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# Toward a Model for Personal Health Record Interoperability

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***Abstract*—Health information technology, applied to electronic health record (EHR), has evolved with the adoption of standards for defining patient health records. However, there are many standards for defining such data, hindering communication between different healthcare providers. Even with adopted standards, patients often need to repeatedly provide their health information when they are taken care of at different locations. This problem hinders the adoption of personal health record (PHR), with the patients' health records under their own control. Therefore, the purpose of this work is to propose an interoperability model for PHR use. The methodology consisted prototyping an application model named OmniPHR, to evaluate the structuring of semantic interoperability and integration of different health standards, using a real database from anonymized patients. We evaluated health data from a hospital database with 38,645 adult patients' medical records processed using different standards, represented by *open*EHR, HL7 FHIR, and MIMIC-III reference models. OmniPHR demonstrated the feasibility to provide interoperability through a standard ontology and artificial intelligence with natural language processing (NLP). Although the first executions reached a 76.39% F1-score and required retraining of the machine-learning process, the final score was 87.9%, presenting a way to obtain the original data from different standards on a single format. Unlike other models, OmniPHR presents a unified, structural semantic and up-to-date vision of PHR for patients and healthcare providers. The results were promising and demonstrated the possibility of subsidizing the creation of inferences rules about possible patient health problems or preventing future problems.**

***Index Terms*—Personal Health Record, Semantic Interoperability, Ontology, Natural Language Processing.**

## I. Introduction

THE area of health information technology has evolved in the application of standards for health record definition, through the adoption of electronic health record (EHR) [1]. The purpose of EHR is to standardize health data, but without determining or specifying which standard to adopt. Another way to obtain patients' health data in an electronic and equalized format is through the personal health record (PHR) [2], [3]. The ISO TR14639-2:2014 indicates that PHR is the "representation of information regarding or relevant to the health, including wellness, development, and welfare, of a subject of care, which may be stand-alone or integrating health information from multiple sources" [4].

There are several health data standards [5]. Many healthcare providers adopt proprietary standards, without integration with others. In some countries, there are recommendations for adopting recognized health data standards. One of the main goals of using standards is to provide interoperability among healthcare organizations. Nevertheless, using open and internationally recognized standards does not guarantee interoperability because many of them are incompatible with each other [6]. In this sense, the patients data are difficult to integrate [7], [8]. Even with the evolution of open specifications and attempts to promote the use of the standards, the adoption of EHR/PHR is still challenging [9]. In the PHR case, which can also aggregate data from wearable devices of the patient, the integration can be more complex. This is because the PHR aims to gather all the patient's health data, regardless of the healthcare provider [10]. In addition, the syntactic standards have limited benefits because their overall purpose is only to structure or standardize the format and terminologies used in the health records [11]. In summary, the problem statement of this work is regarding the difficulty to integrate the several existing standards of patient health data.

The concept of interoperability is quite broad and applied in many contexts [12]. According to the Healthcare Information and Management Systems Society (HIMSS) definition [13], there are three levels of health data interoperability: (a) foundational, which makes the exchange of data between health systems possible without requiring the ability to interpret the data; (b) structural, which defines the syntax for data exchange, ensuring that data interoperability can be interpreted at the data field level; and (c) semantic, which "takes advantage of both the structuring of the data exchange and the codification of the data including vocabulary so that the receiving information technology systems can interpret the data" [13]. Semantic interoperability ensures that systems understand data in the same way, resulting in unambiguous use, understanding, and interpretation of the data [14]. Semantic interoperability brings, besides the standardization and formatting of health data, the possibility of inferring based on the data. Instead, syntactic interoperability refers to the dealing of data with low-level problems, such as in the use of different protocols and formats [15].

This proposal presents an application model to address the integration issues between health data standards, providing

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TABLE I
RELATED WORK

| Reference & Year | Ref. Model[2] | Semantic Interoperability[1] | | | | | Results |
|---|---|---|---|---|---|---|---|
| | | Ar | Dc | Sa | Tm | Tr | |
| [16] Lahteenmaki, 2009 | H | | | | ✓ | ✓ | Occupational health pilot, with content from several apps merged. |
| [17] Goossen, 2010 | H, O | ✓ | | | ✓ | ✓ | Two types of analyses and six initiatives evaluated accordingly. |
| [18] Muoz, 2011 | H, O | ✓ | | | | ✓ | Description of how to achieve sharing and interoperability of clinical data. |
| [19] Alterovitz, 2015 | H[3] | | | | ✓ | ✓ | Feasibility shown by development of three applications. |
| [15] Marcos, 2015 | H, O | ✓ | | | ✓ | ✓ | Implemented in two clinical domains. |
| [20] Moreno-Conde, 2015 | H, O | ✓ | | | ✓ | ✓ | Common patterns to develop clinical information models (CIMs). |
| [21] Mo, 2015 | H | | | | ✓ | ✓ | Proposed 10 desired characteristics for computable phenotype repr. model. |
| [22] Alyami, 2016 | H | | ✓ | | ✓ | | Survey PHR in six categories and framework proposed. |
| [23] Esposito, 2016 | H | | | | ✓ | | Proposes a semantic approach based on ontologies. |
| [24] Hu, 2016 | - | | | ✓ | | | Presents an architecture for PHR recommendation. |
| [6] Mandel, 2016 | H[3], O | ✓ | | | ✓ | ✓ | Relates development experiences and discusses challenges. |
| [25] Heart, 2017 | H, O | ✓ | | | ✓ | ✓ | Reviews and presents needs to integrate EMR, EHR, and PHR. |
| [26] Pais, 2017 | H[3] | | | | ✓ | ✓ | Developed a conceptual model of wellness data using HL7 FHIR. |
| [27] Peleg, 2017 | H, O | ✓ | | | ✓ | ✓ | Subsidized diagnosis change of 2/10 patients and anticipated therapy for 11/20. |

[1] Ar = Archetypes, Dc = Dublin core metadata, Sa = Software agents; Tm = Templates; Tr = Terminologies.
[2] Reference Model (Standards): H = HL7, O = *open*EHR/CEN ISO EN13606;
[3] HL7 Fast Healthcare Interoperability Resources (FHIR) platform specification assists the solution.

a single, semantic, and up-to-date PHR viewpoint, through ontology and artificial intelligence to assist in automation of the conversion of different health standards. These objectives aim to make continuous updates on the PHR possible, independently of the places where patients have their data collected, and to create conditions to promote inferences about patients' health.

## II. MATERIALS AND METHODS

The methodology follows the principle used in the scientific community for designing a model, with the evaluation of a prototype system [28]. The objective of this evaluation is to meet the health record interoperability requirements proposed for PHR. Regarding the research type, the approach is quantitative because the analyzed health data are from existing patients, although with anonymized data. As for the nature of the research, the study involves applied research because it aims at practical applications in the day-to-day lives of patients and healthcare providers. Regarding the objectives, the research used a case study applied to the context of the proposed model. As research materials to support our proposal, we start by investigating how studies of the past decade deal with semantic interoperability in health data. Table I summarizes relevant related works that fit the concept of semantic interoperability according to the HIMSS.

A reference model is a reference standard that uses a clinical information model (CIM), which is a structural standard of health data [20]. As examples of CIMs there are the formats of templates used by the Health Level 7 (HL7) reference model, and the archetypes used in the *open*EHR and CEN/ISO EN13606 standards [14], [15], [20]. As can be seen in Table I, practically all studies mention the HL7 reference model and the use of templates (Tm) in semantic interoperability. However, among these, only three studies mention Fast Healthcare Interoperability Resources (FHIR) [6], [19], [26]. The FHIR platform specification aims to promote and achieve interoperability among health systems using the HL7 reference model [29]. However, only seven studies mention the *open*EHR or CEN/ISO EN13606 standards, and few works mention archetypes (Ar) associated with semantic interoperability. With one work found [22], Dublin core (Dc) consists of metadata that can be used to retrieve and organize the PHR. Another study [24] mentions software agents (Sa), which consist of agent-based systems designed to interact and interpret health data. Analyzing the selected articles, we observed a point in common among all studies. All research seeks to support semantic interoperability using one or more ontologies. Further, most studies cite terminologies (Tr) or vocabularies in health records, such as the LOINC, SNOMED-CT, and ICD standards, linked to the proposed semantic interoperability. However, we observed that few studies implemented or evaluated models with real patient data. Several articles consist of surveys or reviews, being limited to the conceptual description and presenting few concrete numbers regarding the results obtained.

Regarding the evaluation, the proposal is to evaluate the model obtaining a statistical analysis of the solution. In this sense, a metric recognized by the scientific community is the F1-score (or F-measure) [30]. Following this metric, the precision and recall of the algorithm are calculated. We also calculated the accuracy, to have a measure in relation to the total records. The precision (or $ppv$ = positive predictive value, also known as $confidence$) is given by

$$ppv = \frac{tp}{tp + fp} \tag{1}$$

The recall (or $tpr$ = true positive rate, also known as $sensitivity$) is given by

$$tpr = \frac{tp}{tp + fn} \tag{2}$$

And accuracy ($acc$, also known as $trueness$) is given by

$$acc = \frac{tp + tn}{tp + tn + fp + fn} \tag{3}$$

Where $tp$ = true positives, $tn$ = true negatives, $fp$ = false positives, and $fn$ = false negatives. The F1-score is defined as follows:

$$F1 = 2 \cdot \frac{ppv \cdot tpr}{ppv + tpr} \quad (4)$$

Applied to this proposal, accuracy represents the proximity measure between the number of converted and unconverted fields, as expected, in relation to the total measured fields. Precision represents the number of fields converted correctly, as expected, divided by the number of fields returned in the process execution. Recall represents the number of successfully converted fields, as expected, divided by the number of fields that should have been converted. The harmonic mean of precision and recall results in the F1-score.

## III. OmniPHR Model

The OmniPHR ("Omni" comes from "omnipresent") [31] model aims, at this stage of the project, to deliver for patients and healthcare providers the integration of different health data standards. OmniPHR also aims to aggregate semantic interoperability among different PHR formats. Our focus is the structuring of semantic interoperability regarding health records. Figure 1 illustrates the architecture model, with the OmniPHR middleware highlighted in green, representing the core business layer.

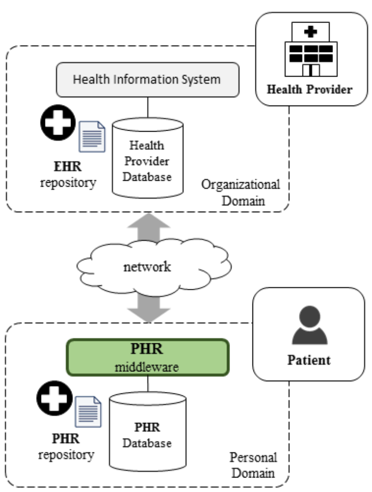


Fig. 1. OmniPHR overview with middleware highlighted

The model has two different domains. The first domain, the organizational domain, addresses the context of artifacts under the control of healthcare providers. The second domain, the personal domain, addresses the artifacts that hold the core of the model implementation. The organizational domain addresses the private context of health organizations. The proposal is to keep the original data contained in the databases of healthcare providers. Therefore, in OmniPHR, the healthcare provider can integrate its database with the model through two options: (a) using a reference model that follows an open standard supported by the model, such as *open*EHR, CEN/ISO EN13606, or HL7 FHIR; and (b) maintaining the current data definition standard, but providing the necessary subsidies for a semantic conversion of the internal model. Figure 2 shows a detailed view of the model, following the division presented in Figure 1, with two domains: (a) one is the organizational domain, in which the objective is to preserve the health record structure used by the organization; (b) the second is the personal domain, composed of the middleware, which is a business model layer and includes the repositories where PHR is stored.

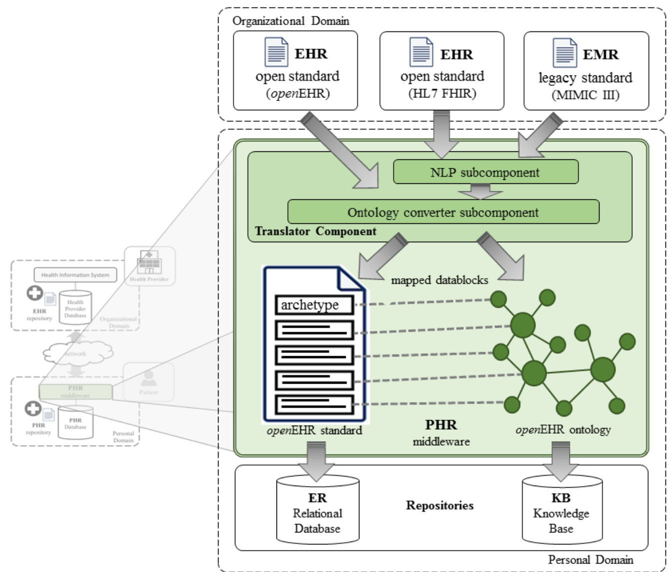


Fig. 2. OmniPHR architecture detailed view

In the organizational domain, OmniPHR predicts the entry of open and legacy standards. We have two representatives of open standards: (a) *open*EHR and (b) HL7 FHIR. To evaluate the legacy standards, we have one reference model: (c) Medical Information Mart for Intensive Care (MIMIC-III) [32]. In the middleware, there is a main component, the translator component, which has two subcomponents: (a) natural language processing (NLP) and (b) ontology converter. The health organization can submit to the OmniPHR middleware any of the three formats supported (*open*EHR, HL7 FHIR, or legacy), which read and convert to the *open*EHR ontology through the NLP processing phase. OmniPHR uses NLP resources to automate the conversion process. With ontology, we can integrate different standards, allowing the realization of inference about these data [33]. After the health records are converted to the *open*EHR ontology, the data are stored in a semantic database repository, i.e., in a knowledge base (KB). In conjunction with this, the OmniPHR middleware replicates the health records, based on the *open*EHR archetypes, to the relational database.

Considering the health records as controlled natural language (CNL), which is a language based on a certain natural language [34], the main problem that OmniPHR addresses is extracting data from this CNL and converting it to *open*EHR ontology. In this way, the content that composes the PHR can be structured and unstructured data. The proposal is, besides promoting health record interoperability, to create the basis for enabling extraction and to infer possible health problems from the PHR unified viewpoint. We propose with OmniPHR

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a mechanism for health record conversion, using machine learning with NLP to automate the conversion to *open*EHR ontology. We have, in Figure 3, the details of the semantic interoperability model, where we can see the subcomponents of the translator component.

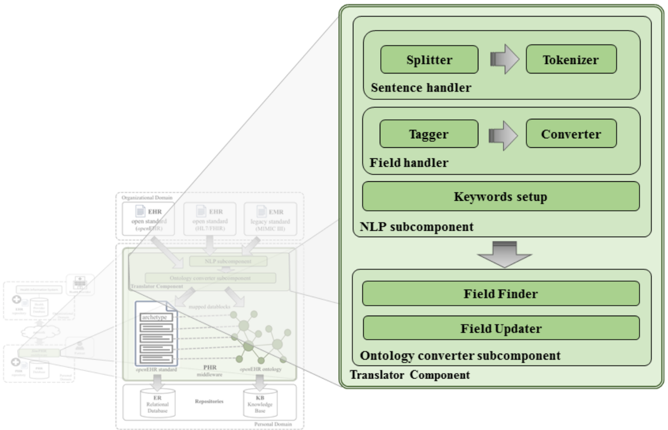


Fig. 3. OmniPHR semantic interoperability method

The translator component is the main component responsible for the interoperability method. The method of converting the heterogeneous standards to the standard supported by OmniPHR begins receiving the corpus text and passing through the NLP subcomponent. The corpus can be a text in the XML or JSON format, represented by the HL7 FHIR, or CSV format represented by the legacy MIMIC-III. According to the background of syntactic interoperability, we address the issues of syntactic interoperability through (a) functional and (b) data instance interoperability with the help of an XSD document (XML Schema Definition), which describes in detail the types and formats sent by sources. Considering the semantic interoperability issues with metadata, OmniPHR addresses the problem with training in the NLP component, through a neural network.

In the `NLP subcomponent`, the sequence of steps starts with the corpus text passing through the `Sentence handler`. This subcomponent has two stages, one that splits the sentence into words with `Splitter`, and the `Tokenizer`, which tokenizes the sentence identifying and separating relevant words from prepositions. Then, the text passes through the `Field handler` subcomponent, which has two functions: (a) tagging the words meaningfully through `Tagger`, identifying them according to the `Keywords setup`; (b) and afterward, the words are converted through the `Converter` to the standard used by the OmniPHR model. At this point, the conversion to the *open*EHR archetype is complete. What remains is updating the OmniPHR model's ontology. The `Ontology converter subcomponent` is used to update the *open*EHR ontology, which has an object localization feature in the `Field handler`, and the feature used to update the ontology by adding, updating, or removing objects is called the `Field updater`. In this way, the steps of the working method of converting the heterogeneous standard to the OmniPHR standard are complete. OmniPHR updated the *open*EHR archetypes and the ontology, as well as stored them in the respective relational and KB repositories.

The following is the main algorithm that represents the extraction and conversion service in the Translator component:

```
Algorithm: Extraction and conversion service.
input: list of sentences (S) to translate
input: setup of keywords (K) to verify
output: ontology (O) filled
01 O ← queryCurrentOntology();
02 var: current sentence (s) to convert
03 loop for each s ∈ S do
04     var: current element (e)
05     e ← splitter(s);
06     e ← tokenizer(s);
07     loop for each e do
08         var: current word (w)
09         w ← tagger(e, K);
10         w ← converter(e);
11         O ← fieldFinder(w);
12         O ← fieldUpdater(w);
13     end loop
14 end loop
```

The input parameters for the conversion algorithm are the list of sentences ($S$) to convert and the keyword setup ($K$). The output parameter and final goal of the algorithm is to fill the ontology ($O$). The execution begins by loading the current ontology using the `queryCurrentOntology` function and proceeds according to the steps of the translator component. In line 3 starts the main loop, which deals with the sentence, splitting the phrases and the tokens (words). Then, in line 7 another loop manages the conversion of words, finding the corresponding field to store the specific data. Finally, the ontology is updated, completing the process.

## IV. Results and discussion

To help the conversion of the heterogeneous standards to the standard adopted by the OmniPHR, we investigated some well-known and recognized NLP parsing solutions to integrate with ontologies. Because of the range of functionalities available for manipulation and processing of natural languages, mainly in relation to the populating ontologies, as well as due to the current state of the tool, which remains up-to-date, the project team selected the GATE platform [35]. The GATE platform provides mechanisms that promote the interpretation and conversion of controlled text to an ontology, with a set of tools for NLP, such as tokenizers, taggers, and parsers.

In the OmniPHR architecture, we have PHR repositories divided in two instances, one for the relational repository of the *open*EHR archetypes and other for the semantic repository of the *open*EHR ontology. Because of the characteristics of providing access, both relational and RDF triple store, allowing the realization of inferences natively, we selected the OpenLink Virtuoso database as data repository solution. To illustrate an execution of the proposed method, we present in Figure 4 the execution of the extraction of the HL7 FHIR standard in XML and JSON formats, as well as the extraction of the legacy represented by a CSV file from MIMIC-III.

Analyzing the recognized reference models *open*EHR and HL7 for health records structures, we chose to use the *open*EHR standard because of the flexible combination of archetypes and the existence of ontologies for this health standard. The use of *open*EHR ontology aims to promote the use of a single open language that provides interoperability

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between heterogeneous standards. The *open*EHR standard also integrates with vocabulary and medical terminology such as SNOMED-CT, LOINC, ICD and ISO. In addition, this aims to provide the ability to infer and prevent possible health problems that the patient may have [4]. Since the model uses the *open*EHR standard, if the health organization uses the same standard, then there is no need to use the NLP subcomponent. To automate the translation process of the heterogeneous health standards to the standard used by the model, the Translator component uses NLP to perform the conversion to the *open*EHR ontology. This translation subcomponent is required when the health organization uses a different standard than the one adopted by the model.

We used anonymous patient data available in the MIMIC-III database [32] as input data to OmniPHR prototype. We used the version 1.4 of MIMIC-III, with 38,645 adults patients. We represented each patient with the standards supported by the model, i.e. (a) *open*EHR, (b) HL7 FHIR and (c) legacy (MIMIC III). The MIMIC III database has real patient health data, although anonymized. In case of *open*EHR standard, we used the EHRServer platform through the EHRCommiter component to populate its database in PostgreSQL with data extracted from MIMIC III. We used this component to extract data in XML format. We obtained a document in the *open*EHR format generated from a solution that admittedly follows this standard. In case of HL7 FHIR standard, we followed the same script, using both the API and documentation in XML and JSON format, available on the FHIR website. In case of patient data that represented the legacy standard, we extracted data directly from the MIMIC III database for plain text, in CSV format. OmniPHR receives, interprets and tags all three formats through the NLP component. Then, OmniPHR converts the sentence to the *open*EHR archetypes and ontology model.

In the Figure 4, we can observe that in the HL7 FHIR standard the patient identifier is `Id`, whereas in MIMIC-III it is `subject_id`. The *open*EHR standard allows mapping the patient's original identifiers in the Health Information System (HIS), referenced as `subjectID`, to a common identifier, called `ehrID`. The principle is that identifier in *open*EHR follows a universal identification pattern (UID) [36]. In this way, we can maintain the interoperability of patient identification codes.

The first step in the process is performed by the `Sentence handler` subcomponent, which reads the original format and parses to a key=value sentence. The second step is performed by the `Field handler` subcomponent, which identifies the fields and uses the tagger to create a tag=value sentence. Thus, the `NLP subcomponent` has the ability to learn, with a machine-learning algorithm, about input formats, and identify them the next time an equal input occurs. We evaluated the model using the Virtuoso database, which we populated through the OmniPHR. OmniPHR populates the relational portion of the database with the *open*EHR archetype data and the KB portion with the *open*EHR ontology data. We employed SQL queries to check the consistency of the replicated data in OmniPHR against the original patient data. Also, with the patient data filled in the *open*EHR ontology, we employed SPARQL queries on the KB portion of database to verify the populated data from OmniPHR compared with the original data.

In the database, the inserts execute with the following SPARQL syntax:

```
insert in graph <openehr> { <http://subject>
<http://predicate> <http://object> };
```

Moreover, we can use SPARQL queries in the normal way (W3C standard) or through SPASQL (SPARQL within SQL), which follow a pattern similar to SQL, with the syntax:

```
SPARQL SELECT * FROM <openehr> WHERE { ?Subject
?Predicate ?Object };
```

In this way, in the same database, we can verify the data with the same query pattern, in either SPARQL or SPASQL. Moreover, with data in both formats stored in the same database, we avoid possible integration problems between different databases. This feature proved to be efficient for verifying the inserted and updated data in relational and semantic formats. To collect the results, we ran SQL and SPARQL queries in Virtuoso to compare the conversions performed by the model, compared with the original data of the three formats. In the first execution of the selected data set, no manual interference or training adjustment was performed. Only the relevant fields and values were determined. The accuracy achieved on the first run was on the order of 66%. The accuracy represents the part of fields converted correctly, as expected, plus the fields that were not selected and not converted as expected, in relation to the total population of the records. The precision reached was 78.57%, i.e., the percentage of relevant fields that have been successfully converted. Recall achieved 74.32%, i.e., the percentage of fields that have been selected for conversion. Finally, the F1-score reached 76.39%, i.e., the harmonic mean of the precision and recall results. These numbers were initially lower than expected. To improve the failures of conversions on the first run, we had to perform additional training, improving the unfilled fields, as well as investigating the reasons.

Taking as sampling, consider the gender field. The name of this field is `gender` in HL7 FHIR and the values are defined by extensive writing (`male/female/other/unknown`). In MIMIC-III, this field has the same name, but the possible values are characters (`M/F`). However, in the *open*EHR standard, this field has several possibilities of filling because there is a dedicated archetype for this purpose. This archetype has several items, such as: administrative gender, legal gender, anatomical sex, gender expression, gender identity, and preferred pronoun. To maintain compatibility with the HL7 FHIR standard, we filled the fields that are compatible between the two standards. In this case, the compatible type is the administrative gender field. According to the *open*EHR documentation: "This aligns with HL7 FHIR 'Person.gender'" [36]. We trained the OmniPHR model based on the possible *open*EHR definitions and values. In this case, the first time the prototype ran, it did not populate completely the gender field because the possible types and possible values in the source were different. After training the network, stating that `gender` could receive characters as abbreviations, we re-executed the model, and OmniPHR recognized these types populating the ontology correctly. Another example, in the case of unstructured data, is related to allergies.

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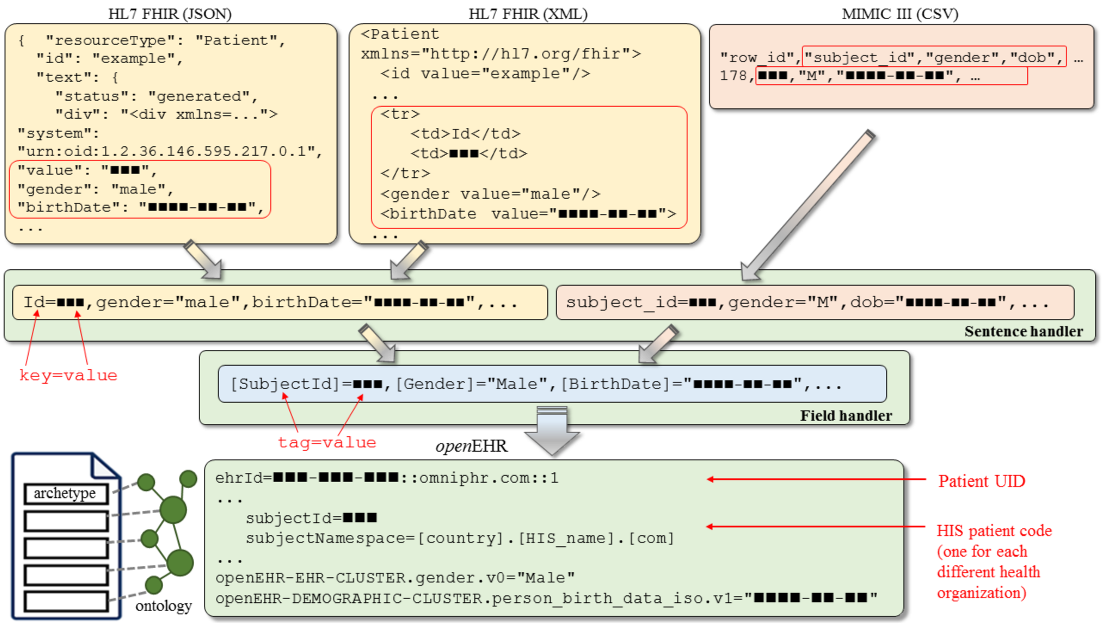


Fig. 4. Extraction and conversion in OmniPHR

In MIMIC-III allergies are described in a descriptive text field, e.g., Allergies: "Codeine and shellfish", or Allergies: "Codeine/Ambien/Shellfish Derived", or Allergies: "He has an allergy to CODEINE,...". However, in *open*EHR, it is a structured field forming an adverse reaction list. With the help of NLP, OmniPHR can extract the relevant data from the sentences and convert this unstructured information to the *open*EHR structured list.

We retrained the model with the new possible values for the unconverted parts. Specifically, in the case of the GATE platform, it provides an API with a series of machine-learning components [35], which we used to recognize the patterns sent according to the standards adopted in *open*EHR. Then, OmniPHR could convert more data sent to the tests, returning a larger number of expected results in the *open*EHR format. After the tuning and training, the accuracy scores improved and reached 81%, precision 87.34%, recall 88.46%, and the F1-score 87.9%.

One of the major difficulties in promoting the interoperability of health records is dealing with a range of different data types and content variability of EHRs, not only considering their structure, but also considering that many data are stored in textual format inside descriptive fields. The experiments on OmniPHR were limited to the data and types provided by MIMIC-III, as well as patient data and data types provided by *open*EHR and HL7 FHIR. Considering the effort involved in training, we believe that it would be possible to extend it to other formats because *open*EHR can be translated into other languages that follow the ISO 639-1 standard; however, further experimentation is needed.

Revisiting the related work and analyzing the results obtained for comparison, it was difficult to draw a parallel. Likewise, it was difficult to find studies that used a metric of statistical analysis to verify, quantitatively or qualitatively, the treatment of the health records' interoperability. Thus, to obtain a more accurate evaluation of the model, we used the F1-score metric. In this way, we obtained a parameter for the algorithm regarding the precision, recall, and accuracy. Initially, we observed that the algorithm obtained low precision, recall, and accuracy. Lower than we expected. However, with machine-learning training, we observed that there was an improvement. In addition to the low score in the first run, a manual intervention effort was necessary to correct and train the model to improve the results. However, there is the advantage of the ability to reuse training learned in new executions, extracting data from structured or unstructured fields. Finally, the model was limited to tests with the MIMIC-III database and using the English language. Thus, as future directions, the model needs to be evaluated using other databases, following other health standards, and tested using other languages.

## V. Conclusion

There are several health standards for PHR use. Revisiting the proposal of scientific contribution, this research aimed to present a model to promote the interoperability between different standards with semantic capability. We identified many ways to promote interoperability between health records, such as the use of archetypes, metadata, ontologies, software agents, templates, and terminologies. To ensure interoperability, the model selected the *open*EHR reference model as the component centralizer. We proposed in OmniPHR the use of NLP as a CNL component to help automate the conversion process. The results obtained with the evaluation of the prototype were promising, demonstrating the feasibility of the OmniPHR model using the health records from the MIMIC-III database. OmniPHR demonstrated compliance with the requirements of semantic interoperability and unified view of patient data. The results of this contribution demonstrated the possibility of obtaining a unified and up-to-date view of health data, presenting a solution based in artificial intelligence with NLP, ontology, and an open health standard to achieve semantic interoperability. In addition, OmniPHR presented benefits, such as the possibility of obtaining inferences about the patients health. In future work, we intend to evaluate the model with data from larger health databases and focus on increasing the possibilities of benefits for patients and healthcare providers. Other important aspects to discuss are data distribution, scalability, security, and privacy. In addition, the prototype can expand to integrate with other open and proprietary health standards.

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