalized diagnostic and treatment options (e.g., cancer) have generated a plethora of diagnosis codes and the LOINCs that diagnose them and provide a prognosis, and the CPTs and RxNorms that treat and manage them. One APS summary service confided that they track over one billion different variables to support this translation process, clearly outside the bandwidth of even the largest carriers and reinsurers in today's industry.

Figure 6.



While some proprietary data standards have evolved in the past few years, their authors, and the members of the ACORD EHR Data Standards team see value in industry-wide conformity through adoption of common EHR data standards capable of driving underwriting data transmission throughout the entire life insurance value chain. That value proposition includes:

- After translation and standardization, consumed client data can be used and reused in a myriad of ways, including, but not limited to, being fed into the decision engine to automate the underwriting decision.
- Analysis to optimize the application and reflexive questions.
- Enabling the automation of the facultative reinsurance process.
- Enabling reinsurance audit automation.
- Identification of good client risk profiles for market segmentation and additional coverage with abbreviated underwriting.
- The growth of optimal wellness offerings to address known risk factors and improve client longevity.
- Actuarial analysis to identify portfolio trends and patterns.

Improvements Enabled in Underwriting

The traditional underwriting process has three distinct challenges that will be addressed by improved adoption of, and improvements in, using EHRs. Those problems are consistency, efficiency and scalability.

Consistency

Common industry wisdom suggests, "If you give a case to five underwriters, you will get five answers." In reality, voluminous data elements need to be considered to make a life underwriting decision, as well as multiple interpretations of the significance of the risk factors identified, and various opinions on the weight placed on credits identified in the file. Increased adoption, consumption and standardization of EHR from applicant records will enable a higher percentage of cases to be approved without review, or with minimal review by an underwriter, thereby improving underwriting consistency. These decisions will be more objective, quantitative and evidence-based, and not be subject to human error, interpretation or bias.

Efficiency

Like consistency, the increase in the percentage of cases that can be automatically approved will drive improved efficiency. If underwriters are only required to review a subset of the cases and a subset of the data in each case, their ability to process cases and time service should be greatly improved.

Scalability

This improved efficiency will enable greater scalability. When volume increases, fewer underwriters will need to be added to the production line.

Underwriting Evolution	Consistency	Efficiency	Scalability
Figure 1 – PDF Review Only	Low	Low	Low
Figure 2 – PDF and Structured Data Easily Extracted from EHR	Moderate	Moderate	Moderate
Figure 3 – APS Structured Data from EHR	High	High	High

The Boundless Possibility of EHR Data Standards

EHRs have evolved quickly in the last few years. Carrier adoption has accelerated rapidly, and the incorporation of EHR into underwriting processes will continue. This current evolution is being led by the larger carriers with teams of data scientists dedicated to improving underwriting automation using data. However, without data standards, this adoption will lack uniformity and only benefit carriers that are investing heavily. It will pose a challenge for these carriers to pass any benefits to their reinsurers, even though doing so could lead to lower reinsurance costs.

The creation of the Electronic Health Record Data Standards for underwriting is primed to catalyze significant automation and efficiency gains across the industry. These gains will benefit all, be it smaller carriers, retrocessionaires and players in between. They will lead to more efficient communication (sending data rather than just PDFs) among all parties, and enable automation to triage and stratify best and worst cases that can be automatically approved/declined, leaving the more complex cases for underwriters to review manually. Vendors have improved their ability to extract data and will continue to do so. Standards will allow for cost-conscious technology connections to transmit data consistently and will enable reinsurers to receive files in a data format rather than a PDF format, driving automation through their homegrown triage tools and thereby reducing cycle time. With evolving health data legislation and interoperability in the health care delivery domain and in the insurance industry, the once novel PDF may become the exception rather than the rule.

Note

If you are interested in participating in this project, please contact one of the authors. Participants are not required to be ACORD members, but only ACORD members will have access to the final data standards when they are published. After publication, the data standards will need to be maintained as the underlying taxonomies evolve and underwriting needs change. We will be seeking involvement to help in the governance and approval processes needed to maintain these standards.

About the Authors

Andy Kramer, FLMI, ACS, has over 30 years of experience in many facets of the industry, from full underwriting at a primary carrier, direct to consumer simplified underwriting, and reinsurance underwriting. Throughout his career he has focused on process improvement activity, which includes obtaining his Six Sigma Master Black Belt certification at GE and overseeing two major underwriting system implementations. Andy has an MBA from the University of Missouri-Kansas City and a BS from Saint John's University (MN).

Paulo Pinho, MD, DBIM, is currently the Chief Medical and Strategy Officer for Discern Health, a predictive analytics company looking to improve healthspans and lifespans of at-risk patients using clinical and social data. Prior to his current role, he was VP and Medical Director for Innovation for Availity Clinical Solutions (formerly Diameter Health), the Chief Medical Officer at Optimum Life Reinsurance, and the Lead Medical Director for Prudential International Insurance's global offerings in Asia and Latin America. Paulo has practiced medicine for close to 20 years. He is dual board-certified in Internal Medicine and Pediatrics and is a Diplomate of the Board of Insurance Medicine. He remains clinically active and is an active volunteer leader with the Arthritis Foundation and with MyLifeSpeaks, an organization that provides care at a village-based clinic near Leogane, Haiti. He enjoys running and has completed a half-marathon in all 50 states.