

Intelligent Mortality Reporting With FHIR

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Abstract—One pressing need in the area of public health is timely, accurate, and complete reporting of deaths and the diseases or conditions leading up to them. Fast Healthcare Interoperability Resources (FHIR) is a new HL7 interoperability standard for electronic health record, while Sustainable Medical Applications and Reusable Technologies (SMART)-on-FHIR enables third-party app development that can work “out of the box.” This paper demonstrates the feasibility of developing SMART-on-FHIR applications that enables medical professionals to perform timely and accurate death reporting within multiple different USA State jurisdictions. We explored how the information on a standard certificate of death can be mapped to resources defined in the FHIR standard Draft Standard for Trial Use Version 2 and common profiles. We also demonstrated analytics for potentially improving the accuracy and completeness of mortality reporting data.

Index Terms—Biomedical informatics, health information management, public healthcare.

I. INTRODUCTION

THERE are approximately 56 million deaths per year worldwide [1], with 2.6 million happening in the United States of America (USA) [2]. Accurate and timely mortality reporting is essential for gathering this important public health data in order to formulate emergency response to epidemics and new disease threats, to prevent communicable diseases such as flu, and to determine vital statistics such as life expectancy, mortality trends, etc. However, accurate collection and aggregation of high-quality mortality data remains an ongoing challenge primarily due to issues such as the average low frequency with which physicians perform death certification (on the order of 1-2 times a year), inconsistent training in determining the causes

of death, complex data flow among the funeral home, the certifying physician and the registrar, and non-standard practices of data acquisition and transmission [3], [4]. In addition, the US National Center for Health Statistics (NCHS) aggregates mortality data from the 57 reporting jurisdictions around the country, where the precise regulations and local laws of each reporting jurisdiction differ [5]. Current efforts towards mortality reporting standardization using technologies such as Clinical Document Architecture (CDA) [6], [7] and Health Level 7 (HL7) V2 [8] have some shortcomings in integrating with large-scale web services, and Integrating the Healthcare Enterprise (IHE) have limited adoptions that result in the non-optimal flow of information among various providers and registrars. Thus, the emerging solutions are (1) to use the new meaningful use of electronic health records (EHR) as the government requires healthcare institutions to show at least partial support of patient-facing application programming interfaces (APIs) for sharing data, interoperability and clinical decision support [9]; and (2) to develop a death decision support system capable of assisting the physician in determining the appropriate cause of death to put on the death certificate in a standardized format.

In this article, we designed and developed a platform that utilizes the new HL7 health standard Fast Healthcare Interoperability Resources (FHIR) to access EHR data. FHIR aims to streamline and standardize healthcare communication in electronic death reporting using a resource-centric approach (as opposed to document-centric) to specify data elements. It adopts existing technologies such as RESTful (Representational State Transfer) APIs, OAuth security, and XML (Extensible Markup Notation)/JSON (JavaScript Object Notation) data to form an application platform [10]; it uses APIs to work with current EHR systems and supports the addition of data analytics [11], [12]; and it is vendor-neutral and scalable. Specifically, FHIR can pre-populate sections of the death certificates to provide information from the decedent’s health history. Also, it can incorporate data-driven analytics to provide mortality decision support for physicians in reporting the causes of death. Ultimately, the accurate and timely reporting will provide valuable mortality information for registrars, public health departments, and other authorized parties in deciding public policies. We have presented a preliminary version of this work at the IEEE Biomedical and Health Informatics (BHI) conference in February 2017 [13]. In this article, we report the complete system.

II. WEB APPLICATION DESIGN

To enable timely, accurate, and complete capture of the chain of diseases or conditions leading to death, we developed

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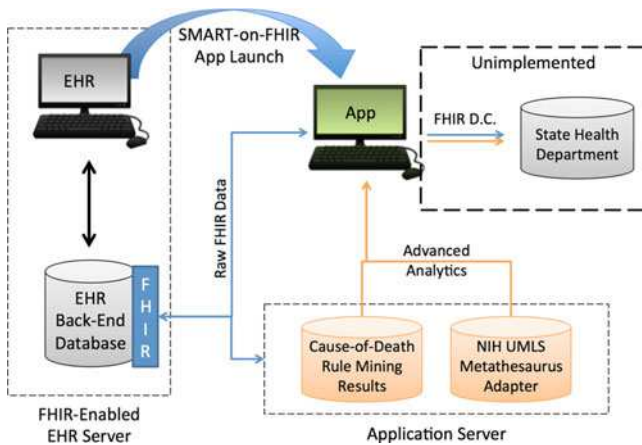


Fig. 1. Proposed infrastructure for death reporting application. A user's existing EHR system with compatible FHIR interface can directly launch the application with patient context. The application can contact an internal or external analytics server for decision support and other tools, before packaging the death certificate object and sending it.

SMART-on-FHIR-based mortality reporting system consisting of two parts as shown in Fig. 1 architecture diagram: the SMART-on-FHIR compliant EHR server, and the application server. First, we developed a SMART-on-FHIR JavaScript client library (<https://github.com/smart-on-fhir/client-js>) being tested over a virtual FHIR server. Using this library and HTML (Hypertext Markup Language) JavaScript, we implemented a web application that securely accesses the FHIR server using OAuth2 authentication. Then we developed interactive visualization of a large portion of the decedent's health history by using simple RESTful interfaces to UMLS (Unified Medical Language System) and data mining functionality. The application's graphical user interface (GUI) is broken into sequential pages, with each page addressing a section of the death certificate to assist in determining the causes of death. Because US mortality reporting has adopted the ICD-10 standard since 1999, by using UMLS Metathesaurus, our application enables crosswalk among medical event coding systems, and allows interoperability among records retrieved from a variety of coding systems and downstream analytics.

To aid in GUI prototyping, we used synthetic patient data available in the Cerner SMART-on-FHIR app development sandbox (<https://code.cerner.com>). As shown in Fig. 2, diseases and conditions displayed on the timeline are spaced logarithmically, with the axis anchoring at the time of death. The interactive patient history timeline is generated using the D3 and D3-tip visualization libraries (<https://d3js.org>, <https://github.com/Caged/d3-tip>). This enables simultaneous visualization of events occurring around the time of death, along with relevant context from the patient's more distant history. The events shown on this timeline are generated using Condition resources accessible through the FHIR server. In addition, scrolling adjusts the scaling to allow users to focus on distant past or recent events. The bottommost section is designed to recreate the familiar-to-users appearance of the cause-of-death field layout in the US Standard Certificate of Death, with a chain of one or more causes occurring as consequences of one



Fig. 2. Prototype application user interface. The web-based application runs in the user's browser. The app pulls patient information and notes from the EHR to provide context. Conditions are laid out on a timeline, alongside proposed sequential linkages between those events. Several conditions are selected. The user can edit, add, or remove conditions.

another. Buttons are provided to access additional pages with fields such as injury information, the provider's information, and submission / download controls.

The application can be downloaded from <http://miblab.bme.gatech.edu/software>. In addition, we include the output of the application after initial processing of the Cerner sandbox test patient "Joe Smart" as a supplementary file "sample.json" for this article.

III. REPRESENTING DEATH CERTIFICATE DATA IN FHIR

Unlike the older HL7 CDA document standard, FHIR documents are modular compositions of full EHR Resources, which can be readily split apart and incorporated into another interoperable system. FHIR documents are a Bundle of resources, where the first entry in the Bundle is a Composition that contains a human readable summary of the Bundle's contents. Additional Resources are then added to the bundle to support the information contained in the document. A significant milestone in developing a FHIR-based electronic death record (EDR) is the mapping of all elements in a death certificate to FHIR Resources and common profiles. Our mapping is: (i) easy to use so that application developers can get what various Resource elements are used for; (ii) scalable and modular so that the rich variation in data elements in different USA State's health agencies can be represented by an interoperable set of Resources, contained in a Bundle; (iii) idiomatically correct so that potential users do not misuse the standard fields; and (iv) designed with stakeholders' current data practices in mind to mirror existing processes wherever feasible so that the integration friction is minimized and

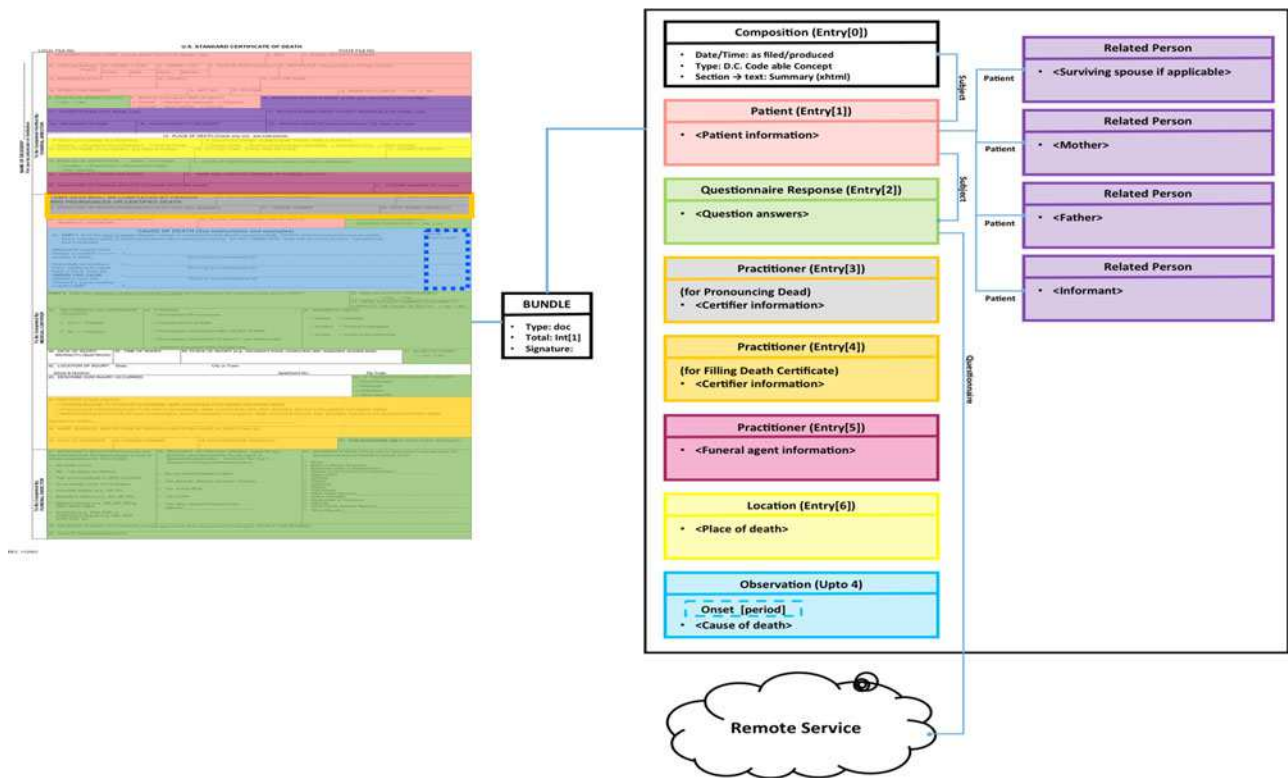


Fig. 3. Resource-level mapping overview. (Left) The U.S. Standard Certificate of Death is overlaid with colored blocks representing mapped FHIR resources, to be bundled into a death certificate document (Right). The exact number of Conditions will vary with the circumstances of death, and specific observations may be specified by public health reporting jurisdictions.

TABLE I
DEATH RECORD LAYOUT IN MULTIPLE CAUSE-OF-DEATH MORTALITY DATA FROM NCHS

Type	Information Included
Demographics	Age, Gender, Residence, Death Time, etc.
Underlying Cause of Death	Cause of death coded according to ICD and several other coding systems.
Conditions	A maximum of 20 conditions that correlate with the death
Race and Ethnicity	The reported race for States that are reporting single race or the bridged race for States that are reporting multiple race.

TABLE II
FREQUENT SEQUENCE COUNT OF DIFFERENT LENGTHS

Length	Count
2	22,450
3	29,344
4	7,661
5	405
6	4
≥7	0

more adoption is accomplished. In this application profiling, we mapped death certificate data to FHIR Draft Standard for Trial Use (DSTU) 2 resources and data elements because it has much wider acceptance over the newer Standard for Trial Use (STU) 3 version at the time of development.

We used the standard FHIR metaphor of a “document” to represent a death certificate object. As illustrated in Fig. 3,

we profiled a FHIR document with a defined minimum set of resources to represent death certificate data elements. To maximize its usefulness and to enable interoperability before electronic death reporting systems are truly or fully FHIR-enabled, we have completed a mapping of this profile FHIR resource data elements to known standard HL7 Vital Records Domain Analysis Model (VR DAM) section on mortality reporting. The complete mapping table is available as a supplementary file “mapping.xlsx” for this article.

Some death certificate data elements map very naturally and directly to FHIR Resources (e.g., the decedent name and address map directly to a FHIR Patient). Others require more careful thought and design. For example, to choose between FHIR Patient.contacts or RelatedPersons in representing the decedent’s family members, assuming both representations are complete, are able to represent all of the data elements from the U.S. Standard Certificate of Death and the HL7 VR DAM without extension, and are easy to understand, the deciding factor becomes

TABLE III
RULES FROM 2012 NCHS MORTALITY DATA

Rule	Count	Percent
Unspecified mental and behavioral disorder due to use of tobacco -> Chronic obstructive pulmonary disease, unspecified	99587	3.91%
Unspecified mental and behavioral disorder due to use of tobacco -> Malignant neoplasm of bronchus or lung, unspecified	72211	2.83%
Atherosclerotic heart disease -> Cardiac arrest, unspecified	70490	2.77%
Rheumatic heart disease, unspecified -> Atherosclerotic heart disease	62927	2.47%
Rheumatic heart disease, unspecified -> Cardiac arrest, unspecified	56497	2.22%
Atherosclerotic heart disease -> Acute myocardial infarction, unspecified	45916	1.80%
Atherosclerotic heart disease -> Congestive heart failure	45721	1.79%
Unspecified mental and behavioral disorder due to use of tobacco -> Atherosclerotic heart disease	44285	1.74%
Rheumatic heart disease, unspecified -> Congestive heart failure	42919	1.68%
Unspecified mental and behavioral disorder due to use of tobacco -> Rheumatic heart disease, unspecified	38518	1.51%
Congestive heart failure -> Cardiac arrest, unspecified	35406	1.39%
Rheumatic heart disease, unspecified -> Unspecified diabetes mellitus without complications	34966	1.37%
Unspecified diabetes mellitus without complications -> Atherosclerotic heart disease	33793	1.33%
Chronic obstructive pulmonary disease, unspecified -> Respiratory failure, unspecified	32287	1.27%
Rheumatic heart disease, unspecified -> Acute myocardial infarction, unspecified	32042	1.26%
Hyperlipidemia, unspecified -> Rheumatic heart disease, unspecified	31846	1.25%
Chronic obstructive pulmonary disease, unspecified -> Cardiac arrest, unspecified	30581	1.20%
Rheumatic heart disease, unspecified -> Chronic obstructive pulmonary disease, unspecified	29440	1.16%
Unspecified diabetes mellitus without complications -> Rheumatic heart disease, unspecified	29211	1.15%
Rheumatic heart disease, unspecified -> Stroke, not specified as hemorrhage or infarction	28401	1.11%

“idiomatic FHIR correctness” – i.e., which choice most clearly follows from the originally intended uses. The contacts field of a FHIR Patient is intended primarily to enable contacting the patient or his/her decision-makers in a clinical setting, whereas RelatedPerson resources are sources of patient information with non-healthcare relationships to the patient.

Another informative example is the choice between a collection of Observation resources or Questionnaire/QuestionnaireResponse resources to represent the demographics and medical history sections of the death certificate (shown in green in Fig. 3). Using questionnaire to represent a list of questions on a physical death certificate form is attractive. However, we used Observations instead because the variations in lists of medical history questions and valid responses among different US State reporting jurisdictions makes it infeasible to develop a single comprehensive Questionnaire for the entire US. If each jurisdiction were using a unique, “flat” Questionnaire to represent their set of questions and answers, it would complicate the processes of designing decision support systems in US interoperable across 57 State jurisdictional boundaries.

IV. SEQUENTIAL PATTERN MINING ANALYTICS

As illustrated in Fig. 1, with FHIR-based platform in place, using data-driven analytics to extract possible causes of death can help accomplish timely, accurate mortality reporting. Thus, we have tried sequential pattern mining on one year of US public causes of death data from the National Center for Health Statistics in US National Vital Statistics System (NVSS) to derive a list of frequent sequences of events (i.e., diseases and conditions) that may have led to death.

The temporal models commonly seen in the literature are sequence analysis [15]–[19] and association rule mining [18], [20], [21]. Sequential Pattern Mining (SPM) seeks temporal relationships among a sequence of events [22], [23] with multiple algorithmic approaches such as AprioriAll [24], SPADE [25],

PrefixSpan [26], and MEMISP [27]. In diseases modeling with multiple patient conditions, Association Rule Mining (ARM) [23] only outputs rules like “[Condition 1, Condition 2]”, meaning that Condition 1 is likely to coexist with Condition 2 for some confidence. It doesn’t take temporal relations into consideration. On the other hand, SPM outputs an ordered list of sequences relate to the target outcome with rules such as “Condition 1 -> Condition 2”, which means that if we observe Condition 1, we can assert that Condition 2 will possibly follow Condition 1. SPM was applied successfully to clinical data [28], [29] ranging from heart disease prediction [30], healthcare auditing [31], neurological diagnosis [32], and violent death reporting [33]. Thus, we chose SPMs to discover the most probable sequence of events that lead to a death to help certifying physicians in filling out death certificates.

A. SPM Problem Formulation

Through the National Vital Statistics System (NVSS), the National Center for Health Statistics aggregates data from death certificates reported by 57 vital records jurisdictions across the United States [14]. Each record in this data set contains a list of ordered conditions (up to 20 conditions) that could lead to a person’s death as the causes of death recorded by physicians, medical examiners, and coroners, and other details such as the demographics, race and ethnicity. The available fields are shown in Table I.

In SPM, support of a candidate pattern is the proportion of sequences in the data that exhibit the pattern [34]. The relative support of a rule R in the set of sequences D is defined as the percentage of sequences that contain this rule, i.e.,

$$rel_support(R) = \frac{| \{ S | S \in D \& R \subset S \} |}{|D|},$$

where $| \cdot |$ is the cardinality of a set. SPM aims to discover sequential patterns that have support larger than a pre-specified

minimum support (e.g., the support is a number between 0 and 1 and we can specify the minimum support of a pattern of interest). If we use $C = [C_1, C_2, \dots, C_K]$, $K = 20$ to represent 20 unique underlying conditions/diseases as the causes leading to death, under a pre-specified minimum support requirement, SPM will discover all valid sequential patterns $S = \langle s_1, s_2, \dots, s_T \rangle$ that can occur. More specifically, we used one SPM approach BI-Directional-Extension-based frequent closed sequence mining (BIDE) proposed by Wang *et al.* [35]. Closed frequent sequences are those sequences that are not subsets of other frequent sequences having equal support. Because conventional sequence mining algorithms must maintain a list of discovered closed sequences, while using the patterns to determine whether new sequences are promising to be closed, it cannot scale up in both time and storage for the number of frequent closed sequences. Thus, the BIDE approach was developed by Wong *et al.* to find all the frequent closed sequences without candidate maintenance.

In our project, under given outcomes (i.e., mortality) and comorbidities, we applied BIDE to find the list of most frequent sequence conditions $S = \langle s_1, s_2, \dots, s_T \rangle$ that can occur. Using 2012's Multiple Cause-of-Death Mortality Data from the NVSS public that contains 2,547,864 deaths, we set the minimum support to be approximately 2×10^{-5} (equivalent to 50 occurrences for this data set). We identified a total of 59,864 frequent closed sequences of length-2 or greater for the most frequent sequences of diseases or conditions before people's deaths as shown in Table II. We present the top 20 sequences of length-2 in Table III for illustration. The full table is available as supplementary file "patterns.xlsx" in this article.

To use these analytics for FHIR-enabled mortality reporting, a lookup table service with simple CGI-based API is developed to access the full results, where a user can review the most frequent patterns present in a given patient's history as illustrated in orange in Fig. 2.

V. CONCLUSION AND FUTURE WORK

This work demonstrates the feasibility of using the SMART-on-FHIR application framework in order to improve the timeliness and accessibility of public health mortality reports. This platform is able to incorporate intelligent analytics to further improve the accuracy of death reporting. Future work includes: (i) using alternative data sets, and more complete patient information made accessible through the interoperability of FHIR, to construct more personalized and precise analytics systems; and (ii) developing precise FHIR resource profiles to concisely, completely, and flexibly represent death certificate data.

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