Data interoperability in health surveillance: a literature review to support the development of One Health frameworks

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Abstract

This literature review aims to investigate the state-of-art in data interoperability solutions in health surveillance. Focus was given to the identification of methodologies which can support the construction of a framework for One Health (OH) Surveillance. As OH relies on data reuse across multiple health sectors, and preservation of the original context of the data is fundamental for correct inference and decision making, particular focus was given to semantic interoperability (ensuring the integrity and meaning of the data across systems). Papers were grouped and presented by the context of interoperability application. Within each context, we highlighted interoperability needs and the solutions reported. In all contexts presented, however, a clear narrative was repeated, with approaches based on the use of data models and coding of data based on specific terminologies (schema representation approaches) being replaced by knowledge modeling and ontology-based solutions as systems evolved, and in particular as the complexity of the data usage context increased. While challenges to implementation in practice and scalability are still present, the evidence brought up by this review made it clear that it is possible to build a framework of OHS that is designed as a knowledge layer capable of connecting data on demand, while preserving data sources context and structure.

1 Introduction

One current definition of One-Health surveillance (OHS) is "the systematic collection, validation, analysis, interpretation of data and dissemination of information collected on humans, animals and the environment to inform decision for more effective, evidence- and system-based health interventions"(1). Bordier et al, 2018 (2) pointed out that other concurrent definitions of OHS all emphasize the role of cross-sectoral collaboration in the improvement of health management.

Barriers to data sharing are often listed when evaluating challenges to the establishment of such cross-sectoral frameworks (1–3). The challenge of extracting information from data coming from such heterogeneous contexts goes far beyond the simple access and aggregation of data. Ammon and Makela (2010) (4) described in details the integrated collection and analysis of data on zoonoses in the European Union (EU), first established in 1992, and currently a joint task of the European Centre for Disease Prevention and Control (ECDC) and the European Food Safety Agency (EFSA). Despite this opportunity for joint data analysis, the authors pointed out several challenges to data comparability, from methodological differences between countries, and challenges of data quality and validation, to differences of population structure and population reporting level among sectors. The experience reported highlighted the complex data and meta-data structure needed to capture and take into account all the contextual information needed about the data collected and the data collection processes.

Within individual countries, activities of surveillance in public health (PH), animal health (AH) and food safety (FS) all generate data which can contribute to OHS. Converting those data into valuable information for decision requires not necessarily that those data are aggregated, but that they are interoperable, so that sharing can be performed on demand, for specific problems, respecting various models of data disclosure. Interoperability focuses on cooperation among systems, referring to their ability to continuously communicate and exchange information, and *use* the information that has been exchanged (5,6).

This literature review aimed to investigate the state-of-art in data interoperability solutions in health surveillance. Focus was given to the identification of methodologies which can support the construction of an OHS framework. That is, support the multidisciplinary reuse of data from multiple knowledge domains in a collaborative environment, producing information for decision making across all sectors involved.

2 Methods

The following search string was entered in Scopus on 1st of July, 2020:

TITLE-ABS-KEY(data AND (((public OR population OR animal) AND health) OR ((health OR disease OR infectio* OR zoono* OR veterinar* OR medic*) AND (surveillance OR monitoring)) OR (outbreak* OR epidem* OR epizoot*)) AND (interoperability))*

The string searches title, abstract and keywords of all published resources indexed in Scopus, to match the following criteria:

1. Must have the word "data"
2. Must have the word "interoperability"
3. The health surveillance scope can be defined by:
    a. the occurrence of the expressions "public health", "population health", or "animal health"; OR
    b. the words "surveillance" or "monitoring" in combination with any of the following words: health, disease, any word with the root "infectio"(covering infection, infectious, etc), any word with the root "zoono"(zoonoses, zoonotic, etc), words with root "veterinar", or words starting with "medic".

We did *not* exclude conference abstracts, as we were interested in state-of-art solutions, and new ideas and solutions may still not be published in full original articles. Titles and abstracts of all retrieved papers were read by the two authors, who voted on inclusion or exclusion. The authors were able to vote blind to each other's vote using the freely available literature review tool Rayyan (7).

The following overarching inclusion criterium was used: the publication must refer to a specific data interoperability solution, addressing joint analysis of data from different sources. The following exclusion criteria were applied:

- Not available in English.
- Not primary research.
- Publications which refer to data interoperability in the "data format" sense, not as a challenge to combining content. A particular example of this case were the many papers addressing data interoperability between computers and wearable devices.
- Publications which discuss needs and demands for interoperability, not presenting any particular data interoperability solution.
- Publications focused on data collection guidance (that is, standardisation of data collection, rather than addressing the issue of interoperability of already existing data), data collection tools or database development.
- Publications describing a specific terminology, standard or ontology, but not discussing the scenario of data interoperability it aims to address.

Abstracts accepted by at least one reviewer were subjected to full-text review, during which the same inclusion and exclusion criteria were applied focusing on exclusion criteria that were not obvious from reading only the abstract.

3 Results

The search returned 1198 unique results, after we excluded publications duplicated or not in English. After abstract screening, 324 papers were subjected to full-text review, and 135 were accepted after the two rounds of screening.

As we read the full-texts during the screening, it became clear that there were two dimensions of interoperability being discussed: structural and semantic. Structural or syntactic interoperability refers to the format of data exchange (6). In the EU, the particular context within which we aimed to inform the advancement of an OHS framework, EFSA and ECDC have done significant work, in their respective domains, to solve the problem of *structural interoperability* among datasets from different European member states (MS). These agencies gather standardised and validated data into the Data Collection Framework (DCF)(8) and The European Surveillance System (TESSy)(9), respectively. These standardised datasets, collating surveillance information at the European level, can be accessed through different resources made available by these agencies.

Semantic interoperability, on the other hand, is concerned with ensuring the integrity and *meaning* of the data across systems (6). Semantic interoperability is particularly important in OHS in order to allow data reuse across sectors, and reuse of data for research and knowledge discovery, while preserving the original context of the data.

From the 135 papers subjected to full-text review, 43 addressed only structural interoperability. These papers are listed in the Supplementary Material, and will not be discussed further.

The 92 remaining papers were reviewed to identify and try to group the data sources used, the knowledge domains involved, the nature of the interoperability problem they addressed, and the type of interoperability solution adopted. None of these characteristics alone provided an easy way to categorize and group all papers to present their findings, but smaller groups started emerging from this classification, from which we could gather lessons.

Grouping papers based on their data sources, we first discuss 4 papers which addressed specifically the integration of geographical data into health research.

A large number of papers used electronic health records (EHR) as a data source, but in different contexts. The 44 that used EHR in the context of individual health care or clinical research are presented first, and then the 13 which attempted to reuse knowledge for the construction of population level applications, in particular surveillance applications.

Moving beyond the data source into system application goals, we present 10 further papers which dealt with the construction of public health surveillance systems, and 14 which presented other multi-domain interoperability contexts within health.

Lastly, we present 7 papers which bring forward semantic interoperability frameworks developed and made available for use in biomedical applications – these are generic frameworks, developed to be used anywhere where semantic interoperability is needed.

As we review the papers' contributions, we highlight needs addressed and *solutions employed.* It is outside the scope of this review to provide a theoretical background for these solutions and the technologies listed. Rather, we focus on the context in which they are applied. We will also not address issues related to data sharing, access, or governance.

3.1 Data source: geographical data (n=4)

Three papers from Gao and collaborators, published over four years (10–12), give a good overview of the evolution of methods and solutions for incorporating geographical information services in health surveillance.

In the first paper, Gao et al. (2008) (12) identified four major challenges for the development of health geographic applications: (i) implementation of various health mapping methods in many web-based applications without proper data source description and methods declaration; (ii) need to support many mapping dimensions for health data representation; (iii) constrains to integration and reusability of health applications; and (iv) lack of interoperability between applications. Within the interoperability problems (iv) described by the authors, there are two dimensions to differentiate: data interoperability, versus system (service) interoperability. The first, of interest in this review, was addressed by the authors by the development of a Health Representation Extensible Markup Language (XML) *schema* for sharing of health results.

In a following paper (11) the authors again reflected on the challenges to develop collaborative systems of disease mapping that can empower disease outbreak detection and control in a multi-institutional, cross-border environment, this time adding concerns over appropriate cartographical representations and sensitive dissemination of disease data as a current challenge. The authors also extended the discussion on data heterogeneities to highlight the difference between semantic and syntactic interoperability, already addressed here, plus the issue of "schematic heterogeneities", defined by the authors as referring to "diversity in representations or storage models". The authors suggested that all levels of heterogeneities could be overcome with proper *schema representation approaches*. Their new proposed architecture had an additional layer responsible for data matching and transformation tasks, responsible for converting data from multiple sources into a common schema. The authors were able to demonstrate disease data sharing in a distributed network achieving high flexibility and interoperability. As they discuss, this would make possible for health organizations to generate specific disease mapping and process services, which are then added to a catalogue of interoperable, similar solutions, sharing the costs of disease data collection and analysis, while building the capacity for cross-border disease management. As the authors report, however, the schema-based solution represents very low semantic interoperability, and the development of a *standard ontology* for spatio-temporal disease data would improve the effectiveness and efficiency of the architecture, empowering the construction of truly interoperable distributed disease services.

Following this goal, their next paper reviewed (10) was focused on a health information system allowing semantic querying. Based on the premise that "with well-designed ontologies, the meaning of distributed data can be unambiguously defined; semantic heterogeneity can be resolved, and therefore data sharing and integration can be enabled", the authors developed an architecture where *ontologies* are used in the map/visualization tier, to allow semantic querying by the user; and also in a reasoning server able to connect the various concepts needed to correctly display health data geographically. Rules are defined in the reasoner to allow deducing of new information based on ontologies and facts.

The authors also pointed out that ontologies allow enrichment of data as well as metadata, naming four types of ontologies needed in this specific application: health domain ontologies, geometric ontologies, topological ontologies and cartographic ontologies. For this application, a respiratory disease ontology was built. While various ontologies for health exist, the authors highlight efforts to map and translate between ontologies.

Lastly, Martins and Rocha (2012)(13) studied the feasibility of a distributed web based application to support integration of data on bluetongue (an infectious disease of domestic and wild ruminants) surveillance across European countries. The authors reported that "syntactical interoperability was guaranteed by the use of Open Geospatial consortium standards", and "semantic interoperability was assured by design, by developing a *unique data model*". As the full-text was not available, we don't have more information about how this common data model was enforced or implemented.

3.2 Data source: EHR; applications focused on individual health care (n=44)

Data integration across different systems that produce EHR, such as different clinics, was an issue more often addressed only through syntactic interoperability (see Supplementary Material). If all data sources belong to the same domain, and the data produced will be used in the same context (within domain), the integration was mostly structural. In that context of syntactic interoperability, data standards were a commonly employed solution.

Moving towards semantic interoperability, Hamm et al. (2007)(14) and Khan et al. (2013)(15) highlighted that there is no universally accepted coding scheme, and interoperability based on *standards* is restricted to data coded using the same specific terminology. Paraiso-Medina et al. (2015)(16) further pointed out that data integration based on data coding is still mainly a manual task. All three group of authors proposed *semantic modelling* of concepts among different clinical terminologies. In the work of Hamm et al. (14) an *automated code matching process* was investigated.

Semantic interoperability was introduced when there was a clear emphasis in data re-use. A typical scenario of data re-use within health care was the information flow between various components of medical information systems. Akatkin et al (2017) (17) compared semantic integration to classic interaction via mediators, and the creation of *standard data models in XML*. Their conference abstract concludes on the advantages of a semantic core for the creation of a digital health ecosystem (but very limited information is provided in this abstract). Already in 2006, Orgun and Vu (18) proposed a framework for interactions in a distributed medical systems environment. Their multi-agency system relied on model based on the *Health Level Seven (HL7) message standard*, widely adopted to exchange health data. This provided a semi-automatic tool to map among the various distributed sources within the information system, in replacement of relying solely on manual coding by human analysts. The use of a healthcare *ontology* was the solution proposed by Miller and Maccaull (2009)(19) to connect the various tasks in a health care flow, from assessments, to procedures, therapies, laboratory diagnostics, etc. Kiourtis et al. (2018)(20) proposed a mechanism for doing that while matching ontology content to HL7 resources. Wang et al. (2013) (21) extended the idea further, using the power of knowledge representation through ontologies to not only connect systems and allow data to flow among them, but to create personalised clinical pathways for individual patients, improving treatment quality and efficiency of healthcare organisations.

Rosenbloom et al. (2017)(22) and de Madariaga et al. (2014)(23) also emphasized the role of semantic integration when the goal is knowledge discovery from the data available. The former authors reviewed initiatives based in standardized data models to support clinical research from EHR data, while the latter emphasized data re-use in a context of evolving knowledge. They proposed an *explicit separation of information and knowledge*. A reference model is proposed for representation of clinical data, while the knowledge that connects the concepts in the data is modelled with higher degree of semantics, and can be subjected to updates.

When EHR was specifically reused to improve clinical research, eight papers proposed solutions based on establishing *common data models or elements*, relying on the mapping of individual data sources into these single models or standardized terminologies (24–31). Mohanty et al. (2008) (28) demonstrated how these common data elements (CDE) can be used to construct information models. A formalization of these models into *ontologies* to support cross-domain data integration and reuse in clinical research was the solution described in three other clinical research papers (32–34). Rath et al. (2012) (34) presented the evolution of Orphanet, a multilingual information portal for rare diseases, and stated that the need for an ontology grew from the increasing complexity of the knowledge base in terms of maintenance, quality control, and interoperability needs. Antoniades et al. (2017) (33) presented Linked2Safety, an ontology based solution for knowledge discovery over multiple, distributed EHR sources, while keeping their anonymization and security. In this approach, data are aggregated into *data cubes*, which are then semantically annotated with a reference ontology.

The remaining papers promoting semantic interoperability among EHR data sources, with the specific goal of improving clinical decision support, all implemented solutions based on the use of *ontologies and knowledge modelling*. These were 10 papers discussing the general integration of EHR data sources and their reuse to build models for clinical decision or knowledge discovery (35–44); and 12 papers addressing clinical research in a very specific context (such as child obesity or brain imaging) or even specific diseases (45–56). Among the latter, the work of Li et al. (2020) (56) was published early during the COVID-19 pandemic, proposing clinical guidelines for the disease using an openEHR template. OpenEHR are a set of community maintained programmes to support open specifications of clinical models in health care, allowing explicit modeling of the domain knowledge separated from the data representation (57). As Li et al. (56) noted, the fast evolving knowledge about the disease demanded the use of frameworks that supported semantic explicit and collaborative modeling to meet the dynamic data requirements during the global crisis.

These papers notably emphasized the adoption of solutions that do not require data to be aggregated – rather, they take into account the increasingly distributed nature of the data sources, and the impossibility of attempting to aggregate all data into a single database or server. Connectivity and interoperability are implemented in this *federated architecture* through the use of smart clients, capable of placing queries over the distributed data sources. As ontologies can be constructed to be interoperable among themselves, there is potential to build large knowledge graphs that connect models from various domains and contexts, and can then be applied to networks of distributed data. When it comes to realizing this potential in practice with currently available technology, however, authors identify challenges related both to the availability of tools that can be easily integrated into workflows used by medical experts, as well as the capacity to reason over large amounts of data. Regarding the latter, in particular, Barisevičius et al. (2018) (58) joined many publicly available ontologies of biomedical relevance into one *Linked Data Graph* (LDG), attempting to use the resulting model to empower a chatbot in the medical app Babylon. The authors cautioned against the rapid growing complexity of the model, and concluded with a decision to redo their LDG from scratch, using a more conservative and parsimonious approach.

3.3 Data source: EHR; applications focused on population health (n=13)

In a series of three papers (59–61), Lopez and Blobel described a business and information architecture for the specification of a national system in Colombia that provided semantic integration between public health surveillance and clinical information systems. In the system proposed by the authors, normalization was ensured by adopting the Unified Modeling Language (UML) a *standard language* to express the information. UML is widely used in clinical systems and was mentioned in a large number of the EHR papers reviewed above. The authors discussed the need for balance between languages that allow for domain knowledge modeling with participation of domain experts, such as UML, and more formal models, which allow more strict semantic control by expressing programmatically additional constraints that are normally expressed in UML diagrams in natural language. An approach suggested by the authors to achieve such balance is the harmonization of UML diagrams using domain reference models, terminologies and vocabulary. The idea was developed in (61), where the authors focused more on the semantic interoperability issues of the system developed, and presented the construction of *UML profiles*. These profiles are UML packages containing the model that allows repurposing of clinical data for the public health information system, and are exchanged between tools using XML metadata interchange (XMI).

The creation of a "*public health profile*" within the systems already in place for exchange of individual health records was also the approach suggested by Renly et al. (2009) (62). Syntactic and semantic interoperability were addressed by enforcing the use of a *common vocabulary* (SNOMED-CT), but a specific profile was created with the agreed information that should be reported in cases of laboratorial confirmation of foodborne pathogens. Population level utility was further created by allowed queries that were not patient centric, that is, queries where the patient field was left empty. Khalique and Khan (2019)(63) developed a framework that could be installed in participating hospitals to *map* their EHR data into a public health record model, and transmit this information further for use at the population level.

Two abstracts described an initiative to improve surveillance at the national level in Namibia by connecting hospital systems with the specific purpose of sharing and exchanging disease-surveillance information (64,65), but details about the interoperability solutions used were not available.

The CrowdHEALTH project (66) aimed to "introduce a new paradigm of Holistic Health Records (HHR)", and proposed a platform to augment EHR records with other sources of information that allow building knowledge on health determinants. In the proposed structure, the authors point to an "Interoperability Layer", where they describe that "data are aggregated into HHR through different data models and query languages". More details about this part of the system were not the focus of the publication found.

An *ontology-based* approach to integrate data from different health care providers, and even incorporate data from air pollution to enable research on this as a risk factor for stroke over time, was adopted in (67). The authors describe a four-step data transformation approach in which data and metadata are mapped into *Web Ontology Language (OWL)* formats, resulting into an integrated, and semantically queryable set of files.

As an alternative to building systems that integrate or allow notification of data from individuals to a central public health information system, the *federated query approach* sees the existing clinical systems are repositories that could respond to a central query. The "Query Health" system (68) sought to develop a workflow that allowed investigators to compose queries, securely distribute the question through a network of data repositories, and combine the aggregated results. Of particular importance in this review was their pilot application of population-based surveillance using EHR data. Query composition and processing were implemented as a graphical, web-based query builder using the Informatics for Integrating Biology and the Bedside (i2b2) platform. I2b2 provides a set of web-services components (cells). An ontology cell was used to enable translation and data elements integration using the Query Health data *ontology*.

The i2b2 platform was also used by Klann and colleagues (69) to create a multi-sourced medication information platform for postmarketing drug surveillance. This was not simply an exercise of translation or mapping between different standards or terminologies. As the authors discuss, converting medication dispensing data from a HL7v2 (HL7 reference information model, version 2) to the C-CDA (Consolidated Clinical Document Architecture) format used in the EHR required data conversion from a record-level based to a document based format. For input into i2b2, the data were then denormalized into the Patient Data Object (PDO) format, observation-centric. For these data conversions, the authors used the Model Driven Message Interoperability (MDMI) toolkit, a *graphical data-mapping tool* developed with the goal of enabling health data conversion between any types of data format. The tool however had to be adapted to enable a "linked data" functionality that would preserve the linking between sibling records used in HL7v2, relevant for the semantic meaning of records; and to be able to "flatten" the complex hierarchical structures of C-CDA into the PDO structure. To enable querying of the rich database resulting from all these integration efforts, querying through the i2b2 web tool is supported by *ontology hierarchies*.

Yuksel and colleagues (70) also built a tool for pharmacovigilance, using an *ontological framework* to support both syntactic and semantic interoperability when reusing EHR data to generate information for surveillance at the population level. The authors argue that the main shortcoming of initiatives that address interoperability using defined terminologies/schema is that "dynamic eligibility criteria execution on top of the actual data sources is not supported". In contrast, the authors propose an ontological framework that defines both the structural mapping and the semantic modeling of the original data into the representations used for surveillance. This allows local systems to continue using their terminology systems, while providing a translation tool that is "future-proof" – eligibility criteria for the pharmacovigilance system can be evolved. Development of the framework still required significant work to map terminologies in use in the data sources to a common information model ontology. Moreover, it is important to note the challenges reported by the authors to implement a reasoning engine able to perform in reasonable time. This imposed a constraint in the reasoning requirements. A similar framework was used in (71), this time reusing EHR records for the surveillance of Healthcare-Associated Infections (HAI), and supported by the HAI ontology (HAIO). The authors used an upper level ontology (SemanticsScience Integrated Ontology – SIO) for “consistent knowledge representation across physical, processual and information entities”, and aligned with the Extra Simple Time Ontology (ESTO) to support temporal knowledge management.

3.4 Interoperability in public health surveillance (n=10)

Pandiyan et al. (2011) (72) proposed an interoperable “Infectious Diseases Reporting System”, which would improve efficiency and reduce timeliness in tracking and identifying epidemic outbreaks and emerging infectious diseases by connecting disease reporters (clinics and hospitals) directly to a centralized repository accessible by regulatory agencies. To solve the challenges posed by the diversity of software structures and data standardization practices (or lack of) among the healthcare providers, the authors suggested a semantic layer responsible for retrieval and mapping of the information into a unified standard. The solution described by the authors used *Web services as a core component for information exchange*, and the full system architecture can be found in the original publication. The semantic information integration function, of relevance in this review, was made possible using *ontology-based rules*. A central ontology was designed for the system, and expressed in OWL. Besides providing semantic interoperability among various data sources, the ontology also adds a layer of expressiveness – when a patient is diagnosed with an infectious disease in the source healthcare provider, the clinical system launches the Web service that will send data to the centralized system, and the ontology identifies the disease diagnosed and determines the level of “criticality” of the case. Rao et al. (2014)(73) also proposed creating tools to enable reporting of notifiable diseases directly from digital systems used to manage clinical information using a central ontology as the interoperability solution – they developed the Public Health Ontology.

In the only system found for animal diseases reporting, Thaler et al. (2015)(74) also suggests the use of an *ontology-based semantic layer of integration* to connect various organizations collaborating to control outbreaks of exotic animal diseases.

Focusing not on how regulatory agencies gather health and disease information from scattered sources, but on what they do with that information at the population level, Turbelin and Boëlle (75,76) pointed out a lack of adoption of the open data principles, when compared for instance to research data. They proposed a model to expose aggregated, summarized indicators of population health, allowing these data to be available for reuse. The authors propose not a data sharing or data integration model, but the adoption of practices to annotate data with interoperable formats, allowing third parties (including for instance artificial intelligence-based applications for disease monitoring) to access the data irrespective of their own data/system structures. The authors reviewed several non-proprietary *data exchange standards*, deciding to pilot implementation of two of them: The Open Data Protocol (OData)(77) and the Statistical Data and Metadata Exchange – Health Domain (SDMX-HD) (78). The authors disregarded the HL7, for instance, due to its focus on patient data. The original articles by the authors provide a detailed description of each implementation piloted, as well as evaluations from the perspective of both the agency exposing the data and the end-user of the system. The main difference pointed out by the authors, is that SDMX-HD is developed by domain experts, and encourages harmonization. Expressivity relies on the use of a controlled terminology. OData, arising from computer scientists, aims to be a generic application programming interface

(API). While this meant that extra effort was needed to create a representation for the public health data being exposed, this option offered greater extensibility, generalizability and sustainability. The authors also reported that OData made no formal difference between data and metadata, but the authors complemented that both standards allowed annotation of metadata specifying the processing from raw data to surveillance indicators. A big advantage of the more general OData framework was the greater availability of end-user tools. As the authors reported, "SDMX-HD was designed primarily for exchange between institutional information systems", while OData was designed for the exact type of applications the authors conceived, where data owners expose their data, and third parties and applications can crawl a number of federated sources, made interoperable not just syntactically through data terminologies, but semantically through knowledge models.

The use of OData was not reported in any other paper reviewed, but the use of *knowledge models* was commonly highlighted to allow semantic interoperability when integrating multiple data sources, enable extensive exploration of the integrated data, and empower knowledge discovery. Turbelin and Boëlle pointed out that not all the contextual information needed to calculate and interpret population health indicators comes from the raw data of cases. Population baselines/denominators are also needed. Shaban-Nejad et al. (2017) (79) further pointed out that transparency and interoperability further depend on documenting the algorithms and baselines used to calculate the indicators. As these authors agree, the reuse of transformed (aggregated) data relies on proper documentation of not only the data itself, but the processes of transformation used (data and metadata annotation). Associating this information to raw data of individually reported diseases cases is not trivial, and graphical data representations seem to have more and more become the tool of choice as systems got more complex. In particular, *OWL expressed ontologies*.

Shaban-Nejad et al. (2017) (79) presented PopHR, "a knowledge-based platform to support integration, analysis, and visualization of population health data". The architecture presented by the authors relies on ontologies to "collect, normalize, align, integrate, and transform both structured and unstructured data from multiple sources into a consistent framework needed for large-scale analysis of population health data". The authors introduced the concept of evidence-based public health, and described the expression of a model to capture causal knowledge, explicitly linking different population health indicators to determinants-of-health. The use of ontology-based reasoning allowed data integration and supported knowledge discovery from these data in a flexible and adaptable way. The authors did point a problem with scalability. The authors stressed the need to reuse existing ontologies as much as possible, as it is not feasible for a single system to keep up with the ever growing volume and complexity of incoming data.

Al Manir et al. (2018) and Brenas et al. (2017, 2018)(80–82) described a fully implemented system to provide interoperability among data from disparate sources, providing a consistent knowledge source to support (dynamic) malaria surveillance. The authors listed the common challenges of integrating data from multiple data sources, such as sources being scattered, the diversity of access methodologies to the different data sources, and the absence of rich metadata. But more importantly, they pointed out that the target itself – using these data to support decision making – is constantly changing, as our knowledge about the disease and its occurrence in different regions evolve. Moreover, the data sources themselves are constantly evolving, and an integration structure must be capable of reacting to updates, and even adapting the underlying interoperability model to these changes. The "*Semantic Interoperability and Evolution for Malaria Analytics" (SIEMA)* framework presented by the authors allows situational monitoring by providing uninterrupted dynamic surveillance queries of multiple resources. Rather than aggregating data centrally, these resources are queried in the *federated model*. *Domain ontologies* are used to align, merge and integrate various models that contribute knowledge for malaria control. SADI Web services ensure discoverability and interoperability for resources that retrieve and transform data. Additional architecture components are responsible for monitoring changes in the linked resources. As both the data and the knowledge about interpreting the data changes over the time, the authors highlight that the reliability of the system is highly dependent on the interoperability components, and the ability to detect and identify changes that the system needs to adapt to.

An ontological framework to empower malaria surveillance was also developed in India (83). As in the example above, the authors highlighted the number of knowledge domains involved in surveillance against this vector-borne disease, the number of information generation activities that need to be brought together, and the need to use a knowledge model to support integration and reasoning. The authors highlighted, moreover, the capability of *ontologies* not only as an interoperability tool, but also as a <u>knowledge building instrument</u>, capable of providing feedback loops through which the surveillance system and the ontology learn and evolve.

3.5 Other multi-domain contexts in health (n=14)

A set of papers were related to applications within the cancer biomedical informatics grid (caBIG), a "federated program of biomedical information system and tool development" spanning multiple research domains (84). Within this grid, syntactic and semantic interoperability among biomedical information services is provided by the cancer common ontologic representation environment (caCORE). To enter the grid, a system needs to serve, through a documented API, data objects derived from a domain object model that has been expressed as a UML class diagram. Phillips et al. (2006) (84) described the development of the caCORE software development kit (SDK), which provides a workflow to standardize and expedite UML-based modeling, development and deployment of caCORE compliant systems. Vergara-Niedermayr et al. (2013)(85) highlighted that most of the data sources that can enrich the grid are in relational or XML databases. They presented a framework based on *model driven architecture (MDA), common data elements and controlled vocabularies* to encapsulate XML databases. The framework then exposes the backend XML database as an object-oriented (UML-based) semantically annotated information model that can become a potential grid endpoint. Krikov et al. (2011)(86) addressed the issue of legacy compatibility, and the need to migrate existing analytical tools into the integrated grid environment. They were able to achieve semantic integration of GeneHunter (a genetic epidemiology tool) with the caBIG grid also using UML modeling, and the developed model was made publicly available. In 2012, González-Beltrán et al. (87) argued that the querying functionality of the caBIG grid, given at the structural metadata level, was under-utilising the ontology-based annotations, and presented a theoretical foundation for ontology-based queries over the grid's data. The proposed framework brings the power of *Semantic Web tools, and the linked data approach* to the grid by adding a *semantic layer expressed using OWL*. While the approach depends on establishing mapping between the component data schemas to a common schema, the use of OWL-based ontologies, in contracts to common data elements and data models based integration, allows, as highlighted by the authors, to incorporate domain knowledge into the system and make them semantically-queryable. The authors highlighted this as a necessary step to allow the development of systems that need to discover knowledge over datasets from different domains.

The challenges to the <u>identification of patterns and knowledge discovery</u> posed by the heterogeneity of systems and distributed nature of data were brought up in the DebugIT project (Detecting and Eliminating Bacteria Using Information Technology) in the specific context of the fight against antibiotic resistance. The project highlighted that case-based knowledge analysis, over a large amount of cases, would allow the discovery of patterns to guide alignment of antibiotics treatment schemes, and in a series of papers (88–90) described the structure developed to allow data miners to “query distributed clinical information systems in a semantically rich and content driven manner” (88). The system requirements were identified as: providing aggregated information from numerous national sources; no central data storage; providing information online, improving the current timeline of supranational monitoring systems which only provide information in yearly batches; a formal, semantic-aware data model; high performance; and reliable results. To fulfil these desiderata, *Semantic Web technologies* were used to create an architecture where local laboratory databases become semantically aware end points. Data definition ontologies (DDO) are used in each individual location to provide syntactic normalization with the local information system. These are then mapped to a central application ontology, the DebugIT Core Ontology (DCO). In a “view layer” this domain ontology is used to provide the user with query templates to represent antimicrobial resistance clinical questions. A semantic mediator coordinates the access to the different end points, translating the query templates to allow local data aggregation operations. Datasets are therefore loosely coupled in a federated designed, allowing on-demand querying of information to monitor antimicrobial resistance evolution, without any central storage of data. The use of semantically aware models allows the system to be linked to external Web resources, or other clinical research projects, and makes it trivial to expand the coverage of concepts or adapt to new EHR or laboratory information systems (89).

An architecture of federated data sources, united semantically to provide context-aware knowledge discovery using a *central domain ontology*, was used to enable multiscale querying of brain data (91); to develop the Parasite Knowledge Base (92); and to develop the semantic proteomics dashboard (93). A central ontology to provide “an abstraction layer over siloed data” was also used to create a Linked Data-based information system to track vaccines, and allow logistic planning and integration with health information systems (94).

The federation model to create knowledge bases in health care was demonstrated in two examples using different technological approaches based on resources of the *Semantic Web* (95). One example was designed for users wanting to browse broadly over a number of interconnected data sources, and the other for querying distributed databases with a specific focus. In both cases, a user interface allows querying by users not familiar with SPARQL (the protocol and query language used in the Semantic Web to retrieve and manipulate data stored in Resource Description Framework (RDF) format). The examples developed by the authors were specifically focused on neuroscience, but the goal of the work was to demonstrate how Semantic Web can allow the development of global life science models, and point out advantages and challenges that can guide future research and tool development. Data sources not already available in RDF were converted and explicitly annotated using Open Biomedical Ontologies. The authors developed a social tagging tool – *aTags*. The tools suggests terms from DBpedia and other domain ontologies, and users can tag relevant content directly from the browser, generating a XHTML+RDFa output that can be embedded anywhere on the web such as blogs, wikis, emails, or, as in the focus of this work, biomedical databases. Other social tagging tools were cited.

The use of semantic annotation to improve machine usability and interoperability of data already made publicly available was brought up by Natsiavas et al. (2018) (96) in the context of pharmacovigilance. Differently from the EHR-based pharmacovigilance discussed previously, the authors created a *central ontology* suggested to be used to annotate – and integrate – publicly available adverse drug reaction reports. Tilahun et al. (2014) (97) suggested the same approach for health data published regularly by the World Health Organization (WHO). The authors developed a

Linked-Open-Data (LOD) based health information representation joining over 20,000 HIV-related data elements from the WHO global health observatory database with elements from DBpedia, Bio2RDF and LinkedCT. The linked data are represented in RDF, integrated into a triple store, and users can interact with the entire knowledge base created through a SPARQL query interface. To convert the publicly available data into RDF, the authors used an Excel to RDF converter, and expressed the data using the Data Cube vocabulary, a vocabulary that allows representation of statistical data and associated meta-data such as space and time dimensions of the observations.

3.6 Semantic interoperability frameworks for biomedical applications (n=7)

Gessler et al. (2009)(98) pointed three main technology constraints to integration of systems over the web, common in distributed service systems: mutability of traditional interfaces; rigidity and fragility of schemas based on subsumption hierarchies; and confusions between data content and data structure which can "bury" data deep in XML hierarchical structures. The authors postulated that the need to have semantically explicit frameworks is driven not only by the increasing sophistication of science, but also by the need to address technology limitations; and defined the three basic requirements of a semantic web services architecture: common syntax, shared semantic, and semantic discovery. Recognizing, however, the immense value of knowledge already accumulated in legacy systems, and limitations of the Semantic Web frameworks OWL based, the authors developed a hybrid framework - SSWAP (Simple Semantic Web Architecture and Protocol).

The authors redefined the problem of integration from "specifying a syntax and messaging layer used to connect clients and providers", into the need to "provide clients and providers a way to describe their queries and data, find each other on the web, and engage semantic negotiation to determine suitability-for-purpose at transaction time". This redefined problem has three main actors – data providers, data clients, and a discovery server to connect them – and in the SSWAP framework these actors use ontologies to communicate in a semantically consistent manner. No central ontology is enforced, and a web of ontologies grows as more resources are annotated with specific domain/application ontologies. The authors envisage that this opens space for a shared evolution driven by the domain communities.

Any provider can describe their resources using a Resource Description Graph (RDG), which is an OWL document available publicly via Hypertext Transfer Protocol (HTTP). As the framework allows encapsulation of the data in any database into this graph for data transport, "[t]his leaves the manipulation of the data's "raw value" to any particular technology of the day, allowing the system to evolve as new technologies are developed"(98). The authors demonstrated the practical implementation of the framework by using it to semantically describe three major information biomedical resources (99).

While the use of federated, semantically aware data networks has increasingly allowed the querying of data over multiple data sources, and enabled knowledge discovery, Wilkinson et al. (2010)(100) pointed out that the power of Description Logic Reasoners to generate and test hypothesis cannot be leveraged in these networks when they are only able to compute inferences for a single, locally stored dataset. While ontologies and Web Service Workflows are becoming increasingly used to document "explicit, shareable, referenceable representations of how an experiment was done", the authors argued that these technologies had not aided "the aspects of the scientific method relating to explicit discourse, disagreement, and hypothesis generation". To allow the semi- or fully-automatic discovery and pipelining of Semantic Web Services in response to *ad hoc* user queries, the authors introduced a Semantic Web Service Framework composed of two main reusable components – the Semantic

Automated Discovery and Integration (SADI) and the Semantic Health and Research Environment (SHARE) (100,101). SADI provides a set of “best-practices” for modeling Semantic Web Services in the scientific domain, and the authors describe SADI-compliant tools available from both client and service-provider perspectives, such as modules in Perl, Java, and a Protégé Plug-in. SHARE “augments OWL reasoners with the ability o retrieve entities from remote data sources at the time of reasoning” (100). Chepelev and Dumontier (2011)(102) applied the SADI/SHARE framework to create a network of chemistry resources, creating a workflows of reproducible and interoperable computational analyses of the exposed resources.

Postulating that despite awareness of their benefits, adoption of semantic web tools in life sciences had been slow due mainly to barriers of adoption, Lopes and Oliveira (2011, 2012)(103,104) introduced a software stack called COEUS. This “semantic web in a box”, as the authors described, is meant to provide agile transition from primitive to semantically enhanced systems. COEUS internal structure is based on an ontology model, which can be complemented with any external ontology. COEUS is built to generate new information systems from scratch, simplifying the translation process from existing formats, such as comma separated values (CSV) CSV, XML or Structured Query Language (SQL), allowing these formats to be integrated with SPARQL query results. The loaded content can be matched against any chosen ontology in real time. To provide outward interoperability, COEUS provides an external API comprised of three layers: REST (Representational state transfer) services, a SPARQL endpoint and LinkedData views. Data can be requested in different formats.

4 Discussion

We have conducted a literature review of data interoperability solutions applied to health data focusing specifically on cases where semantic interoperability was addressed. In the results section we have listed the interoperability needs and solutions described in the papers included in the review.

A large part of the selected papers referred to work addressing the reuse of EHR, which are arguably the largest source of data in the health context. Interoperability needs within the health-care system, however, are dominated by the demand for system interoperability, and actual data interoperability needs are mainly syntactic if data are not going to be used outside the clinical context. The search string used was purposely designed to focus on health applications at the population level in general, and health surveillance in particular, but a lack of focus on surveillance was not included in the exclusion criteria. From the 57 articles reviewed which presented applications based on EHR, 13 were indeed focused on population level applications. The other 44 were included because they specifically addressed semantic interoperability.

Semantic interoperability is a necessary condition for data re-use outside its primary context of collection, integration of data from different domains, and knowledge discovery. These are all necessary conditions for the development of a framework of One-health surveillance.

A deliberate choice was made to group and present papers not by the type of methodological approach used, but by the context of application. In all contexts presented, however, a clear narrative was repeated, with approaches based on the use of data models and coding of data based on specific terminologies (schema representation approaches) being replaced by knowledge modeling and ontology-based solutions as systems evolved, and in particular as the complexity of the data usage context increased.

Schema-based solutions included extensive use of UML and HL7 in the health-care context, and various XML-based terminologies in population health. These tools were mainly used in architectures that relied on transferring of data to a central database. The increase in data volume, velocity and variety created the demand for solutions that can be applied over distributed data sources, without requiring these source data to be recoded or transferred. Federated architectures became more common, with OWL expressed ontologies being used as a “knowledge layer” able to connect, query and even reason across the disparate data sources connected by the architecture. In this model, data owners increasingly make their data available through HTTP services or SPARQL endpoints, rather than transferring data.

In this model of integration, as Gessler et al. (2009) (98) stated, data providers and data users are not directly connected by a messaging layer. Instead, a semantic-explicit model is used by data providers to describe their data, and for applications to define their queries. A “discovery server” is used to connect these two ends, and establish fit-for-purpose “transactions” on demand. All the general semantic interoperability frameworks reviewed work in this model, and OWL expressed ontologies were the language used for semantically consistent communication between the actors.

The advantages of semantic explicit, ontology-based approaches were highlighted in every step of the data to information continuum. Data owners can use data collection and storage practices that best fit their purpose without compromising interoperability with other systems. Moreover, there is no imposing of specific data models or coding practices that could impose a significant amount of manual coding (16), or compromise legacy compatibility.

Data analysis and processing in this new model is not focused on gathering and cleaning data, but in passing data through an information flow. Miller and Maccaull (2009) and Wang et al. (2013) (19,21) demonstrated the creation of information flows at the individual care level. At the population level, Shaban-Nejad et al. (2017)(79) demonstrated how the information flow can gather data from external sources that allow monitoring of population health indicators and risk factors, augmenting the information contained in clinical data. Klann et al. (2015) (69) also highlighted that when data are reused in a new context, tools for mapping data are not enough. The process may require transforming, aggregating and/or denormalizing data. Authors pointed out that the data analysis process itself can be modelled and documented through the use of ontologies. Any assumption and analysis choices made when aggregating data or building population health indicators, for instance, can be explicitly annotated and linked to the data.

As Gao et al. (2012) (10) and Turbelin and Boëlle (2013)(76,105) pointed out, the use of semantic explicit models allows enrichment also of metadata. This is particularly important when data needs to be integrated over multiple domains, so that the context in which the data were captured can be explicitly documented and taken into consideration when used for inference.

On the last step of the continuum, presenting information to users, various authors reported the construction of graphical semantic querying interfaces. Cheung et al. (2009)(106) presented even the use of social tagging to semantic explicitly annotate even data delivered as narrative texts.

What is continued being highlighted through these examples is the separation of data from knowledge enabled by semantic modeling. Several authors (22,23,56,70,80–82) pointed out that this is needed to create future-proof applications. As knowledge itself evolves, knowledge models can be updated without imposing change in the structure of source data. Any data classification, aggregation and filtering needed is performed on demand, keeping up to dynamic data requirements.

Besides promoting data interoperability, ontologies are themselves interoperable tools, and efforts into knowledge modeling become cooperative. As modeling the knowledge in any domain is a daunting task, especially in a scenario of ever evolving knowledge, this is another feature that promotes sustainability of this approach.

The evidence brought up by this review makes it clear that it is possible to build a framework of OHS that is designed as a knowledge layer capable of connecting data on demand, while preserving data sources context and structure. But it also highlighted that realizing this potential in practice would come with great challenges. Set aside the data access and governance issues that will not be discussed in this review, many of the applications reviewed were research projects, and evidence of implementation in practice is still scarce. There is a lack of tools that can be readily adopted by domain experts, and scalability of semantic tools was a documented limitation (58,70).

5 Conclusions

OHS relies on the reuse of data from different domains – animal health, public health, food safety, as well as environmental data and indicators of risk and health. This review showed that this can be achieved by explicitly modelling the knowledge needed to integrate disparate data sources under specific context questions. If modelled using ontologies, this would allow this daunting task to be performed collaboratively and reusing knowledge already coded in biomedical ontologies. This will further allow OHS to continue evolving, as our own understand of what “One-Health” means evolves. More importantly, it would prevent One-Health to becomes just one more silo of information into which we transform and transfer data.

6 Abbreviations

AH - animal health
API - application programming interface
C-CDA - Consolidated Clinical Document Architecture
CDE - common data elements
CSV - comma separated values
ECDC - European Centre for Disease Prevention and Control
EFSA - European Food Safety Agency
EHR - Electronic Health Records
EU - European Union
FS - food safety
HL7 - Health Level Seven (HL7) message standard
HTTP - Hypertext Transfer Protocol
LDG - Linked Data Graph
LOD - Linked-Open-Data
MDA - model driven architecture
MS - member states (in the European Union)
OGC - Open Geospatial consortium
OHS - One-Health Surveillance
OWL - Web Ontology Language
PDO - Patient Data Object
PH - public health
RDF - Resource Description Framework
REST - Representational state transfer

SDMX-HD - Statistical Data and Metadata Exchange – Health Domain
SPARQL - SPARQL Protocol and RDF Query Language
UML - Unified Modeling Language
WHO - World Health Organization
XML - Extensible Markup Language

7 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

8 Author Contributions

Both authors acted as reviewers in all stages of the literature review. FCD wrote the first draft and both authors reviewed the final text.

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10 References

1. Stärk KDC, Arroyo Kuribreña M, Dauphin G, Vokaty S, Ward MP, Wieland B, et al. One Health surveillance - More than a buzz word? Prev Vet Med. 2015;120(1):124–30.

2. Bordier M, Uea-Anuwong T, Binot A, Hendrikx P, Goutard FL. Characteristics of One Health surveillance systems: A systematic literature review. Prev Vet Med [Internet]. 2018;(October):0–1. Available from: https://doi.org/10.1016/j.prevetmed.2018.10.005

3. Johnson I, Hansen A, Bi P. The challenges of implementing an integrated One Health surveillance system in Australia. Zoonoses Public Health [Internet]. 2018 Feb 1 [cited 2019 Aug 5];65(1):e229–36. Available from: http://doi.wiley.com/10.1111/zph.12433

4. Ammon A, Makela P. Integrated data collection on zoonoses in the European Union, from animals to humans, and the analyses of the data. Int J Food Microbiol [Internet]. 2010;139(SUPPL. 1):S43–7. Available from: http://dx.doi.org/10.1016/j.ijfoodmicro.2010.03.002

5. Cardoso L, Marins F, Portela F, Santos M, Abelha A, Machado J. The next generation of interoperability agents in healthcare. Int J Environ Res Public Health. 2014;

6. Definition of Interoperability. In: HIMSS Dictionary of Healthcare Information Technology Terms, Acronyms and Organizations. 2nd editio. 2010. p. 190.

7. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan — a web and mobile app for systematic reviews. Syst Rev [Internet]. 2016;5:210. Available from: https://rayyan.qcri.org

8. European Food Safety Authority. Data Collection Framework (DCF) guidelines for Data Providers for the 2013 Reporting Season. EFSA Support Publ [Internet]. 2013; Available

from: https://efsa.onlinelibrary.wiley.com/doi/pdf/10.2903/sp.efsa.2013.EN-444

9. European Centre for Disease Prevention and Control. The European Surveillance System (TESSy) [Internet]. 2019 [cited 2020 Oct 30]. Available from: https://www.ecdc.europa.eu/en/publications-data/european-surveillance-system-tessy

10. Gao S, Anton F, Mioc D, Boley H. Non-spatial and geospatial semantic query of health information. In 2012. p. 167–72.

11. Gao S, Mioc D, Anton F, Yi X, Coleman DJ. Online GIS services for mapping and sharing disease information. Int J Health Geogr [Internet]. 2008;7. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-41749101487&doi=10.1186%2F1476-072X-7-8&partnerID=40&md5=d7140286d19561782a7f8c301f0d733c

12. Gao S, Mioc D, Yi X, Anton F, Oldfield E. Geospatial services for decision support on public health. In 2008. p. 1361–6. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85044166130&partnerID=40&md5=e9980f68539ff5cd3df2d623e867537b

13. Martins H, Rocha JG. Distributed geospatial data management for entomological and epidemiological studies. In: Discovery of Geospatial Resources: Methodologies, Technologies, and Emergent Applications [Internet]. 2012. p. 220–40. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84898317986&doi=10.4018%2F978-1-4666-0945-7.ch011&partnerID=40&md5=928db14bbfde6822db6a3cd4a6aa3bc4

14. Hamm RA, Knoop SE, Schwarz P, Block AD, Davis 4th. WL. Harmonizing clinical terminologies: driving interoperability in healthcare. Medinfo [Internet]. 2007;12:660–3. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-38449120110&partnerID=40&md5=4f7a956e8438bee666dcafe0818a6e9a

15. Khan WA, Hussain M, Afzal M, Amin MB, Saleem MA, Lee S. Personalized-detailed clinical model for data interoperability among clinical standards. Telemed e-Health [Internet]. 2013;19(8):632–42. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84899778383&doi=10.1089%2Ftmj.2012.0189&partnerID=40&md5=49724da5c5ca9c4016593afc7b4c4177

16. Paraiso-Medina S, Perez-Rey D, Bucur A, Claerhout B, Alonso-Calvo R. Semantic normalization and query abstraction based on SNOMED-CT and HL7: Supporting multicentric clinical trials. IEEE J Biomed Heal Informatics [Internet]. 2015;19(3):1061–7. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84929327432&doi=10.1109%2FJBHI.2014.2357025&partnerID=40&md5=826cdd20ec7542e3429c6afc217ab622

17. Akatkin YM, Yasinovskaya ED, Bich MG, Shilin A V. Application of semantic integration methods for cross-agency Information sharing in healthcare. In 2017. p. 324–9. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85040323351&partnerID=40&md5=e233fedea22c42d3f8198ec2869163dd

18. Orgun B, Vu J. HL7 ontology and mobile agents for interoperability in heterogeneous medical information systems. Comput Biol Med [Internet]. 2006;36(7):817–36. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-

33646842835&doi=10.1016%2Fj.compbiomed.2005.04.010&partnerID=40&md5=8ebe773f698c5099c51af2be91fc60a1

19. Miller K, Maccaull W. Toward web-based Careflow Management Systems. J Emerg Technol Web Intell [Internet]. 2009;1(2):137–45. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-77954025496&doi=10.4304%2Fjetwi.1.2.137-145&partnerID=40&md5=b7e9282cd4c4907da3267d6a55e98201

20. Kiourtis A, Mavrogiorgou A, Kyriazis D. Matching Ontologies to HL7 FHIR Towards Their Syntactic and Semantic Similarity [Internet]. Vol. 251, Studies in Health Technology and Informatics. 2018. p. 51–4. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85049584848&doi=10.3233%2F978-1-61499-880-8-51&partnerID=40&md5=7fc1212609875f52ccf909979bf544b8

21. Wang H-Q, Li J-S, Zhang Y-F, Suzuki M, Araki K. Creating personalised clinical pathways by semantic interoperability with electronic health records. Artif Intell Med [Internet]. 2013;58(2):81–9. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84878109502&doi=10.1016%2Fj.artmed.2013.02.005&partnerID=40&md5=3224883054ad43c262e8792db5f50568

22. Rosenbloom ST, Carroll RJ, Warner JL, Matheny ME, Denny JC. Representing Knowledge Consistently Across Health Systems. Yearb Med Inform [Internet]. 2017;26(1):139–47. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85041819854&doi=10.15265%2FIY-2017-018&partnerID=40&md5=2ac1c70904aabdf9c6115fd3463aa58f

23. de Madariaga RS, Tello JC, Carrero AM, Gil OM, Aza I V, Serrano AC, et al. Public electronic health record platform compliant with the ISO EN13606 standard as support to research groups. In 2014. p. 1254–7. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84891309103&doi=10.1007%2F978-3-319-00846-2_310&partnerID=40&md5=01b446ab94d4f804c3fd9662b66e040b

24. El Fadly A, Rance B, Lucas N, Mead C, Chatellier G, Lastic P-Y, et al. Integrating clinical research with the Healthcare Enterprise: From the RE-USE project to the EHR4CR platform. J Biomed Inform [Internet]. 2011;44:S94–102. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-83955161855&doi=10.1016%2Fj.jbi.2011.07.007&partnerID=40&md5=e02c1ee8acc2b8d50bbdb85cd18f0061

25. Marco-Ruiz L, Moner D, Maldonado JA, Kolstrup N, Bellika JG. Archetype-based data warehouse environment to enable the reuse of electronic health record data. Int J Med Inform [Internet]. 2015;84(9):702–14. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84946500646&doi=10.1016%2Fj.ijmedinf.2015.05.016&partnerID=40&md5=e3a871d4996be4b04da8d1cfaede7235

26. Sinaci AA, Laleci Erturkmen GB, Gonul S, Yuksel M, Invernizzi P, Thakrar B, et al. Postmarketing Safety Study Tool: A Web Based, Dynamic, and Interoperable System for Postmarketing Drug Surveillance Studies. Biomed Res Int [Internet]. 2015;2015. Available

from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84946012618&doi=10.1155%2F2015%2F976272&partnerID=40&md5=d8bd08dd947768a832d1702483013e15

27. Daniel C, Ouagne D, Sadou E, Forsberg K, Gilchrist MM, Zapletal E, et al. Cross border semantic interoperability for clinical research: the EHR4CR semantic resources and services. AMIA Jt Summits Transl Sci proceedings AMIA Jt Summits Transl Sci [Internet]. 2016 [cited 2018 Jul 29];2016:51–9. Available from: http://www.ncbi.nlm.nih.gov/pubmed/27570649

28. Mohanty SK, Mistry AT, Amin W, Parwani A V, Pople AK, Schmandt L, et al. The development and deployment of Common Data Elements for tissue banks for translational research in cancer - An emerging standard based approach for the Mesothelioma Virtual Tissue Bank. BMC Cancer. 2008;8.

29. Hayman JA, Dekker A, Feng M, Keole SR, McNutt TR, Machtay M, et al. Minimum Data Elements for Radiation Oncology: An American Society for Radiation Oncology Consensus Paper. Pract Radiat Oncol. 2019;9(6):395–401.

30. Otero Varela L, Le Pogam M-A, Metcalfe A, Kristensen PK, Hider P, Patel A, et al. Empowering knowledge generation through international data network: The IMeCCHI-DATANETWORK. Int J Popul Data Sci. 2020;5(1).

31. Ji H, Kim S, Yi S, Hwang H, Kim J-W, Yoo S. Converting clinical document architecture documents to the common data model for incorporating health information exchange data in observational health studies: CDA to CDM. J Biomed Inform. 2020;107.

32. Guidry AF, Walson JL, Abernethy NF. Linking information systems for HIV care and research in Kenya. In 2010. p. 531–5. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-78650981395&doi=10.1145%2F1882992.1883078&partnerID=40&md5=4b9bd5f1d42da5a3777427894d517b45

33. Antoniades A, Aristodimou A, Georgousopoulos C, Forgó N, Gledson A, Hasapis P, et al. Advancing clinical research by semantically interconnecting aggregated medical data information in a secure context. Health Technol (Berl) [Internet]. 2017;7(2):223–40. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85034765376&doi=10.1007%2Fs12553-017-0188-0&partnerID=40&md5=f191eceb11751f9800ff9521e8413837

34. Rath A, Olry A, Dhombres F, Brandt MM, Urbero B, Ayme S. Representation of rare diseases in health information systems: The orphanet approach to serve a wide range of end users. Hum Mutat [Internet]. 2012;33(5):803–8. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84864358886&doi=10.1002%2Fhumu.22078&partnerID=40&md5=bee0ddb3cc9a0489b3450653cfe04c67

35. Lewalle P, Rodrigues JM, Zanstra P, Ustun B, Kalra D, Surjan G, et al. A deployment and research roadmap for semantic interoperability: The EU semanticHEALTH project. In: Studies in Health Technology and Informatics. 2008. p. 635–40.

36. Min L, Tian Q, Lu X, An J, Duan H. An openEHR based approach to improve the semantic interoperability of clinical data registry. BMC Med Inform Decis Mak [Internet]. 2018;18. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85044221285&doi=10.1186%2Fs12911-018-0596-8&partnerID=40&md5=4f88adb54d77857892b2b700b1b47720

37. Abburu S. Ontology driven cross-linked domain data integration and spatial semantic multi criteria query system for geospatial public health. Int J Semant Web Inf Syst [Internet]. 2018;14(3):1–30. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85047736932&doi=10.4018%2FIJSWIS.2018070101&partnerID=40&md5=350d3313623373a951a98a0a25e4116d

38. Teodoro D, Choquet R, Schober D, Mels G, Pasche E, Ruch P, et al. Interoperability driven integration of biomedical data sources. Stud Health Technol Inform. 2011;169:185–9.

39. Marco-Ruiz L, Pedrinaci C, Maldonado JA, Panziera L, Chen R, Bellika JG. Publication, discovery and interoperability of Clinical Decision Support Systems: A Linked Data approach. J Biomed Inform [Internet]. 2016 Aug 1 [cited 2018 Jul 29];62:243–64. Available from: https://www.sciencedirect.com/science/article/pii/S153204641630065X?via%3Dihub

40. Ethier J-F, Curcin V, Barton A, McGilchrist MM, Bastiaens H, Andreasson A, et al. Clinical Data Integration Model. Methods Inf Med [Internet]. 2015 Jan 22 [cited 2018 Mar 31];54(1):16–23. Available from: http://www.thieme-connect.de/DOI/DOI?10.3414/ME13-02-0024

41. Sinaci AA, Laleci Erturkmen GB. A federated semantic metadata registry framework for enabling interoperability across clinical research and care domains. J Biomed Inform [Internet]. 2013;46(5):784–94. Available from: https://www.sciencedirect.com/science/article/pii/S1532046413000750?via%3Dihub

42. Ethier J-F, Dameron O, Curcin V, McGilchrist MM, Verheij RA, Arvanitis TN, et al. A unified structural/terminological interoperability framework based on LexEVS: application to TRANSFoRm. J Am Med Inform Assoc [Internet]. 2013 [cited 2018 Jul 29];20(5):986–94. Available from: http://www.ncbi.nlm.nih.gov/pubmed/23571850

43. Pierce CD, Booth D, Ogbuji C, Deaton C, Blackstone E, Lenat D. SemanticDB: A semantic Web infrastructure for clinical research and quality reporting. Curr Bioinform [Internet]. 2012;7(3):267–77. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84866679963&doi=10.2174%2F157489312802460730&partnerID=40&md5=6964d6956f5c31f3fb02fdbb725d4bb9

44. Riazanov A, Klein A, Shaban-Nejad A, Rose GW, Forster AJ, Buckeridge DL, et al. Semantic querying of relational data for clinical intelligence: A semantic web services-based approach. J Biomed Semantics. 2013;4(1):1–19.

45. Paraiso-Medina S, Perez-Rey D, Alonso-Calvo R, Claerhout B, De Schepper K, Hennebert P, et al. Semantic interoperability solution for multicentric breast cancer trials at the integrate EU project. In 2013. p. 34–41. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84877987237&partnerID=40&md5=e8eec4b6a5807b84d88ff2774645c136

46. Addy NA, Shaban-Nejad A, Buckeridge DL, Dubé L. An innovative approach to addressing childhood obesity: A knowledge-based infrastructure for supporting multi-stakeholder partnership decision-making in Quebec, Canada. Int J Environ Res Public Health [Internet]. 2015;12(2):1314–33. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84921840918&doi=10.3390%2Fijerph120201314&partnerID=40&md5=1804a92aa1b0a1bf819f5f25365cdf30

47. Kolias VD, Stamou G, Golemati S, Stoitsis G, Gkekas CD, Liapis CD, et al. A semantically-aided architecture for a web-based monitoring system for carotid atherosclerosis. In 2015. p. 1373–6. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84953264151&doi=10.1109%2FEMBC.2015.7318624&partnerID=40&md5=fae0f5139cb06e846c8fed851b2df34c

48. Pellison FC, Lopes Rijo RPC, Lima VC, de Lima RR, Martinho R, Cruz Correia RJ, et al. Development and evaluation of an interoperable system based on the semantic web to enhance the management of patients' tuberculosis data. In: Procedia Computer Science [Internet]. Elsevier; 2017 [cited 2018 Apr 5]. p. 791–6. Available from: https://www.sciencedirect.com/science/article/pii/S1877050917323049?via%3Dihub

49. Poulymenopoulou M, Papakonstantinou D, Malamateniou F, Vassilacopoulos G. A health analytics semantic ETL service for obesity surveillance. Stud Health Technol Inform. 2015;210:840–4.

50. Martínez-Villaseñor ML, González-Mendoza M. An enhanced process of concept alignment for dealing with overweight and obesity. J Univers Comput Sci [Internet]. 2013;19(9):1315–33. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84883700921&partnerID=40&md5=1472bbb04d4d90dc8b97eb71c431f460

51. Daniel C, Booker D, Beckwith B, Mea VD, García-Rojo M, Havener L, et al. Standards and specifications in pathology: Image management, report management and terminology. Stud Health Technol Inform [Internet]. 2012;179:105–22. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84872113933&doi=10.3233%2F978-1-61499-086-4-105&partnerID=40&md5=6f861bb678fdc13f053776673a83f1de

52. Saäd MB, Simonet A, Guillon D, Jacquelinet C, Gaspoz F, Dufour E, et al. A dynamic web application within an n-tier architecture: A multi-source information system for end-stage renal disease. In 2003. p. 95–100. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-14044264004&doi=10.3233%2F978-1-60750-939-4-95&partnerID=40&md5=2f291b3494a6e9bad26e98473da7f2f2

53. Draganski B, Kherif F, Damian D, Demonet J-F. A nation-wide initiative for brain imaging and clinical phenotype data federation in Swiss university memory centres. Curr Opin Neurol. 2019;32(4):557–63.

54. Chen L, Lu D, Zhu M, Muzammal M, Samuel OW, Huang G, et al. OMDP: An ontology-based model for diagnosis and treatment of diabetes patients in remote healthcare systems. Int J Distrib Sens Networks. 2019;15(5).

55. Hotchkiss J, Manyisa N, Adadey SM, Oluwole OG, Wonkam E, Mnika K, et al. The hearing impairment ontology: A tool for unifying hearing impairment knowledge to enhance

collaborative research. Genes (Basel). 2019;10(12).

56. Li M, Leslie H, Qi B, Nan S, Feng H, Cai H, et al. Development of an openEHR Template for COVID-19 Based on Clinical Guidelines. J Med Internet Res. 2020;22(6):e20239.

57. The openEHR Foundation. No Title [Internet]. [cited 2020 Oct 28]. Available from: http://www.openehr.org

58. Barisevičius G, Coste M, Geleta D, Juric D, Khodadadi M, Stoilos G, et al. Supporting digital healthcare services using semantic web technologies. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics). 2018;11137 LNCS:291–306.

59. Lopez DM, Blobel BGME. Semantic interoperability between clinical and public health information systems for improving public health services. In 2007. p. 256–67. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-35548959493&partnerID=40&md5=5836b19c722025178ad036dc5dee6599

60. Lopez DM, Blobel BGME. Connecting public health and clinical information systems by using a standardized methodology. In 2007. p. 132–6.

61. López DM, Blobel B, Lopez DM, Blobel B. Enhanced semantic interoperability by profiling health informatics standards. Methods Inf Med [Internet]. 2009 [cited 2018 Apr 5];48(2):170–7. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-68549101770&doi=10.3414%2FME9216&partnerID=40&md5=da2a405efb924315202636e9c23155b9

62. Renly SR, Kaufman JH, Ram R. Improving disease surveillance capabilities in ihe health information exchanges. In 2009. p. 92–8. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-77955601951&partnerID=40&md5=c0e3ef070d2deea53c12812ace91c90f

63. Khalique F, Khan SA. An FHIR-based framework for consolidation of augmented EHR from hospitals for public health analysis. In: 11th IEEE International Conference on Application of Information and Communication Technologies, AICT 2017 - Proceedings. 2019.

64. Angula N, Dlodlo N. Towards a framework to enable semantic interoperability of data in heterogeneous health information systems in Namibian public hospitals [Internet]. Vol. 721. 2018. p. 835–45. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85041019607&doi=10.1007%2F978-3-319-73450-7_79&partnerID=40&md5=0a1a7793eb917b535f1664f96d008edf

65. Angula N, Dlodlo N. A Standard Approach to Enabling the Semantic Interoperability of Disease Surveillance Data in Health Information Systems: A Case of Namibia. In: 2018 International Conference on Advances in Big Data, Computing and Data Communication Systems, icABCD 2018. 2018.

66. Kyriazis D, Autexier S, Boniface M, Engen V, Jimenez-Peris R, Jordan B, et al. The CrowdHEALTH project and the hollistic health records: Collective wisdom driving public health policies. Acta Inform Medica. 2019;27(5):369–73.

67. Liang SF, Taweel A, Miles S, Kovalchuk Y, Spiridou A, Barratt B, et al. Semi automated transformation to owl formatted files as an approach to data integration: A feasibility study using environmental, Disease register and primary care clinical data. Methods Inf Med [Internet]. 2015;54(1):32–40. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84921308160&doi=10.3414%2FME13-02-0029&partnerID=40&md5=a9e9bde5cf8554e904c09643322604f5

68. Klann JG, Buck MD, Brown J, Hadley M, Elmore R, Weber GM, et al. Query Health: standards-based, cross-platform population health surveillance. J Am Med Informatics Assoc [Internet]. 2014 Jul 1 [cited 2018 Apr 5];21(4):650–6. Available from: https://academic.oup.com/jamia/article-lookup/doi/10.1136/amiajnl-2014-002707

69. Klann JG, Pfiffner PB, Natter MD, Conner E, Blazejewski P, Murphy SN, et al. Supporting Multi-sourced Medication Information in i2b2. AMIA . Annu Symp proceedings AMIA Symp [Internet]. 2015;2015:747–55. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85041000219&partnerID=40&md5=5ef3a409880acd4997a980e0b7b9858e

70. Yuksel M, Gonul S, Laleci Erturkmen GB, Sinaci AA, Invernizzi P, Facchinetti S, et al. An Interoperability Platform Enabling Reuse of Electronic Health Records for Signal Verification Studies. Biomed Res Int [Internet]. 2016;2016. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84971386816&doi=10.1155%2F2016%2F6741418&partnerID=40&md5=74efb10c41ec620c4f897416531e122e

71. Shaban-Nejad A, Riazanov A, Charland KM, Rose GW, Baker CJO, Tamblyn R, et al. HAIKU: A semantic framework for surveillance of healthcare-associated infections. In 2012. p. 1073–9. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84896957757&doi=10.1016%2Fj.procs.2012.06.151&partnerID=40&md5=eee4aa45f308fd3140cb87ee53480953

72. Pandiyan M, El Hassan O, Maamar Z, Rajasekaran P. Semantic interoperability for infectious diseases reporting system. In 2011. p. 363–7. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-83155184692&partnerID=40&md5=8926a038efd80830baaf313848776659

73. Rao RR, Makkithaya K, Gupta N. Ontology based semantic representation for Public Health data integration. In 2014. p. 357–62. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84949922167&doi=10.1109%2FIC3I.2014.7019701&partnerID=40&md5=8c1977c55f9d733c2b3909b8a35b2863

74. Thaler S, Den Hartog J, Ayed D, Sommer D, Hitchens M. Cross-domain attribute conversion for authentication and authorization. In 2015. p. 652–9. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84961575526&doi=10.1109%2FARES.2015.41&partnerID=40&md5=cb8da805a3c6a91971b64017794f7a79

75. Turbelin C, Boëlle P-Y. Open data in public health surveillance systems: A case study using

the French Sentinelles network. Int J Med Inform [Internet]. 2013 Oct 1 [cited 2018 Apr 5];82(10):1012–21. Available from: https://www.sciencedirect.com/science/article/pii/S1386505613001378?via%3Dihub

76. Turbelin C, Boëlle P-Y. Exposing public health surveillance data using existing standards. In 2013. p. 802–6. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84894312498&doi=10.3233%2F978-1-61499-289-9-802&partnerID=40&md5=d0192cdcce02dcfb21820cd02b3551c9

77. Microsoft. Open Data Protocol [Internet]. 2012 [cited 2020 May 24]. Available from: https://www.odata.org/

78. Statistical Data and Metadata Exchange - Health Domain (SDMX-HD) - Global Inventory of Statistical Standards [Internet]. [cited 2020 May 24]. Available from: https://unstats.un.org/unsd/iiss/Statistical-Data-and-Metadata-Exchange-Health-Domain-SDMX-HD.ashx

79. Shaban-Nejad A, Lavigne M, Okhmatovskaia A, Buckeridge DL. PopHR: a knowledge-based platform to support integration, analysis, and visualization of population health data. Ann N Y Acad Sci [Internet]. 2017 Jan 1 [cited 2018 Apr 5];1387(1):44–53. Available from: http://doi.wiley.com/10.1111/nyas.13271

80. Brenas JH, Al-Manir MS, Baker CJO, Shaban-Nejad A. A Malaria Analytics Framework to Support Evolution and Interoperability of Global Health Surveillance Systems. IEEE Access [Internet]. 2017;5:21605–19. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85031795111&doi=10.1109%2FACCESS.2017.2761232&partnerID=40&md5=efe9c1b8417a6c5b3beab8c316ce475b

81. Al Manir MS, Brenas JH, Baker CJO, Shaban-Nejad A. A surveillance infrastructure for malaria analytics: Provisioning data access and preservation of interoperability. J Med Internet Res. 2018;20(6).

82. Brenas JH, Al Manir MS, Zinszer K, Baker CJO, Shaban-Nejad A. Exploring semantic data federation to enable malaria surveillance queries. Stud Health Technol Inform. 2018;247:6–10.

83. Sreeganga SD, Mitra SG, Ramaprasad A. Architecture of a learning surveillance system for malaria elimination in India. In: HEALTHINF 2020 - 13th International Conference on Health Informatics, Proceedings; Part of 13th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2020. 2020. p. 377–82.

84. Phillips J, Chilukuri R, Fragoso G, Warzel D, Covitz PA. The caCORE Software Development Kit: streamlining construction of interoperable biomedical information services. BMC Med Inform Decis Mak [Internet]. 2006 Jan 6 [cited 2018 Jul 29];6:2. Available from: http://www.ncbi.nlm.nih.gov/pubmed/16398930

85. Vergara-Niedermayr C, Wang F, Pan T, Kurc T, Saltz J. Semantically Interoperable XML Data. Int J Semant Comput [Internet]. 2013 Sep [cited 2018 Jul 29];7(3):237–55. Available from: http://www.ncbi.nlm.nih.gov/pubmed/25298789

86. Krikov S, Price RC, Matney SA, Allen-Brady K, Facelli JC. Enabling GeneHunter as a grid service. Methods Inf Med [Internet]. 2011;50(4):364–71. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-83455195771&doi=10.3414%2FME10-01-0005&partnerID=40&md5=19210ae83b1bb47cf0fa49e729833f6b

87. González-Beltrán A, Tagger B, Finkelstein A. Federated ontology-based queries over cancer data. BMC Bioinformatics [Internet]. 2012 Jan 25 [cited 2018 Jul 29];13 Suppl 1(Suppl 1):S9. Available from: http://www.ncbi.nlm.nih.gov/pubmed/22373043

88. Schober D, Boeker M, Bullenkamp J, Huszka C, Depraetere K, Teodoro D, et al. The DebugIT core ontology: Semantic integration of antibiotics resistance patterns. Stud Health Technol Inform. 2010;160:1060–4.

89. Teodoro D, Pasche E, Gobeill J, Emonet S, Ruch P, Lovis C. Building a transnational biosurveillance network using semantic Web technologies: Requirements, design, and preliminary evaluation. J Med Internet Res [Internet]. 2012;14(3). Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84864272496&doi=10.2196%2Fjmir.2043&partnerID=40&md5=ca7ce4fd516e83409f16839736afd5c5

90. Schober D, Choquet R, Depraetere K, Enders F, Daumke P, Jaulent M-C, et al. DebugIT: Ontology-mediated layered data integration for real-time antibiotics resistance surveillance. In 2014. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84920001166&partnerID=40&md5=67415a2b2e32e3120a6cc8de42c19a3c

91. Bug W, Astahkov V, Boline J, Fennema-Notestine C, Grethe JS, Gupta A, et al. Data federation in the Biomedical Informatics Research Network: tools for semantic annotation and query of distributed multiscale brain data. AMIA . Annu Symp proceedings AMIA Symp [Internet]. 2008 Nov 6 [cited 2018 Jul 29];1220. Available from: http://www.ncbi.nlm.nih.gov/pubmed/18999211

92. Parikh PP, Minning TA, Nguyen V, Lalithsena S, Asiaee AH, Sahoo SS, et al. A semantic problem solving environment for integrative parasite research: identification of intervention targets for Trypanosoma cruzi. PLoS Negl Trop Dis [Internet]. 2012 Jan [cited 2018 Jul 29];6(1):e1458. Available from: http://www.ncbi.nlm.nih.gov/pubmed/22272365

93. Jayapandian CP, Zhao M, Ewing RM, Zhang GQ, Sahoo SS. A semantic proteomics dashboard (SemPoD) for data management in translational research. BMC Syst Biol [Internet]. 2012;6(SUPPL3):S20. Available from: http://www.biomedcentral.com/1752-0509/6/S3/S20

94. Bhattacharjee PS, Solanki M, Bhattacharyya R, Ehrenberg I, Sarma S. VacSeen: A linked data-based information architecture to track vaccines using barcode scan authentication. In 2015. p. 39–48. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84964005669&partnerID=40&md5=a44c71c2af1e312712e8ba7b400e9a76

95. Cheung K-H, Frost HR, Marshall MS, Prud'hommeaux E, Samwald M, Zhao J, et al. A journey to Semantic Web query federation in the life sciences. BMC Bioinformatics [Internet]. 2009 Oct 1 [cited 2018 Jul 29];10 Suppl 1(Suppl 10):S10. Available from: http://www.ncbi.nlm.nih.gov/pubmed/19796394

96. Natsiavas P, Boyce RD, Jaulent M-C, Koutkias V. OpenPVSignal: Advancing information search, sharing and reuse on pharmacovigilance signals via fair principles and Semantic Web Technologies. Front Pharmacol [Internet]. 2018;9. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85049095117&doi=10.3389%2Ffphar.2018.00609&partnerID=40&md5=d62939483afe8ba1aaab603a566aa334

97. Tilahun B, Kauppinen T, Keßler C, Fritz F. Design and development of a linked open data-based health information representation and visualization system: potentials and preliminary evaluation. JMIR Med informatics [Internet]. 2014 Oct 25 [cited 2018 Jul 29];2(2):e31. Available from: http://www.ncbi.nlm.nih.gov/pubmed/25601195

98. Gessler DDG, Schiltz GS, May GD, Avraham S, Town CD, Grant D, et al. SSWAP: A Simple Semantic Web Architecture and Protocol for semantic web services. BMC Bioinformatics [Internet]. 2009 Sep 23 [cited 2018 Jul 29];10:309. Available from: http://www.ncbi.nlm.nih.gov/pubmed/19775460

99. Nelson RT, Avraham S, Shoemaker RC, May GD, Ware D, Gessler DD. Applications and methods utilizing the Simple Semantic Web Architecture and Protocol (SSWAP) for bioinformatics resource discovery and disparate data and service integration. BioData Min [Internet]. 2010 Jun 4 [cited 2018 Jul 29];3(1):3. Available from: http://www.ncbi.nlm.nih.gov/pubmed/20525377

100. Wilkinson MD, McCarthy L, Vandervalk B, Withers D, Kawas E, Samadian S. SADI, SHARE, and the in silico scientific method. BMC Bioinformatics [Internet]. 2010 Dec 21 [cited 2018 Aug 1];11(Suppl 12):S7. Available from: http://bmcbioinformatics.biomedcentral.com/articles/10.1186/1471-2105-11-S12-S7

101. Wilkinson MD, Vandervalk B, McCarthy L. The Semantic Automated Discovery and Integration (SADI) Web service Design-Pattern, API and Reference Implementation. J Biomed Semantics [Internet]. 2011 Oct 24 [cited 2018 Aug 1];2(1):8. Available from: http://jbiomedsem.biomedcentral.com/articles/10.1186/2041-1480-2-8

102. Chepelev LL, Dumontier M. Semantic Web integration of Cheminformatics resources with the SADI framework. J Cheminform [Internet]. 2011 May 16 [cited 2018 Jul 29];3:16. Available from: http://www.ncbi.nlm.nih.gov/pubmed/21575200

103. Lopes P, Oliveira JL. COEUS: "semantic web in a box" for biomedical applications. J Biomed Semantics [Internet]. 2012 Dec 17 [cited 2018 Jul 29];3(1):11. Available from: http://www.ncbi.nlm.nih.gov/pubmed/23244467

104. Lopes P, Oliveira JL. A semantic web application framework for health systems interoperability. In 2011. p. 87–90. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-83255173885&doi=10.1145%2F2064747.2064768&partnerID=40&md5=d3fe4867205ee2afde373a407eb39c65

105. Turbelin C, Boëlle P-YP-Y. Open data in public health surveillance systems: A case study using the French Sentinelles network. Int J Med Inform [Internet]. 2013 Oct 1 [cited 2018 Apr 5];82(10):1012–21. Available from:

https://www.sciencedirect.com/science/article/pii/S1386505613001378?via%3Dihub

106. Cheung K-H, Frost HR, Marshall MS, Prud'hommeaux E, Samwald M, Zhao J, et al. A journey to Semantic Web query federation in the life sciences. BMC Bioinformatics. 2009;10:S10–S10.