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HEALTHINFO 2020

Forward

The Fifth International Conference on Informatics and Assistive Technologies for Health-Care, Medical Support and Wellbeing (HEALTHINFO 2020), held on October 18 - 22, 2020, tackles with particular aspects belonging to health informatics systems, health information, health informatics data, health informatics technologies, clinical practice and training, and wellbeing informatics in terms of existing and needed solutions.

The progress in society and technology regarding the application of systems approaches information and data processing principles, modeling and information technology, computation and communications solutions led to a substantial improvement of problems in assistive healthcare, public health, and the everyday wellbeing. While achievements are tangible, open issues related to global acceptance, costs models, personalized services, record privacy, and real-time medical actions for citizens' wellbeing are still under scrutiny.

We take here the opportunity to warmly thank all the members of the HEALTHINFO 2020 technical program committee as well as the numerous reviewers. The creation of such a broad and high quality conference program would not have been possible without their involvement. We also kindly thank all the authors that dedicated much of their time and efforts to contribute to the HEALTHINFO 2020. We truly believe that thanks to all these efforts, the final conference program consists of top quality contributions.

This event could also not have been a reality without the support of many individuals, organizations and sponsors. We also gratefully thank the members of the HEALTHINFO 2020 organizing committee for their help in handling the logistics and for their work that is making this professional meeting a success.

We hope the HEALTHINFO 2020 was a successful international forum for the exchange of ideas and results between academia and industry and to promote further progress in health informatics research.

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A Mobile Health Application for Medication Reconciliation using RxNorm and FHIR

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***Abstract*— Medications are a large and growing component of the prescriber's armamentarium and are the first line treatment for 88% of chronic diseases. The percentage of patients taking multiple prescription medications is also increasing. According to the most recent data (2011-2014) from the Centers for Disease Control and Prevention (CDC), 40.7% of seniors (65 years or older) and 10.9% of the total population were taking five (5) or more prescription medications within the past 30 days. For seniors, the 40.7% represents almost a three-fold increase from the period of 1988-1994 (13.8%). Because a patient's medication regimen is the basis for many treatment decisions, it is extremely important that medication lists are accurate in order to maximize therapeutic impact and prevent potentially life-threatening patient safety events. This paper presents our work on a mobile health (mHealth) application for medication reconciliation that can: retrieve medications from multiple electronic health records, personal health records, and other health information technology systems; combine and reconcile medication into a medication list that identifies potential conflicts between the same and/or different medications; develop an adaptive multi-use algorithm for medication reconciliation for multiple medications pulled from different sources; and, provide a Fast Healthcare Interoperability Resources FHIR-based extensible software solution for medication reconciliation which can seamlessly include new medication sources and algorithm modifications.**

Keywords-Medication reconciliation; FHIR; Mobile health; Interoperability

I. INTRODUCTION

The healthcare industry is increasingly adopting new techniques for sharing secure healthcare data. Health Information Exchange (HIE) [1] allows multiple Health Information Technology (HIT) systems (e.g., electronic health records (EHRs), e-prescribing systems, pharmacy information systems, patient portals, etc.) to interact with one another in order for healthcare data to be effectively shared between providers. This has the potential to both positively affect patient outcomes and satisfaction. This exchange is increasingly being facilitated utilizing newer standardized technologies such as the Fast Healthcare Interoperability Resources (FHIR) [2], a health information exchange (HIE) standard created by HL7 to promote secure sharing of healthcare data among multiple health information technology (HIT) systems.

Medications are one of the most critical kinds of healthcare data that need to be shared. Medications are a large and growing component of the prescriber's armamentarium and are the first line treatment for 88% of chronic diseases [3]. The percentage of patients taking multiple prescription medications is also increasing. According to the most recent data (2011-2014) from the Centers for Disease Control and Prevention (CDC), 40.7% of seniors (65 years or older) and 10.9% of the total population were taking five (5) or more prescription medications within the past 30 days. For seniors, the 40.7% represents almost a three-fold increase from the period of 1988-1994 (13.8%). Because a patient's medication regimen is the basis for many treatment decisions, it is extremely important that medication lists are accurate in order to maximize therapeutic impact and prevent medication misadventures which could potentially result in life-threatening patient safety events. Recognizing this critical need, the Connecticut General Assembly in May 2018 passed Special Act 18-6: An Act Requiring the Health Information Technology Officer to Establish a Working Group to Evaluate Issues Concerning Polypharmacy and Medication Reconciliation (MRP Workgroup) [4]. This paper reports on our efforts to develop a mobile health application for medication reconciliation that integrates information from multiple HIT systems.

The MRP Work Group utilized the Joint Commission's (TJC) [5] definition of Med Rec:

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"Medication reconciliation is the process of comparing a patient's medication orders to all of the medications that the patient has been taking. This reconciliation is done to avoid medication errors such as omissions, duplications, dosing errors, or drug interactions. It should be done at every transition of care in which new medications are ordered or existing orders are rewritten. Transitions in care include changes in setting, service, practitioner, or level of care. This process comprises five steps:

1. Develop a list of current medications;
2. Develop a list of medications to be prescribed;
3. Compare the medications on the two lists;
4. Make clinical decisions based on the comparison; and
5. Communicate the new list to appropriate caregivers and to the patient."

The current medication management process often impedes our ability to determine a current and accurate list of medications for each patient. Major challenges of the current state include:

- Despite widespread adoption of (attempting to perform) medication reconciliation at each transition of care, a large number of medication-related errors occur.
- Substantial difficulty remains in compiling a patient's medication list from numerous disparate sources, often containing duplicate, missing, or inaccurate information.
- Not knowing a clear indication or reason why each medication was prescribed impedes best practice for both pharmacist and physician decision-making and reduces patient understanding and engagement.
- Under-utilization of the available messaging standard, CancelRx, to electronically discontinue a medication puts patients at risk for adverse outcomes and this standard should be more routinely adopted and used by prescribers and pharmacies.
- Physicians often bear the responsibility for reconciling complex medication regimens outside their professional expertise and this can have a significant impact on effective medical decision-making. A robust solution that allows shared reconciliation of medications could potentially improve this.
- We currently lack an efficient, effective, and patient-centric means of incorporating patient-reported medications and a method of sharing that information in a methodical manner.

Current EHRs have built-in processes for updating the patient's medication list from external sources using national health networks (e.g., Surescripts) using similar data sharing standards and even share it with other EHRs. However, this often creates a number of unique instances of a list of current medications that exist in data silos. An interoperable "Medication Service" available to each data user could allow the HIE to host the patient's current med list and allow each EHR to interact and update the HIE list, rather than create a standalone list that may no longer be up to date beyond the single EHR encounter.

The work reported in this paper is the first step to collect and reconcile medications across disparate clinical and pharmacy information systems. An enhanced solution for medication reconciliation has the potential for substantial safety benefits. An additional intent of this paper is to address the industry recognition that there is under-documentation of patients' over-the-counter medications and supplements that could potentially be improved through a patient-facing system. The primary objective of this paper is to explore current technology standards, such as the FHIR RESTful API and other data standards, that could support medication reconciliation and improve the acquisition of a more accurate medication list from a number of electronic and human sources. In support of this, we discussed the current development of a new mobile health application and its user interface and features that can be leveraged by a patient (or guardian/parent) to report useful information (e.g., side effects, adherence, and undocumented OTC meds, prescriptions and supplements) that is often overlooked today. This should lead to the improvement of the longitudinal sharing of this information across the various health IT platforms and venues of care.

This paper presents our work on a mobile health (mHealth) application for medication reconciliation that can: retrieve medications from multiple electronic health records, personal health records, and other HIT systems; combine and reconcile medication into a medication list that identifies potential conflicts between the same and/or different medications; develop an adaptive multi-use algorithm for medication reconciliation for multiple medications pulled from different sources; and, provide a FHIR-based extensible software solution for medication reconciliation which can seamlessly include new medication sources and algorithm modifications. The remainder of this paper is organized into 4 additional sections. Section II presents background on medication reconciliation, relevant medication standards such as National Drug Code (NDC), RxNorm, and RxTerms and the browser RxNav, and FHIR. Section III introduces our approach and efforts in medication reconciliation. Section IV presents a discussion of our prototype mobile health application for medication reconciliation. Section V has a conclusion for the paper.

II. BACKGROUND

This section provides background information for the remainder of the paper. Section II.A provides a brief introduction to medication reconciliation in the medical field. Section II.B reviews two common drug nomenclature and identifier systems, NDC, and RxNorm. Section II.C briefly reviews the FHIR standard.

A. Medication Reconciliation (Med Rec)

An optimal Med Rec process would begin with an accurate list of the patient's current medications. We often find it difficult to establish an individual's true and accurate list of medications. It is not uncommon for each caregiver and the patient to have their own unique version of "current medications". Unfortunately, medication errors due to omission (missing medications) and commission (giving the wrong medication, duplications, and mis-dosing) are all too common.

The very tools we designed to help us make clinical care safer and more efficient, such as ePrescribing (ordering medications electronically), and our EHRs, may have inadvertently led to further complexity as we store information in different formats and locations, often complicating our efforts to access and collate it accurately. One significant opportunity to improve clinical care and reduce unnecessary harm is our vision to develop and maintain an up-to-date, accurate, and shareable medication list for patients, their families, and clinical

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providers. Experts and accrediting bodies champion medication reconciliation as a solution to "get everyone on the same page" [6]. Despite this effort, obtaining a true and accurate list of medications remains elusive due to a multitude of problems.

The current state of medication management in the U.S. is significantly tied to transitions of care, which represent the most dangerous time for patient care due to communication gaps as one (or more) provider(s) hands off to another provider(s). Transitions of care can occur in all of the following settings:

- Ambulatory Office visits with Primary Care or Specialty Clinicians
- Emergency Department visits
- Admissions to a hospital or skilled nursing facility
- Transfer from one level of care to another within the same facility (e.g., critical care to standard inpatient care and vice versa)
- Hospital discharge to home

Forty percent of Americans have one or more chronic conditions and take more than one medication [7]. As age increases, the number of chronic conditions and medications increase. According to the CDC, by age 85, most individuals have two or more chronic conditions and take six or more medications [7]. In the United States, formal medication reconciliation occurs over 1 billion times each year and consumes over 64 million person-hours (> 32,000 Full-Time Equivalents) of physician, pharmacist, and nursing time [3]. Transitions of care between one care location and another are the most dangerous times for patients due to communication gaps (i.e., lack of transfer of an accurate medication list). This is especially true when a different (or no) HIT system or EHR is used between care locations, with medication errors a major component of this harm. In fact, medication errors account for over 1 million ED visits, 3.5 million physician office visits, and over 125,000 hospital admissions annually [7].

It should be possible to address all of these issues, by defining a digital health service within the HIE that would compile a list of medications from various HIT systems into a single source-of-truth database which users would access seamlessly within their clinical and pharmacy HIT systems for medication management. A single place to manage transactions (add, modify, cancel, comment, validate, and reconcile) can theoretically improve medication management safety and reduce medication-related errors, even ensuring that the "right prescriber" validates and updates the right information on a patient's medication list, reducing the risk that specialists and primary care physicians would inadvertently make errors on medications prescribed outside the scope of their usual clinical practice. In support of this, Connecticut is in the midst of developing a "Network of Network" HIE that will use a modern API and Web-service architecture. Medication Reconciliation is one of the stated "Use Cases" that this HIE is attempting to improve. The challenge of data silos for medication is exacerbated by proprietary semantic and database ontologies and storage differences between EHR systems. In addition, the "prescribed" medicine in an EHR might be different (brand name) than a filled medication at a pharmacy (generic). Correctly matching them via corresponding product identifiers (RxNorm, NDC) linked through standardized mapping tables is an area needing further research, which will be one of our tasks. FHIR, a requirement for the Office of National Coordinator (ONC) certification for EHRs, can extract data from each of these source HIT s and affords a potential to aggregate through the HIE and direct abstraction from various EHRs to combine data. We have already set up a series of FHIR enabled data sources to evaluate de-duplication, semantic matching, and data presentation layers to allow end users to visually understand and choose the best medication list that can be shared back to various source systems via another FHIR interface.

B. NDC, RxNorm, RxTerms, and RxNav

An NDC [9] code is required for each medication under the authority of the Food and Drug Administration (FDA) and are 10-digit/character, 3-segment numeric identifier assigned by the FDA to each product. The FDA registers an NDC for each medication intended for human use, yet those codes can be recycled at times and therefore may not be unique to each medication. Each NDC code contains 3 segments that identify the vendor, product and trade package of the drug:

- Segment 1: is 4-5 digits long and represents the "Labeler code" A labeler is any firm that manufactures, repacks, or distributes a drug product.
- Segment 2: is 3-4 digits long and identifies a specific strength, dosage form, and formulation of a particular firm/manufacturer.
- Segment 3: is 1-2 characters long and identifies the package forms and sizes. This segment may contain numbers and/or letters.

NDC's have been historically reused from time to time. Note also that CMS has created an 11-digit NDC derivative to create a fixed 5-4-2 segment length with a leading zero as needed in each segment. Some applications use a 9-digit code with a 5-4 representation of first two segments (whenever packaging is irrelevant.). Despite their flaws, NDCs are used primarily for billing and have become ubiquitous in EHRs and PHRs as a product identifier to aid in interoperability.

RxNorm [10], produced and updated weekly by the National Library of Medicine (NLM) is a free drug terminology that provides standard normalized names (active ingredient + strength + dose form) and unique identifiers for commercially available drug products. It serves as a tool for supporting semantic interoperability with the goal of efficiently and unambiguously communicating drug-related information. RxNorm creates an RxNorm name for every unique concept and assigns an RxNorm concept unique identifier (RxCUI) to each concept and a RxNorm atom unique identifier (RxAUI) to each atom. Furthermore, RxNorm creates RxNorm names and relationships with different levels of granularity (e.g., ingredient + strength or ingredient + dose form) and uses term types (TTYs) to delineate branded and generic drugs names at different levels of specificity (e.g., Sematic Clinical Drug [SCD], Semantic Brand Drug [SBD])

In the spring of 2019, the University of Connecticut hosted a Medication Reconciliation Hackathon [10] that demonstrated how current and emerging technology standards, such as the FHIR RESTful API and RxNorm, could improve the acquisition of a medication list and permit new user interfaces and features (e.g., specialty applications or features in a patient portal that could empower the patient (or guardian/parent) to report useful information (e.g., side effects, adherence, and undocumented OTC meds, prescriptions, and supplements)) and improve the

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longitudinal sharing of this information across platforms and venues of care.

RxTerms [12] improves drug search capabilities by further normalizing the full drug names found in RxNorm. While RxNorm presents full drug names in multiple formats identified by a term type, the RxTerms database separates RxNorm's full names into drug name + route and strength + dose form. The increased granularity of medication names allows easier automatic matching to EHR medication lists, where prescriptions may be recorded with more free-form names that do not match any of the provided RxNorm term type formats. Once a drug name has been identified via an RxTerms search, the RxCUI, for the drug can be retrieved and utilized to match discovered drugs with the entries in RxNorm.

RxNav [13] is a browser that ties together multiple medication information sources including RxNorm and RxTerms. The RxNorm and RxTerms sources are also provided through a REST API, allowing access to both RxNorm and RxTerms databases through simple REST calls including: search by RXCUI or NDC, approximate term search, search by RxNorm full name parts, and support for drug-drug interaction search. RxNav also provides the RxNorm and RxTerms data sets as downloadable databases for more efficient local search.

Utilizing the APIs provided by RxNav, the RxNorm, RxTerms, and RxCUI provide a powerful combination for parsing natural language or free-text entered prescriptions and identifying potential duplicates. RxNorm, through its approximate term search, provides a list RxCUIs corresponding to possible candidate drugs and RxAUIs. With these IDs, a search by RxCUI retrieves the full name of the candidate medications which can be matched against records pulled from EHRs. An RxTerms search by the RxCUI retrieves a full normalized version of the drug name and dosage, allowing easier matching when the medication entry provided by the EHR combines the drug name and dosage in one field. The enhanced capabilities of RxTerms eases the identification of potential duplicate entries caused by mismatches of the dosages in the EHR.

RxNorm is often used for clinical decision support (CDS) systems that determine risks for drug-drug, drug-food and drug-allergy interactions. Lack of such a system puts reliance on free-text entry of medications which would limit the ability for clinical decision support (CDS) rules to address duplications, interactions, and validations. However, while RxNorm can assist in providing a single source of truth normalization, gaps remain in ensuring an accurate summary of a patient's comprehensive medication regimen. Furthermore, RxNorm is still being continuously expanded and may lack some over-the-counter (OTC) medications and supplements, which may interact with the patients current prescribed medications thereby hampering full interoperability. This can therefore jeopardize the comprehensiveness of the vital link among physicians and pharmacists and impacts the efficiency, effectiveness, and safety of the medication reconciliation process. That said, RxNorm hold great promise and may be a superior system to NDC's [33].

C. The Fast Healthcare Interoperability Resource, FHIR

The Office of the National Coordinator for Health Information Technology (ONC) under the U.S. Department of Health and Human Services continues to drive the adoption of digital health records and their interoperability. With this comes a drive to improved sharing of information among providers of healthcare. All of this occurs with the overarching need to address the privacy and security of medical information. The recently announced 21st Century Cures Act NPRMs from ONC and CMS specify the use of FHIR as the API for EHR certification and access to health information by patients, providers, and payers.

FHIR [2] is a standard for healthcare data exchange published by HL7 and leverages common tools and approaches like: RESTful architectures, HTTP, XML, JSON, and RDF, which have transformed HIE through the Internet. This approach allows developers to use the tools of the World Wide Web to tackle healthcare challenges. FHIR is web-based and free for use, and allows extensibility (i.e., the ability to address unique, local needs) in addition to the interoperability features. FHIR is now another tool including: HL7 version 2; HL7 v3, which has a steep learning curve; and, the CDA (Clinical Document Architecture), which is a standard for exchange of common clinical documents which may contain such elements as medication and problem lists, allergies, demographics, and immunizations. In other words, healthcare is moving from a model of siloed data in propriety EHRs to open standards that will readily allow developers to leverage common web-based standards for health data interoperability. This will potentially result in a healthcare "app" economy [14], allowing patients and their care provides easy access to relevant health data in a timely and convenient manner without vendor lock-in.

In December 2018, FHIR R4 (4.0.0) [2] was released, which was the first "Mixed Normative" (i.e., a number of FHIR resources have reached a normative state) content, which should provide a reliable foundation for development. Changes, if any, to Normative content are expected to be infrequent and are subject to strict FHIR Inter-version Compatibility Rules. Previous FHIR releases and parts of the current content are "Trial Use", meaning that they are subject to potentially breaking changes, but significant effort is under way to bring these parts of the specification to Normative status as rapidly as possible. With the increasing acceptance and promotion of FHIR by the major EHR vendors and the ONC, and the availability of Normative content, FHIR became the logical choice for use in the Medication Reconciliation Hackathon [11].

The decision to use FHIR enables support for SMART on FHIR application development, CDS hooks [15] (providing clinical decision support services), and support for the Apple Health Kit. Further information on SMART on FHIR is available at SmartHealthIT.org. FHIR provides structures for sharing EHR data between healthcare providers. Data is accessed through *resources*. Resources are accessed utilizing a location URL as part of a REST API in conjunction with a logical ID. This allows data that resources describe to sync between separate FHIR systems.

FHIR enables the retrieval of healthcare data by providing a common API to locate and exchange healthcare records. FHIR's data exchange structure is built on the concept of a resource, which provides a meaningful set of healthcare related data for transfer. FHIR provides over 125 different resources for: patients, observations, medications, patient consent, etc. Requests for a specific resource are available through a REST API that supports instance level interactions such as: read, vread (version read), update, patch (update a portion of a resource),

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delete, and history interactions. FHIR [16] and Google has created a cloud healthcare API using FHIR [17]. Large EHR providers such as Epic [18] (Epic Systems Corporation, 2020) and Cerner (Cerner, 2020) [19] have leveraged FHIR to facilitate HIE for patient use.

FHIR resources are organized in categories: *foundation resources*, *base resources*, *clinical resources*, *financial resources*, and *specialized resources.* We highlight only a subset relevant for the paper. The *base* resources describe: patients, practitioners, and family relationships; organizations, services, appointments, and encounters. The *clinical resources* are for a patient's health history, including: diagnostic data, medications, care provision, and request/response communication. *HAPI FHIR* [20] is a Java implementation of the FHIR resources including: Patient, FamilyMemberHistory, Condition, Observation, Diagnostic Report, Medication, Immunization, AllergyIntolerance, Coverage, EligibilityRequest, Claim, PaymentNotice, etc. The resources are available through the FHIR standard's REST API.

On a final technical note, electronic prescribing in the United States occurs through standards set through the National Council for Prescription Drug Programs (NCPDP). SureScripts is the largest of the vendors that provides an electronic prescribing communications hub between providers, pharmacies, and pharmacy benefit managers. The standards provide that the Diagnostic code (ICD-10-CM) and SNOMED CT (used in Problem Lists and Conditions) codes can be used for indications during electronic prescribing. Both the SCRIPT v10.6 (previous but still in use) and v2017071 (effective 1/1/2020) standards include a field for this indication.

III. MEDICATION RECONCILIATION

This section provides an in-depth discussion of the issues that are critical for medical reconciliation in the healthcare domain along with our research objectives for our overall research on medication reconciliation as applicable to this paper. Section III.A reviews the critical issues for medication reconciliation including why reconciliation is so important in the problems that need to be solved. Section III.B discusses our three research objectives in detail. Section III.C reviews personas of four different patients that have interesting medication profiles which are utilized for testing. Section III.D explores related research from medication reconciliation and computer science perspectives.

A. Issues

Despite this huge investment of time and resources to perform medication reconciliation, medication management is still difficult as we struggle to address a number of critical issues:

1. Define a true and accurate list of current medications for each individual, in the face of multiple medication list sources,
2. Ascertain the gaps between what has been prescribed to what is being taken (i.e., adherence),
3. Understand why each medication has been prescribed (i.e., "Indication"), and
4. Reconcile this information into a new medication list (i.e., new "current medication list") that defines the medication management plan and can be accurately communicated to the patient, care givers, and any members of the patient's care team both now and in the future.

It is essential to consider that the medication list is not static. It is forever in flux based on changes in medications, changes in doses of current medications and the fact that it changes the minute a patient stops taking a medication whether or not they have made their doctor or pharmacist aware.

B. Medication Reconciliation Research Objectives

The research objectives for medication reconciliation as discussed in this paper are as follows:

A. Develop adaptive multi-use algorithms for medication reconciliation and drug-drug interactions for multiple medications pulled from different EHRs, entered by different individuals over time and reusable in different contexts; such as patients via mobile apps, physicians via an EHR, visiting nurses in a remote setting, etc.

B. Research and develop a prototype technology starting with a mobile health application for medication reconciliation which is under development and will be available in mid-August. This will be coupled with an appropriate server and database backend solution that demonstrates a method to incorporate the ONC Interoperability Rules within a state or regional HIE using Medication Reconciliation as the key use case and the state of CT HIE infrastructure as the model.

C. Develop and test a FHIR-based extensible software solution for medication reconciliation that facilitates: a seamless integration of new data sources; and easily updating the medication reconciliation algorithm to address emergent pharmaceutical needs. The solution should be transferable to multiple settings for use by patients/medical stakeholders via mobile apps, web app, or direct embedding into HIT systems via SMART on FHIR. This effort will leverage user-centered design and development to arrive at a best possible medication list across all settings.

Medication reconciliation requires the application of skills and knowledge from computer science and healthcare perspectives. From a computer science perspective, medication reconciliation requires the ability to: obtain potentially incomplete or erroneous patient medication lists from multiple secure sources; extract the exact medications listed in a potentially free-form format suitable for physicians and pharmacists to understand but difficult for a computer; match medications with similar effects but different names (e.g., generic or multiple brand names) or doseages; perform both tasks efficiently so as not to keep a physician waiting; and, create an intuitive user interface for reconciling potential matches between drugs targeted at physicians who need to balance device usage with patient interaction. Additionally, the retrieval of patient medication lists and the dissemination of reconciled medication lists must be able to utilize popular healthcare interoperability standards such as FHIR. In support of objective/goal A, achieving medication reconcilation will require an adaptive algorithm that is able to read and match medications from multiple HIT systems with varying structure, implemented in a prototype mobile health application with an appropriate server and database backend solution. This must adhere to the most current ONC interoperability rule [21] and leverage the FHIR standard with support for new data sources

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and updating to address emergent pharmaceutical needs; this supports objectives/goals B and C.

From a healthcare perspective, medication reconciliation requires: knowledge of medication components and standards for expressing the medication in an EHR, freeform clinical notes, or normalized medication repositories such as RxNorm and RxTerms; knowledge of the way physicians categorize medications on an intuitive level and interact with EHRs; and. understanding the way EHRs store, categorize, and retrieve medications. Most important is the unification of computer science and healthcare perspectives into a coherent set of research that is easy to understand, easy to incorporate into existing HIT systems, and useful to the stakeholders and policy makers in both the computer science and healthcare communities, which also supports objectives/goals B and C. This knowledge is needed to create an adaptive algorithm that finds and annotates duplicates in medication lists and displays in a coherent manner to a physician or pharmacist in support of objective/goal A.

C. Patient Personas

In support of medication reconciliation in testing the app, we developed personas of four different patients. Millie Bryant's journey began with problems around obesity, which led to diabetes mellitus type 2 with peripheral neuropathy and increasing issues with mobility, especially with her hips and knees. Now 72 years old, Millie is battling an increasing number of health problems, her son has medical power of attorney but everything regarding her healthcare still feels hard. Recently, Millie was admitted to the local emergency room with chest pains. Following the onset of atrial fibrillation, Millie was admitted to the Emergency Department due to a heart attack.

George Tullison suffers from Type 2 Diabetes brought about because of obesity. He also has hypertension, Hepatitis C, and a history of alcohol abuse. Recently, George lost his job, which has put his healthcare, home, and life at risk. George recently had an inpatient visit and was diagnosed with congestive heart failure. Since the diagnosis George has frequently landed in the hospital or ER with complications from his congestive heart failure, diabetes, hepatitis C, and hypertension. George's complex care needs make him a high risk for re-hospitalization after discharge.

Sarah Thompson suffered a back injury while working, and was prescribed Oxycodone for pain. In hindsight, if she knew where it would lead, she would have never taken the drug. Sarah quickly became addicted to the drug, but she had no health insurance through work, and she could no longer afford it. A co-worker offered her heroin as an affordable alternative. Sarah said no at first, but the pain persisted and before she knew it she was addicted. Sarah was charged with DUI and possession of a Level 1 controlled substance after being pulled over by the police while speeding down the interstate. She was given the choice of "getting clean" or going to jail. Sarah spends time in and out of methadone clinics before maintaining her sobriety. Recently, Sarah visits her PCP but doesn't share her history of narcotic dependence for using IV heroin.

Christy Munson has never been the kind of person to give her health a second thought. She is now 38 and has seen her weight rises and lowers each year. In the last year, Christy's weight increased more than usual and for the first time began to impact her emotional well-being as well. Then other problems began to emerge. She complained to her doctor about fatigue as well as pain in her lower back and hips. After a multitude of tests, Christy felt no better and her doctor was no closer to providing her with a diagnosis or reason for the pain. Christy's doctor even noted at one point that her symptoms could possibly be a manifestation of depression or psychosomatic in nature. This idea really angered Christy. Christy's pain only seemed to increase. She changed doctors (after the psychosomatic comment) and began to see specialists, most focused on pain. After another round of blood draws and scans, Christy and her specialists could not pinpoint the problem either. Christy had a recent flare up and her intolerable pain resulted in a visit to the ER where they prescribed her a 30-day opioid prescription.

D. Related Research

In this section, we review related research on medication reconciliation from two perspectives. One perspective is in terms of medication reconciliation and its utility, relevance, and usage by medical providers in different care settings. The second perspective is from a computer science viewpoint considering algorithmic issues and user interface issues in support of medication reconciliation. For the first perspective, we explored 6 related works. In this perspective, the first effort [22] involves the way that a personal health record (PHR) can be utilized to achieve medication accuracy and safety for patients. The intent was to compare the medications entered by a patient in a PHR with the documented medications in an EHR. The study concluded that when PHR medication review was conducted against the provider's EHR, it is possible to identify medication discrepancies that might be harmful. Our medication reconciliation approach could pull data from the PHR in addition to the multiple HIT systems in order to reconcile all of the known prescribed medications with the ones that the patient has been tracking. The second effort [23] involves an analysis of CancelRx which is an e-prescribing standard to communicate among EHRs and pharmacies regarding the discontinuation of medications to arrive at an accurate medication list. The study demonstrated that correctly utilizing CancelRx can improve clinical workflow required to remove medications from an EHR or pharmacy IT system in order to ensure that unnecessary risks to patient safety are avoided. In our medication reconciliation approach, when pulling data from multiple HIT systems, leveraging a CancelRx message sent from an EHR could be useful in order to ensure that discontinued medications are identified when arriving at the reconciled medication list.

The next effort [23] considers a scenario where the medications need to be reconciled when the patient visits his/her primary care physician after a hospitalization. During a hospitalization, new medications may be prescribed, existing medications may be discontinued or have altered dosages, and both situations need to be assessed in the primary care office in order to reveal errors and discrepancies. The medication reconciliation process is critical to be undertaken after hospitalization. The study revealed errors even when there was electronic discharge information, as sometimes that information was not available when the patient saw the primary care doctor after the hospitalization or it was in a format that was not automatically incorporated into the EHR. Our approach could assist in this effort by drawing the medications from the hospital and other HIT sources of the patient.

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The fourth effort [25] involved the performance of medication reconciliation in the medical home. A medical home is a primary care practice that encompasses clinicians and medical staff, and incorporates the family as appropriate in order to oversee comprehensive care for a patient. The Medication Reconciliation challenge in this work is to ensure that the prescriber or on-staff pharmacist can obtain access to all of the medications for the patient in order to do the reconciliation process. This study demonstrates that the medication reconciliation process can be quite time-consuming for complex patients, taking 24 minutes on average when all data is available, but taking up to 2 to 4 weeks for historical outside records to be returned. The fifth effort [25] is related since it involves the medication review for a patient by a pharmacist at the patient's home. This effort demonstrated that it was very challenging to try to identify medication-related problems for patients who had issues that included storing multiple drugs in the same container and having illegible labels. Our medication reconciliation approach can assist in both of these efforts by gathering medications from all of the HIT systems for a patient.

The final effort [27] involves a study in Taiwan that investigated the utility of having access to cloud-based data from medication claims in order to improve the reconciliation process. This effort studied a cloud-based solution that provided access to claims data from insurance reimbursements for medications. This instant access to data assisted in collecting and detecting medication-related information that could inform a physician about medication safety problems. Their cloud-based approach pulls data from multiple sources which is similar to our approach.

For the second perspective, we review four efforts related to computer science. The first effort [28] utilizing the Timeline software from MIT employed visualization in order to provide a pictorial view of the way that pharmacy orders and discharge summary reports are overlapped, concurrent, or contiguous over time. This is very important for medical providers when a patient is moving between care settings such as from a hospital to a rehabilitation facility or from the facility back to home. The second effort [29] involves the development of a clinical decision support algorithm in order to reconcile medications to arrive at a complete medication history. The approach uses regular expressions to parse medication information which could be represented differently in different EHRs, using RxNorm and RxTerms to assist in that process. The next effort [30], as with [28], was focused on user interface design and utilized animations to show the medication reconciliation process in order to recommend suggestions for which drugs may need to be reconciled. The final effort [31] utilized machine learning and natural language processing (NLP) to match drugs in clinical notes and discharge prescriptions to look for discrepancies between the notes and discharge prescription. This is critical since medications in different EHRs can have radically different formats that need to be reconciled with one another.

IV. INFRASTRUCTURE AND MOBILE APP FOR MED REC

This section provides a discussion of our prototyping efforts for the development of: a back-end infrastructure that is capable of pulling medications from multiple HIT sources; an algorithm that is capable of doing medication reconciliation for a particular patient; and, a mHealth application that allows a stakeholder to view and reconcile medications for a particular patient. Section IV.A reviews the overall architecture and infrastructure of our medication reconciliation framework. Section IV.B discusses the MedRec FHIR API for aggregating and reconciling FHIR resources from multiple HIT systems using the NDC, RxNorm, and RxTerms APIs. Section IV.C reviews the capabilities and functionality of the MedRec mHealth app. Section IV.D explains the current version of our medication reconciliation algorithm.

A. HAPI FHIR VMs & Test HITs

In order to support the medication reconciliation app, we have developed an infrastructure and installed a set of HIT systems. From the hackathon we sponsored in spring 2019 [10], we developed 4 personas as given in Section III.D, each of whom had specific health conditions and appropriate medications. To establish our test environment, we set up 4 separate HIT systems: 1 HIT is set up as a gold standard to have the exact correct medications for every patient without any duplications or problems; the other 3 HIT systems are set up with perturbed versions of that gold standard with missing medications, different medications, errors in dosage, old medications etc. The intent is to be able to support testing of our algorithm against these 4 different HIT systems. The architecture for our MedRec application is shown in Fig. 1 and includes the following technologies and systems:

- Three copies of [32] set up as simulated EHRs with patient and medication data as shown at the top of Fig. 1 along with a set of Docker containers for OpenEMR (middle right of Fig. 1) which is an open source EHR [34] which will serve as a gold standard of 6 to 10 patient personas. Note that three simulated EHRs contain perturbations each with a different subset of the 6 to 10 personas in order to demonstrate the situation where a patient is seen by multiple medical stakeholders, which could result in different medications. Collectively all of these 4 EHRs and their differences in medications will allow testing on reconciliation.
- A Docker multi-container application with containers for: a MySQL database with the Spring 2019 Hackathon patient and drug data, OpenEMR installation with a custom API for sharing data, and a HAPI FHIR interface for sharing the OpenEMR data with the FHIR standard on the mid right of Fig. 1. The box contains three containers.
  - Container 1 has the MySQL database with the patients/medications from the Spring 2019 Hackathon, plus one added patient with copies of Lipitor created within a minute of each other with two different dosages, all other fields matching. Patient data is loaded via .sql file backup at the container's volume's creation. Connection parameters are specified via the provided .env file, which allows access to connection parameters to the OpenEMR container.
  - Container 2 has the modified OpenEMR version 5.0.1 installation. The modifications include an API for retrieving Patient and MedicationStatement data from the MySQL database. It is also modified to pull MySQL connection parameters from environment variables, which allows it to connect to the MySQL

database via environment variables specified in the provided .env file.

- Container 3 has a modified version of the 2019 Hackathon FHIR installation. The modifications pull in the OpenEMR connection parameters from environment variables, which allows it to connect to the OpenEMR container via environment variables specified in the provided .env file.

The left middle of Fig. 1 lists all of the different APIs related to medications, names, formats, dosage, etc. from Section II.B that allows all of the standards information and common terminology on medications to be pulled in in support of the algorithm for the reconciliation process. The MedRec backend server in the middle of Fig. 1 is where all of the logic for the medication reconciliation algorithm is located so that all of these medications can be pulled from all the different HIT sources for reconciliation. The server also takes all the communication and interactions to and from the HIT systems using the FHIR standard via the MedRec FHIR interface to be discussed in Section IV.B.

B. MEDREC UConn FHIR Interface

The MedRec UConn HAPI FHIR interface for medication reconciliation aggregates and reconciles FHIR resources from multiple HIT systems. The MedRec FHIR interface uses HAPI FHIR and is configured to pull FHIR resources from a defined list of other FHIR interfaces when a resource request is made to it. A HAPI FHIR client merges the resources into a single Bundle. Reconciliation is then performed on the Bundle by making requests to the RxNorm API for similar medications on a per-medication basis, then attempting to find duplicates within the Bundle. Duplicates are removed from the queue for RxNorm requests for efficiency, since they have already been matched. When a duplicate is found, a DetectedIssue resource is created and added to the bundle. The returned medication list is intact as returned from the multiple FHIR sources and the duplicates must be displayed in the app through processing the DetectedIssue resources so that final authority as to which medications are duplicates rests with the user. The medications are displayed reconciled in the app, allowing the user to confirm that the reconciled medications are correct.

C. Flutter MedRed Application

The Flutter MedRec mobile health app shown in Fig. 1 is being developed supporting iOS and Android and can request, parse, and display FHIR resource data to display the medication list that has been reconciled from multiple HIT systems. Before the discussion of the screens of the flutter MedRec app, we briefly review the medications of the Millie Bryant persona given in Section III.C which are given in Fig. 2. Millie has three different medications, with inconsistencies across the three different EHRs. Medication reconciliation is intended to allow for medical providers to identify these potential discrepancies in order to determine the correct medication list for Millie Bryant. Note that these three EHRs are the copies of [32] set up as simulated EHRs referred to in Section IV.A.

Fig. 3, 4, and 5 contain three of the screens from the MedRec app. The first screen in Fig. 3 is shown after the user has searched for and selected the patient Millie Bryant (search screens omitted due to space). From the screen, the user can either select the button for the complete list of the medications

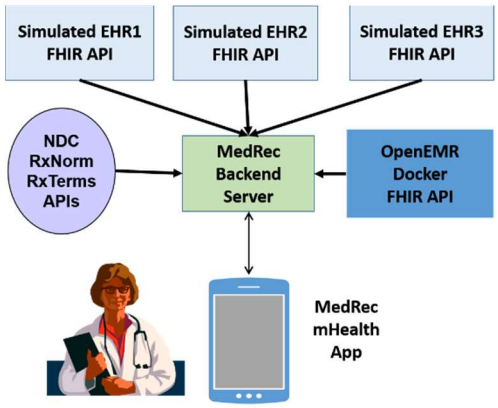

Figure 1. MedRec architecture.

Millie Bryant Meds	EHR1	EHR2	EHR3
Gabapentin 300mg	x	x	x
Warfarin 7.5mg	x		x
Warfarin 5mg		x	
Nitroglycerin 0.3MG	x	x	

Figure 2. Millie's medications across 3 EHRs.

which is shown in Fig. 4, or for the reconciled medications in Fig. 5. Notice that in Fig. 4, the medications are organized by EHR, with the window scrollable to see all the medications. Fig. 5 reconciles the conflict between the two dosages of warfarin, showing the three medications but only the one dosage of warfarin; this is the patient's reconciled medication list.

The patients are queried through the new MedRec FHIR project. When a response is received the app displays the list of patient names that the user can scroll through. When a patient name is selected by pressing it, the app makes a MedicationStatement request to the MedRec FHIR interface for the patient selected by patient ID. The MedRec FHIR interface processes the request and returns a Bundle resource listing the

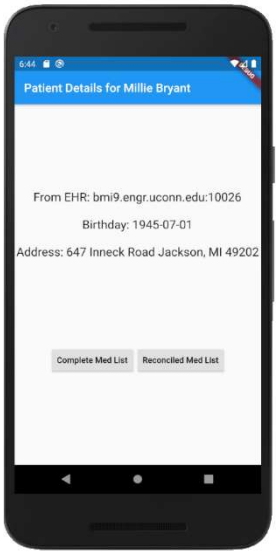

Figure 3. Screen for patient.

Figure 4. Meds from EHRs.

Figure 5. Warfarin reconciled.

patient's medications, with any reconciled drugs also having a DetectedIssue resource in the Bundle naming the matching drugs through the MedicationStatements' FHIR URLs. Although MedicationStatements are parsed and displayed correctly in the medication list screen, parsing the DetectedIssue resources and displaying the DetectedIssues through the interface is still a work in progress.

D. Medication Reconciliation Algorithm

The MedRec reconciliation algorithm begins by retrieving the Bundle supplied by the FHIR interface, created by initiating FHIR requests to all of the HIT systems the MedRec FHIR interface is configured to pull FHIR data from and merging it into one Bundle. A copy of the list is created to perform reconciliation analysis while leaving the original MedicationStatement list intact.

The first MedicationStatement is retrieved from the Bundle and a request sent to RxNorm's approximate term search with the medication's name to retrieve any synonyms of the drug as well as different versions of the drug. The response is parsed for a list of RXCUIs similar to the drug listed in the first MedicationStatement. For each of the RxCUIs returned, the algorithm makes a request to RxNorm's all related API that returns all concepts related to the RxCUI by TTY. The concepts returned by RxNorm are parsed, with both the name and the synonyms of the responses given in the concept groups and concept properties added to a set of potential duplicates to check against. The algorithm then iterates over the list of MedicationStatements removing any MedicationStatement with a name in the set of potential duplicates and creating a set of related resources, later processed into DetectedIssues. Once the algorithm reaches the end of the culled MedicationStatement list, it repeats starting with the second remaining MedicationStatement in the list. This process repeats until there are no remaining MedicationStatements. Once the process is complete, a DetectedIssue is generated for each set of related resources and are added to the original Bundle containing the full MedicationStatement listing originally sourced from the configured HIT systems. Note that full DetectedIssue resource compliance is a work in progress. The bundle is then sent to the flutter app to be displayed to the user.

V. CONCLUSION AND ONGOING RESEARCH

This paper presented our work to date on a mobile health (mHealth) application for medication reconciliation. The paper began with background on relevant medication standards such as NDC, RxNorm, and RxTerms and the browser RxNav, and FHIR in Section II. Then, Section III explored medication reconciliation in detail by reviewing: the critical issues and importance of reconciliation; three research objectives; four different personas of patients that have medication reconciliation needs; and, related research from medication reconciliation and computer science perspectives. The infrastructure and MedRec mHealth application was presented in Section IV by reviewing the overall architecture and infrastructure, discussing the MedRec FHIR API for aggregating and reconciling medications, illustrating the MedRec mHealth app, and reviewing the current version of our medication reconciliation algorithm. We believe that this is a very good initial first step developing the infrastructure and an algorithm that is capable of retrieving medications from multiple HIT systems so that they can be combined and reconciled into a medication list that identifies potential conflicts between the same and/or different medications.

In terms of ongoing and planned research, we are focusing on a number of directions. We intend to continue to evolve and improve the MedRec mHealth app by leveraging user-centered design and development to arrive at best possible medication list across all these multiple settings. This will involve interacting with potential stakeholders including medical students, clinicians, pharmacists, visiting nurses, home health care aides, patients, and other family members. A second direction would involve continued improvements to the algorithm for medication reconciliation particularly in regards to identifying drug-drug interactions which can have serious consequences if they are not found.

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Rated Lexicon for the Simplification of Medical Texts

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***Abstract*—The purpose of our work is to create a rated lexicon in French useful for automatic text simplification of medical texts. Currently, the lexicon contains 11,272 pairs {*technical term*; *paraphrase*} for 6,937 different terms. This lexicon is built automatically using different methods. It is validated manually. Then, the lexicon is rated with several readability formulas and models in order to appraise the readability of terms and paraphrases. The lexicon will be exploited and tested within automatic simplification systems, and will be made available for the research community.**

Keywords–Medical and Health Text; Simplification; Lexicon; Paraphrases; Readability; Readability scores; Patients.

I. INTRODUCTION

The purpose of Automatic Text Simplification (ATS) is to make a given text more understandable for a group of persons, like children, people with pathologies, foreigners, people with no training in a specialized domain, etc. The last few years have seen a growing interest for the ATS, with the main bulk of work done in English and on general-language texts. Very little work exists on simplification of specialized texts, like medical texts, and on languages other than English. Nevertheless, these recent works helped the field to gain in maturity.

Several levels of simplification are distinguished:

- Lexical simplification, in which difficult words are replaced by the corresponding easier words. This kind of simplification is performed on the basis of lexical knowledge, such as synonyms, hyperonyms, definitions, etc. An example from the *SemEval 2012* challenge on English Lexical Simplification [1] is given in (1), in which the word *atrocities* is considered to be difficult to understand and is replaced by *cruelties*;

  (1) *Hitler committed terrible atrocities during the second World War.*
  Hitler committed terrible cruelties during the second World War.

- Syntactic simplification is done at the level of syntactic trees and has the purpose to reduce the syntactic complexity of sentences. Syntactically complex sentences can be transformed into simpler syntactic structures by using to deletion, insertion, separation, merging, and reordering. In example (2), borrowed from [2], the subordinate clause is separated from the main clause;

  (2) *While the law generally supports clampers operating on private land, Mr Agar claims CCSs sign was not prominent enough to be a proper warning.*
  The law generally supports clampers operating on private land. But Mr Agar claims CCSs sign was not prominent enough to be a proper warning.

- Semantic simplification implies that information can be reorganized or added to make the understanding easier thanks to the context [3]. Hence, the word *gabapentine* becomes easier to understand in (3);

  (3) *Gabapentine should be prescribed with caution to pregnant women.*
  Gabapentine medication should be prescribed with caution to pregnant women.

- Pragmatic simplification may imply that the structure of the text is modified [4], and its semantic cohesion becomes more global [5][6].

Currently, the researchers have identified different ways to simplify texts automatically: (1) approaches based on distributional probabilities, such as word embeddings [7][8], which permit to propose simpler candidates for a given word considered as difficult to understand; (2) approaches based on automatic translation systems [9][10], which consider the simplification as a monolingual translation task; (3) rule-based approaches [11][12], which design and exploit specifically defined simplification rules. Whatever the approach, the common point is the need for resources, such as dedicated simplification corpora, syntactic transformation rules, and lexical resources in which difficult words are associated with simpler synonyms, like {*atrocity*; *cruelty*}. Yet, synonyms are not the only lexical information necessary for the simplification. Hence, the few existing works on the typology of simplification [6][13] show that lexical substitution can also be performed with extended forms of abbreviations, hyperonyms, hyponyms, paraphrases and definitions. Such lexical resources must be reliable and propose simpler equivalents for technical terms.

The purpose of our work is to build such reliable lexical resource for French, with the focus on medical language and terminology. Therefore, we need (1) to identify lexical equivalents (synonyms, hyperonyms, definitions, etc.) for technical medical terms, and (2) to assign readability scores to technical terms and to their equivalents.

In our work, *term* or *technical term* correspond to terms that need to be simplified during the simplification process. They

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can correspond to syntactically simple (one word, like *comedo* or *hematuria*) or complex (more than one word, like *systemic lupus erythematosus*) sequences. *Paraphrases* or *equivalences* are the simplified layman versions with the same, or very close, meaning. Both elements are associated within the same pair {*technical term*; *paraphrase*}.

In what follows, we first present the methods designed for the identification of lexical equivalents for technical terms (Section II). We then describe the approaches for rating the lexicon (technical terms and their equivalents) according to the readability and evaluate the results (Section III). Finally, we conclude with some perspectives for future work (Section IV).

II. Identification of Lexical Equivalents for Technical Medical Terms

In this section, we introduce the corpora used and explain the methods proposed for the identification of lexical equivalents (synonyms, hyperonyms, definitions, etc.) for technical terms.

A. Corpora

We use the CLEAR corpus [14], which contains comparable documents differenciated by their technicality and difficulty. In this corpus, technical documents are associated with their simpler or simplified versions. The corpus contains 16,313 pairs of texts (over 57M word occurrences in technical texts and over 35M word occurrences in simplified texts), which are provided from three sources:

- *Drug leaflets* from the French ministry of health [15]. The technical part contains drug leaflets created for medical doctors, while the simple part contains patient package inserts that can be found in drug boxes. These two kinds of documents are created by pharmaceutical companies almost independently from one another;
- *Abstracts of systematic reviews* from the Cochrane collaboration [16]. The technical part contains technical abstracts, while the simple part contains the manually simplified versions of these technical abstracts;
- *Encyclopedia articles* from collaborative online encyclopedias. The technical part contains medicine-related articles from French Wikipedia [17], while the simple part contains the corresponding articles from the French children encyclopedia called Vikidia [18].

We also use a *forum* corpus collected from *masante.net*. This forum provides the possibility for users to ask health-related questions, which are answered by medical doctors. We exploit 6,139 answers available totaling 315,362 word occurrences.

B. Methods for Identification of Lexical Equivalents

We propose several methods for the identification of lexical equivalents (synonyms, hyperonyms, definitions, etc.) for technical terms. We also evaluate the extracted equivalents with the precision measure (percentage of correct equivalents among the extractions proposed by a given method). Each pair {*technical terms*; *paraphrase*} was validated manually by one person with training in NLP (Natural Language Processing) but no training in medicine. Table I summarises the extraction results provided by each method and their precision. In the second part of Table I, we indicate some existing work on acquisition of equivalents for medical terms in English [19][20] and in French [21][22]. The most known resource is the *Consumer Health Vocabulary* (CHV) in English [19], while there is no comparable resources in other languages, such as French. The methods exploited for the creation of CHV are both manual and automatic. Overall, CHV contains 141,213 unique layman terms, among which 11,641 terms are lexically different from their technical terms. This lexicon is the closest work to what we present in this section. Our lexicon currently contains 11,272 pairs {*technical terms*; *paraphrase*} for 6,937 different terms. Because of their specific linguistic function, abbreviations are not included in the lexicon. Besides, several other extractions need yet to be validated manually.

TABLE I. SUMMARY OF DIFFERENT METHODS PROPOSED: NUMBER OF CORRECT EXTRACTIONS AND THEIR PRECISION, AND THEIR COMPARISON WITH THE EXISTING WORK

Methods	*# extractions*	*Precision*
Parallel sentences	626	100
Definitions	1,028	68
Reformulation	7,959	60
Morphological analysis	1,128	86
Morphological affixes and roots	1,939	13
Abbreviations	8,148	94
Online resources	1,165	100
English medical terms [19]	11,641	–
English medical abbreviations [20]	785	95
French medical terms [21]	147	67
French medical terms [22]	109	66

1) Extraction of Equivalents from Parallel Aligned Sentences: Manually aligned parallel sentences from the CLEAR corpus are first manually annotated for transformations observed during the simplification of technical sentences. The annotation is done within the YAWAT annotator [23]. The annotations focus on several types of transformations, among which the most frequent are: (1) synonymy ({*excipients*; *composants*} *(*{excipients*;* components}*)*, {*céphalées*; *maux de têtes*} *(*{cephalalgia*;* headaches}*)*), (2) hyperonymy ({*clyndamicine*; *ce médicament*} *(*{clyndamicin*;* this drug}*)*), (3) hyponymy ({*benzodiazépines*; *bromazépam*} *(*{benzodiazepines*;* bromazépam}*)*), (4) part-of-speech shift ({*peuvent se manifester*; *apparition*} *(*{can appear*;* occurrence}*)*), (5) formal shift ({*des médicaments*; *un médicament*} *(*{drugs*;* drug}*)*). Once the transformations are annotated, we extract the equivalents which correspond to synonyms and hyperonyms, and which are the easiest to exploit during the simplification. This resource includes 626 technical terms with their equivalents. Due to the method, fully relying on manual annotation, this set of equivalents shows 100% precision.

2) Definitions of Technical Terms: Definition context of terms, like *est un (is a)* or *défini comme (defined as)* are exploited to extract definitions of medical terms. An example is given in (4). Technical terms are first detected and, if they occur within definition contexts, the entire sentence is extracted. 2,037 candidate definitions are extracted. After the validation, we keep 1,028 definitions (68% precision).

(4) *L'angiographie est une technique d'imagerie médicale portant sur les vaisseaux sanguins qui ne sont pas visibles sur des radiographies standards. (Angiography is a medical imaging technique for blood vessels which are*

not visible with standard imaging.)

3) Reformulations of Technical Terms: Reformulations usually indicate that there are technical terms and that they are explained by the speaker [24]. We exploit several linguistic markers: (1) brackets like in (5), in which the technical word *hématurie (hematuria)* is reformulated in *trop de globules rouges dans vos urines (too much of red blood cells in urine)*; (2) explicit reformulation markers like *c'est-à-dire (that is (to say))*, *autrement dit (in other words)*, *l'équivalent (the equivalent)* or *encore appelé (also called)*. In example (6), the technical term *périménopause (perimenopause)* is reformulated in *période qui entoure la ménopause (period which surrounds the menopause)*.

(5) *Vous avez effectivement une hématurie (trop de globules rouges dans vos urines). (Indeed, you have hematuria (too many red blood cells in urine).)*

(6) *La prise de poids est normale dans la périménopause, c'est à dire la période qui entoure la ménopause. (Weight gain is expected during perimenopause, that is the period which surrounds the menopause.)*

This method provides 7,959 correct pairs {*technical term*; *paraphrase*} which overall precision is 60%. With this kind of method, it is also necessary to verify the direction of the relation: where is the technical term and where is its layman paraphrase. During the extraction, we consider that the longer sequence is the paraphrase, contrary to the technical term, which is usually a single-word expression or a noun phrase. This feature is also checked in Section III.

4) Word Morphology: In the biomedical language, word morphology may be indicative of technical terms and of their possible paraphrases, like in *myalgia*, composed of *myo- (muscle)* and *algia (pain)*, and meaning *muscle ache*. We exploit information on word morphology in two ways:

- The terms are first analyzed morphologically with Dérif [25] in order to transform them into morphological bases and affixes: *myocardique (myocardial)* is analyzed into *myo (muscle)* and *carde (heart)*. Then, we look into the corpus and search for syntactic groups that contain these words (*muscle* and *heart* in this example). In this way, we can find the sequence *heart muscle* meaning *muscle du coeur* in French. This method provides 1,128 paraphrases for technical terms with 86% precision;
- We start with a set of Latin and Greek affixes (430 prefixes and 103 suffixes) and their semantics, like *dipsy* meaning *thirst*, *a* meaning *absence/without*, *logy* meaning *study of*, or *angio* meaning *blood vessel*. We then combine every prefix with every suffix [26] to coin possible medical terms. In this way, we obtain 15,405 possible medical terms, which are then validated manually: this results in 1,939 terms (13% precision). Supposing that medical terms are compositional, we also combine the meaning of their morphological components for the creation of paraphrases: *angiologie (angiology)* is paraphrased in *étude des vaisseaux sanguins (study of blood vessels)*, while *adipsie (adipsy)* is paraphrased in *absence de soif (absence of thirst)*.

5) Expansion of Abbreviations: Abbreviations are commonly used in the medical language, like *LCR (CSF)* meaning *liquide cérébro-spinal (cerebrospinal fluid)* in example (7). Unless already known, abbreviations are difficult to understand by patients: it is then necessary to provide expanded forms of abbreviations. We extract the expanded forms of abbreviations with an adapted version of published algorithm [20], which processes two kinds of structures: *expanded form (abbreviation)* like in (7), and *abbreviation (expanded form)*. We extract 8,148 abbreviations with precision 94%.

(7) *On l'appelle aussi liquide cérébro-spinal (LCR). (It is also called cerebrospinal fluid (CSF).)*

6) Exploitation of an Online Medical Dictionary: We also exploit already available lexicons from online sources [27]. For each medical term, we keep the first sentence of the definition, which is expected to describe precisely the term. We obtain 1,165 additional medical terms and their paraphrases.

III. Computing the Readability of Technical Terms and of Their Equivalents

In this section, we compute the readability scores for technical terms and their layman equivalences. The purpose is (1) to assign the readability scores to each term and paraphrase, (2) to verify if paraphrases are indeed easier than technical terms, (3) if necessary, to switch the place of terms with their equivalents, which can be relevant with some automatic methods like reformulation extraction, and more specifically (4) to provide indication on simplicity of terms and their equivalents, which can be later used by simplification systems. For instance, some technical terms have more than one equivalent, which differ by their readability. In this situation, it is necessary to choose the equivalent which suits the best the simplification task.

Over one hundred readability formulas have been proposed by researchers [28], from which we choose just few for our work. These are linear regression formulas. They are mainly dedicated for rating the readability at the level of texts. These readability indexes are not considered to be very reliable and are often criticized [19]. Nevertheless, we consider that they can provide useful information on readability of terms and paraphrases. In the rest of this section, we first present the selected readability formulas and how we adapt them for the processing of terms and paraphrases (Section III-A). We then propose our computational readability models adapted to paraphrases, and based on a set of features and machine learning algorithms (Section III-B). The models are evaluated with Precision (correctness), Recall (exhaustiveness) and F-measure (harmonic mean of Precision and Recall). Finally, we present the results obtained with the readability models and indexes (Section III-C).

A. Linear Regression Readability Formulas

Dale index [29] is one of the first readability formulas proposed: $Dale = 0.15x1 + 0.04x2$, where *x1* represents the percentage of words missing from the basic vocabulary, and *x2* represents the average number of words per sentence. The higher *Dale* index, the less the text is readable. We adapt this formula to terms in French as follows: *x1* is the percentage of words missing form the Catach list [30], which is the French

set with 400 basic words; and *x2* is the number of words in a given paraphrase or term. When applied to paraphrases, this formula provides readability scores between 0.08 (*être malade(being sick)*) and 15.4 (*éruption faciale, douleur articulaire, anomalies musculaires, fièvre (facial rash, articular pain, muscle abnormality, fever)*). The scores of terms are lower.

Kandel index [31] is the French adaptation of the very popular Flesch formula [32]: $Kandel = 207-(1.015*ASL)-(73.6*ASW)$, where *ASL* is the average number of words in each sentence, and *ASW* the average number of syllables. The index values are expected to fall between 0 and 100: 0 to 30 for texts difficult to understand, and starting from 70 for texts easily understandable by adults. In our experiments, we consider that *ASL* is the number of words in the paraphrase, and *ASW* the average number of syllables per word. When applied to paraphrases, the index scores are uneven and fall outside the expected scale, going from -188.58 (*hypertension intracrânienne bénigne (benign intracranial hypertension)*) up to 204.96 (*condylomes acuminés (acuminated condyloma)*).

Mesnager index [33] is a variant of the *Dale* index: $Mesnager = (1/2 * AC) + (1/3 * P)$, where *AC* is the percentage of words missing from the basic vocabulary [30], and *P* the average number of words in sentences. The index values are supposed to be between 6 (easy text) and 25 (difficult text). In our case, we consider that *P* is the number of words in paraphrases and terms. When applied to our data, the formula provides scores between 0.66 (*être malade (being sick)* or *point noir (blackhead)*) and 69.3 (*éruption faciale (facial rash)*, *douleur articulaire (articular pain)*, *anomalies musculaires (muscle abnormality)*, and *fièvre (fever)*).

Sitbon index [34] is one of the rare formulas designed for sentences (and not for texts): $Sitbon = 1.12 * ADV - 0.69 * CON + 6.48 * cohesion + 15.58$, where *ADV* and *CON* are, respectively, the number of adverbs and conjuctions, and *cohesion* is the number of phonemes divided by the number of letters. There is no reference scale of values for the *Sitbon* index. When applied to our data, the index provides scores between 18.05 (*groupe de glandes et de cellules du corps fabriquant et libérant des hormones dans le sang, qui contrôlent de nombreuses fonctions comme la croissance, la reproduction, le sommeil, la faim et le métabolisme (group of glands and cells in the body that make and deliver hormones in blood, that control many functions such as growth, reproduction, sleep, hunger and metabolism)*) and 25.37 (*protéine normalement fabriquée par le placenta lors de la grossesse habituellement non présente dans le sang d'une femme en bonne santé qui n'est pas enceinte ou d'un homme en bonne santé (protein that is normally made by placenta during pregnancy, and usually missing in blood of healthy non-pregnant women or healthy men)*). We can see that the scale of values is very narrow and offers reduced discrimination of readability.

Smith index [35] is also adapted to sentences: $L = -6.49 + 1.56WL + 0.19SL$, where *WL* is the average number of letters in words, and *SL* is the number of words in the sentence. When applied to our data, the formula shows scores between -1.44 (*étude de l'os (study of bone)*) and 17.29 (*concrétions gastro-intestinales (gastrointestinal concretions)*). Contrary to other indexes, difficult paraphrases are not the longer ones but rather those composed of polylexical units, like *gastro-intestinal (gastrointestinal)*.

B. Computational Readability Models

For designing the computational readability models, we choose the descriptors mainly issued from the existing typology [36]. The purpose is to design a set of descriptors easy to compute and to use:

- *number of letters*, usually indicating the length, and complexity, of terms and of their equivalents;
- *number of phonemes*. To obtain the number of phonemes, we use the database Lexique3 [37]. It provides over 140,000 French lemmas and associated information, such as their phonetic transcription, number of syllables, and part-of-speech tag. For words missing in Lexique3, we use the Epitran module [38] adapted to French;
- *number of syllables*. Lexique3 is also used to obtain the number of syllables. For words missing in Lexique3, we use Epitran and then their syllabation [39];
- *cohesion between phonemes and spelling* corresponds to the ratio between the number of phonemes and number of letters. It provides values between 0 and 2: 0 if no difference, 1 if one or two differences, and 2 if more than two differences. Words with higher values of cohesion are supposed to be less readable;
- *frequency* is also obtained from Lexique3. For words missing in Lexique3, we fix the frequency to 0 because these are supposed to be rare words;
- *presence in the Catach list [30]*, which is the basic set of French words;
- *syllable components*, which corresponds to three complexity levels according to the structure of syllables (coined with consonants C, vowels V and semi-consonants Y) and their frequency. For instance, syllables like *CYV, V, CVC, CV* are very frequent in French, while syllables like *CCVC, VCC,VC, YV, CVY* are much less frequent in French.

We have to predict two classes for terms and equivalents: *simple* and *difficult*. Training of the biclass models is done on independent reference data: manually rated medical lexicon annotated according to the difficulty of words [40]. This lexicon contains 29,641 medical words. Three classifiers (MultiLayer Perceptron MLP, Decision Tree DT and Random Forest RF), implemented within the Python library ScikitLearn [41], are used. Table II indicates Precision, Recall and F-measure obtained during the training with a 10-fold cross-validation set. We can see that all classifiers show good results, MLP being the best in this task with overall results over 90%.

TABLE II. RESULTS OF THE READABILITY MODEL ON TRAINING REFERENCE DATA WITH 10-FOLD CROSS-VALIDATION

	Precision	*Recall*	*F-measure*
MLP	90.3	90.4	90.0
DT	88.7	89.0	88.6
RF	89.2	89.5	89.2

The models are next applied to terms and their paraphrases from the lexicon. The more the prediction is close to 0 the more difficult is the sequence, and the more it is close to 1 the simpler is the sequence. When the sequence contains

TABLE III. EXAMPLES OF RATING OF TECHNICAL TERMS AND OF THEIR EQUIVALENTS

Terms and their equivalents	*Dale*	*Kandel*	*Mesnager*	*Sitbon*	*Smith*	*MLP*	*DT*	*RF*
difficult	high	low	high	high	high	0	0	0
simple	low	high	low	low	low	1	1	1
comédon (comedo)	15.04	-235.615	66.33	22.06	4.62	0	0	0
point noir (blackhead)	0.08	102.77	0.66	21.34	0.91	1	1	1
vomissements (comiting)	15.04	-88.415	66.33	20.98	12.42	1	1	1
être malade (being sick)	0.08	65.98	0.66	20.76	1.69	1	1	1
lupus érythémateux disséminé (systemic lupus erythematosus)	15.12	-65.91	66.99	21.06	7.6	0.33	0.33	0.66
éruption faciale, douleur articulaire, anomalies musculaires, fièvre (facial eruption, articular pain, muscular abnormalies, fever)	15.4	16.91	69.3	21.11	5.082	0.67	0.67	0.67
condylomes acuminés (condylomata acuminata)	15.08	204.97	66.66	15.58	-6.11	0	0	0
verrues génitales (genital warts)	15.08	20.97	66.66	20.035	6.37	1	1	1
système endocrinien (endocrine system)	15.08	131.37	66.66	21.7	7.93	0.5	0.5	0.5
groupe de glandes et de cellules du corps fabriquant et libérant des hormones dans le sang, qui contrôlent de nombreuses fonctions comme la croissance, la reproduction, le sommeil, la faim et le métabolisme (group of glands and cells in the body that make and deliver hormones in blood, that control many functions such as growth, reproduction, sleep, hunger and metabolism)	9.97	73.7	49.26	18.05	8.00	0.67	0.67	0.5
alpha-foetoprotéine (afp) (alpha-foetoproteine (AFP))	15.08	-15.83	66.66	19.9	12.61	0	0	0
protéine normalement fabriquée par le placenta lors de la grossesse habituellement non présente dans le sang d'une femme en bonne santé qui n'est pas enceinte ou d'un homme en bonne santé (protein that is normally made by placenta during pregnancy, and usually missing in blood of healthy non-pregnant women or healthy men)	8.42	86.45	42.28	25.37	7.17	1	1	1
ostéologie (osteology)	15.04	-126.23	66.33	21.412	9.3	0	0	0
étude de l'os (study of bones)	7.66	94.57	34.32	19.11	-1.44	1	1	0.5
bézoards (bezoars)	15.04	-126.23	66.33	21.25	6.18	0	0	0
concrétions gastro-intestinales (gastrointestinal concretions)	15.08	204.94	66.66	21.41	17.29	0.5	0.5	0.5

more than one word, which is the majority of cases, models are first applied to each non-grammatical word, and then we compute the average probability of the whole sequence to be classified as simple or complex. The probabilities of three algorithms are taken into account individually. For instance, in *abaissement de la température (decrease in temperature)*, all the algorithms predict that *abaissement (decrease)* is simple (with probability value 1) and that *température (temperature)* is simple (with probability 1). This gives the average score 1 for each algorithm, and the term is considered as simple by all of them. As for *ablation de l'abdomen (ablation of abdomen)*, MLP and RF predict that the two words of the paraphrase are simple (probability 1), while DT predicts that *ablation* is simple and *abdomen* is difficult. This gives the average score 1 for MLP and RF, and 0.5 for DT. Overall, this term is also considered as simple but with lesser probability.

C. Results

The result of this step is that technical terms and paraphrases are rated for their readability with the five classical readability indexes (*Dale, Kandel, Mesnager, Sitbon* and *Smith*) and by the proposed computational readability models. In Table III, we present some examples of technical terms and of their equivalents, and indicate their readability scores. In the first line, we indicate the interpretation of the readability values according to indexes and models. For instance, with *Dale*, high scores are expected to be associated with difficult terms, while low scores are expected to be associated with simple terms. The *Sitbon* index is rather sensitive to long terms and paraphrases. In the examples provided, technical terms precede the paraphrases. For instance, *comédon (comedo)* is recognized to be difficult to undestand by all measures: *Dale*, *Mesnager*, *Sitbon* and *Smith* indexes are high, *Kandel* is low, and the three computational models *MLP, DR, RF* show the value 0. As expected, its paraphrase *point noir (blackhead)* is recognized to be easy to understand: *Dale*, *Mesnager*, *Sitbon* and *Smith* indexes are low, *Kandel* is high, while the three comutational models *MLP, DR, RF* show the value 1. The picture may be different with other pairs $\{$*term*; *paraphrase*$\}$. For instance, in the pair $\{$*vomissement (vomiting)*; *être malade (being sick)*$\}$, both elements are considered as understandable by computational models and *Sitbon*, while other indexes consider that the paraphrase *être malade (being sick)* is simpler than the term *vomissement (vomiting)*. The pairs, in which terms are paraphrased with long sequences, may be more difficult to be rated by the indexes and models. This is the case of *système endocrinien (endocrine system)* and its paraphrase *groupe de glandes et de cellules du corps fabriquant et libérant des hormones dans le sang, qui contrôlent de nombreuses fonctions comme la croissance, la reproduction, le sommeil, la faim et le métabolisme (group of glands and cells in the body that make and deliver hormones in blood, that control many functions such as growth, reproduction, sleep, hunger and metabolism)*. Hence, the length of the paraphrase may introduce additional readability factor, which should also be considered in chosing the paraphrases for simplification. Overall, indexes and models provide useful information for the selection of lexical substitutes for technical terms.

The scores also permit us to compare the readability within pairs and indicate that order of terms and their paraphrases is correct. In few cases, the length of paraphrases decreases their readability, but overall their readability remains acceptable.

IV. CONCLUSION

Automatic text simplification is an NLP field whose purpose is to make texts more easily understandable by common readers. While an important progress has been done in this field, the main barrier is still related to the availability of suitable data, such as corpora and lexica. We propose a set of experiments designed for the creation of a lexicon with French technical medical terms and their layman paraphrases. Several approaches and methods are developed and applied for the automatic extraction of paraphrases. The results from each method are evaluated with precision metric and usually show that the extractions are reliable with over 68% precision. Overall, the lexicon contains 11,272 pairs $\{$*technical term*;

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paraphrase} for 6,937 different technical terms. Terms and paraphrases from this lexicon are then rated for their readability with several adapted readability indexes and with specifically designed computational models. Globally, we observe that paraphrases are indeed easier to understand than technical terms. This rated lexicon will be exploited by simplification systems and we expect that readability scores will help to choose the best lexical substitutions. The lexicon will be made available for the research community.

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