Proceedings Paper:

Maikore, F. orcid.org/0000-0001-8294-5283, Mazumdar, S. orcid.org/0000-0002-0748-7638, Offiah, A. orcid.org/0000-0001-8991-5036 et al. (4 more authors) (2024) Understanding inflicted injuries in young children: toward an ontology based approach. In: Alam, M., Rospocher, M., van Erp, M., Hollink, L. and Asefa Gesese, G., (eds.) Knowledge Engineering and Knowledge Management. 24th International Conference on Knowledge Engineering and Knowledge Management, 26-28 Nov 2024, Amsterdam, Netherlands. Lecture Notes in Computer Science, 15370 (1). Springer Nature Switzerland , pp. 260-270. ISBN 9783031777912

https://doi.org/10.1007/978-3-031-77792-9_16

Understanding inflicted injuries in young children: Toward an ontology based approach

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Abstract. Investigations of children experiencing inflicted injuries is often initiated once admitted into the emergency department for injuries, and involves understanding the complex interactions between a range of different factors such as health conditions, fracture biomechanics, family history, carer accounts and so on. In this position paper, we propose the use of ontologies for capturing case details of such radiology investigations in order to create an initial knowledge base of retrospective cases, to be further expanded in the future. We discuss how we developed our ELECTRICA (ELEctronic knowledge base for Clinicians, Trainers and Researchers in Child Abuse) ontology and the different components of the ontology. We are currently using this ontology to create a knowledge base, to be used as a vision demonstrator to access larger datasets. In the longer term, we would like to use the knowledge base to support clinicians and radiologists in making decisions on current cases by offering a mechanism for searching historical cases, identifying similar cases and offering insights on risk factors that may have been missed during investigations.

Keywords: inflicted injury · non-accidental injury · child abuse · ontology development

1 Introduction and context

Protecting children from all forms of violence is their fundamental right, yet inflicted injuries among children are a significant global challenge, recognised as a specific target in the 2030 agenda for Sustainable Development. As such, the UN SDG 16.2 on 'end abuse, exploitation, trafficking and all forms of violence against and torture of children' incorporates indicators such as 16.2.1[5] to ensure the physical or psychological safety of children. Child maltreatment, or the abuse and neglect that occurs to children under 18 years of age is a major public health issue that causes severe socio-economic burden [24] and has enormous impact on individual health, as well as long term persisting mental health issues well into adulthood [12]. Nearly 3 in 4 children, or over 300 million children aged 2-4 years regularly suffer physical punishment and/or psychological violence at the hands of parents and carers[6].

Despite protections such as the United Nations Human Rights' Convention on the Rights of Child, over a billion children experience some form of emotional, physical or sexual violence every year, and one child dies as a result of violence every five minutes[7]. The scale and nature of this challenge is truly global, yet it is incredibly difficult to form a global assessment of the problem, particularly due to sparse and incomplete data (e.g. most recent (from 2019) data for indicator 16.2.1 is available from only 18 of 191 member states). It is in this context that we investigate one of the issues captured within this indicator: inflicted injury among young children. Child maltreatment is also difficult to identify as is often not the primary reason for a child to visit a doctor [12]. Vulnerable children who experience maltreatment are often brought to health services, particularly emergency care and therefore investigating the use of the emergency department offers insights into physical abuse and child maltreatment [34]. In emergency departments, inflicted trauma is often falsely reported, sexual abuse not mentioned and/or emotional abuse is not displayed or witnessed [23,35]. While some screening tools for recognising potential child maltreatment exist (such as SPUTOVAMO [32], ESCAPE [8]), there is a general lack of consistency in policies across departments [26], varying adherence to guidelines [17,28] and suboptimal diagnostic accuracy of tools [18,31].

Factors such as inconsistent history, injuries incompatible with history and/or developmental level of the child, interactions between child and parents, reason for visit, delay in seeking medical help, findings of head-to-toe examinations can offer signals that raise doubts about the safety of the child [12]. Other factors such as age, repeated attendance and injury type may not have as strong predictive capabilities in identifying potential physical abuse [35]. Within radiology, identifying abusive fractures is further challenged due to limited understanding of fracture biomechanics, scarcity of clinicians specialising in child protection and a lack of existing knowledge base. Often, domain expertise and experience in clinical practice is essential to determine potential cases of inflicted injuries, drawing inferences and reasoning based on evidence and arguments. For exam-

[5] Indicator 16.2.1 refers to 'Proportion of children aged 1–17 years who experienced any physical punishment and/or psychological aggression by caregivers in the past month'. More details at `https://sdgs.un.org/goals/goal16#targets_and_indicators`

[6] World Health Organization, Child Maltreatment, https://www.who.int/newsroom/fact-sheets/detail/child-maltreatment

[7] Violence against children, `https://sdgs.un.org/topics/violence-against-children`

ple, inconsistent narratives in the accounts of (guilty?) carers, biomechanics of fractures not consistent with carer history, previous history of injuries and so on. In order to support clinical staff in the process of identification of inflicted injuries, it is therefore important to have some methods to highlight potential inconsistencies, or areas of concern. At the same time, due to the varied practice, and the lack of existing knowledge bases, it has been difficult to establish a standardised approach to the problem.

Ontologies can be used to represent knowledge about a particular domain, as concepts and relationships, and allows this knowledge to be captured in a machinereadable format along with explicit semantics between concepts within that ontology [19]. This, in turn, provides a shareable, common understanding of the domain knowledge. In the biomedical domain, ontologies have been well developed, studied and implemented [29], however they are typically broad and span many medical topics. Therefore, ontologies in highly specific and interdisciplinary domain areas, such as detection of inflicted injuries in young children, have been created to capture more nuanced medical knowledge [21,25]. However, while ontologies like the International Classification of External Causes of Injuries (ICECI) [21] and the Adverse Childhood Experiences Ontology (ACESO) [25] capture external causes and adverse experiences, they do not directly represent the specific medical details of inflicted injuries, such as fractures. These ontologies focus more on classifying incidents or high-level experiences that lead to injuries but lack a detailed representation of the physiological outcomes of these injuries, particularly in young children. Therefore, more specialised ontologies or extensions are needed to capture the medical specifics of injuries like fractures in this context. To address this gap, we propose the ELECTRICA ontology, which represents the detailed medical and physiological aspects of injuries, with a focus on fractures in children under 2 years of age.

In this paper, we present our approach toward developing a knowledge base of retrospective cases of suspected inflicted fractures in children, who attended the Sheffield Childrens' Hospital using an ontology. The knowledge base aims to capture a detailed description of trauma in children, including (but not limited to) injuries sustained, mechanisms of injury and sociodemographic status providing an evidence base against which children presenting with suspected abusive injuries can be compared. Herein, we present how we developed the ELECTRICA ontology and introduce our ontology - we expect this initial work to support access to a large bank of previous cases, and eventually the development of a comprehensive clinical decision support tool for radiologists.

2 Related Work

We divide previous research into two sections: existing work related to biomedical ontologies that capture specific knowledge about children, adolescents, adverse events, and injury, and discussing the available technologies for the detection of inflicted injuries. We extended our search into the adverse childhood events literature to gather a broader view of the available methodologies.

2.1 Existing Ontologies

To the best of our knowledge, the earliest known injury classification ontology is the ICECI [21]. This is a taxonomical vocabulary for the classification of injuries. The vocabulary was developed to systematically describe injuries and the circumstances of injury occurrences, primarily to aid in injury prevention efforts. Although this ontology captures a wide range of information regarding people, locations, and injury types involved with an injury, it fails to capture practical information about a victim's hospital visit. For example, the clinical findings, observations, and image studies taken by a clinician can all provide pertinent knowledge about potential inflicted injuries and patterns of abuse. Works, such as ACEO [25], have looked at how public services may capture knowledge with regards to adverse childhood experiences. This work is focused on early intervention and mental health and may be insufficient to capture more nuanced information regarding a clinician's view of an observed child in their care, and how that child has presented in a clinical setting. Other works from public services have focused on capturing knowledge with regards to the environmental factors that may affect children's lives [15]. The Children's Health Exposure Analysis Resource (CHEAR) was designed to help health researchers access data regarding potential environmental and genetic information and how this may influence particular conditions and experiences. This valuable resource offers great value in capturing environmental factors that may contribute to a child's abuse, however more work is required to capture data with respect to the child's presentation in a clinical setting.

2.2 Inflicted Injury Detection

There is a small but growing area of research regarding the automation of inflicted injury detection. In a systematic review [14], the authors discovered that there is a small body of literature researching child abuse differentiation through the use of natural language processing techniques. Currently, seven related studies have been synthesized in this review, none of which make use of state of the art techniques, i.e., transformer-based large language models (LLM). The authors also raised concerns regarding several elements of these papers; risk of bias, overfitting, and dataset size. This leaves interesting opportunities for creating new baselines and benchmarks in this particular area. It is noticeable that the systematic review does not focus on the use of ontologies or knowledge graphs to enhance the cited systems. Recent works have focused on identifying Adverse Childhood Experiences (ACEs) in a wide range of modalities, including electronic health records [34,4,10,33,3], social media [37] and knowledge graphs [6,1,2]. Attempts to establish automated methods of tracking can be seen through the use of manual ontology mappings [36]. Authors utilise their ACE ontology, and then map this to a wider vocabulary, such as Unified Medical Language System (UMLS). Once a dataset is then tagged with UMLS concepts, the authors can then infer ACE concepts and relationships from the mappings. Other works on detecting ACEs focus on natural language processing (NLP) methodologies such as pretrained embedding techniques [16,3] LLMs to mine and extract information from large quantities of electronic health records (EHR), using lexicons and vector distance metrics to identify similar terms [4]. This allows the capture of more dynamic relationships between salient terminology related to ACEs. State of the art techniques now necessitate the use of LLMs, as seen in works that extract social determinates of health factors from EHR [10]. Researchers demonstrate the efficacy of LLM based extraction methodologies and how further finetuning of embeddings yields improved results compared to knowledge crafted features like bag of words [3].

3 Methodology

We aim to create the ELECTRICA (ELEctronic knowledge base for Clinicians, Trainers and Researchers in Child Abuse) ontology as a standardized framework for organizing, integrating, and analyzing relevant information from diverse sources regarding child abuse. The development of the ontology followed the NeON (Networked Ontologies) methodology, which emphasizes collaboration and interoperability among multiple ontologies to represent complex domains. This approach encourages the reuse of existing knowledge resources, thereby enhancing interoperability and reducing redundancy [30]. More specifically, owing to the specific nature of the domain, we combined scenarios 1 (co-developing the ontology) and 8 (reusing existing ontologies) of the NeON methodology to develop our ontology. Below we describe the different stages of the NeON methodology that we used to develop our ontology.

The **specification** phase of the ELECTRICA ontology involved working closely with paediatric radiologists who are core members of the project team. Their expertise was crucial in identifying the clinical need and defining the ontology's boundaries and focus areas. Together, we formulated essential competency questions to guide the development, ensuring the ontology's relevance and utility in clinical settings. For the **scheduling** phase, we developed a Gantt chart to effectively track the project timeline and milestones, ensuring that all tasks were clearly defined and assigned to the appropriate team groups. In the **conceptualisation** phase, we meticulously analysed reports from investigations of suspected child abuse cases to identify the primary classes and relationships for the ontology. Using this understanding, we created an online form as a pilot to support domain experts in (manually) capturing relevant data from these documents, iteratively developing the form based on their feedback. The key classes and properties were revised multiple times to fine-tune the concepts, ensuring that class names were precise and that the characteristics modelled accurately reflected the unique anatomy of children under 2 years old, who are the primary subjects in the data represented by the ontology. In the **Formalisation** stage, we selected OWL 2 as the language for implementing the ELECTRICA ontology, for it's high expressiveness and reasoning capabilities. To ensure comprehensive coverage of key concepts, we identified additional ontologies to reuse by searching through ontology repositories such as BioPortal and the Ontology Lookup Service (OLS), identifying the Ontology for General Medical Science (OGMS) [22], Basic Formal Ontology (BFO) [7] and Systematized Nomenclature of Medicine - Clinical Terms (SNOMED-CT) [9] as the most relevant ontologies for our use case. We used Protégé to implement and refine the ontology (**Implementation** phase). The **Evaluation** phase involved multiple methods to ensure its accuracy, consistency, and completeness such as getting feedback from domain experts, annotating datasets to ontology classes and using SPARQL queries to answer competency questions, using the OntOlogy Pitfall Scanner! (OOPS!) [20] to identify potential modelling pitfalls, and using Pellet [27] and HermiT [11] reasoners to check for logical inconsistencies.

4 ELECTRICA Ontology

The ELECTRICA ontology[8] is a comprehensive framework designed to systematically represent concepts from reports of child abuse or suspected child abuse cases. The scope of the ontology is anticipated to cover concepts related to fractures identified from radiological investigations, the characteristics of those fractures, and the family and medical history of the patients. At the time of writing this paper, the ontology includes 1,141 classes and 63 properties.

Fig 1 shows a high-level view of the ELECTRICA ontological model focusing on the fracture class, its hierarchy and the associated classes that show the characteristics. The fracture classes are represented by blue boxes; the classes showing characteristics of the fracture and how they are identified are represented in yellow; while classes for describing the case details, patient and family history are represented in green. Reused classes from external ontologies are represented in red boxes.

The ELECTRICA ontology meticulously organises fracture data, emphasising anatomical details relevant to children under two years old. At the core of the ontology's structure is the main class 'Fracture', which is further subdivided into specific subclasses based on fracture location and type. For example, 'Fracture of the Skull' is further divided into classes such as 'Fracture of the left frontal bone', 'Fracture of the left occipital bone', and similarly for the right side of the skull. The 'Fracture of the Facial Bone' class is subdivided into specific classes for different parts of the facial structure. This includes classes like 'Fracture of the left angle of the mandible', 'Fracture of the right condylar process of the mandible', and 'Fracture of the nasal bone', among others. The ontology includes classes for fractures of the neck or trunk, such as 'Fracture of the cervical spine' which is further broken down into detailed classes for each vertebra (e.g., 'Fracture of the C1 Vertebra', with subclasses for specific parts of C1 like 'Fracture of the anterior arch of C1'). This pattern continues for other spinal regions like the thoracic and lumbar spine, as well as the sacral spine or coccyx. For instance, the 'Fracture of the C2 Vertebra' class includes specific subclasses such as 'Fracture of the dens of C2,' which is particularly relevant in young children due to

[8] The ontology is accessible on BioPortal

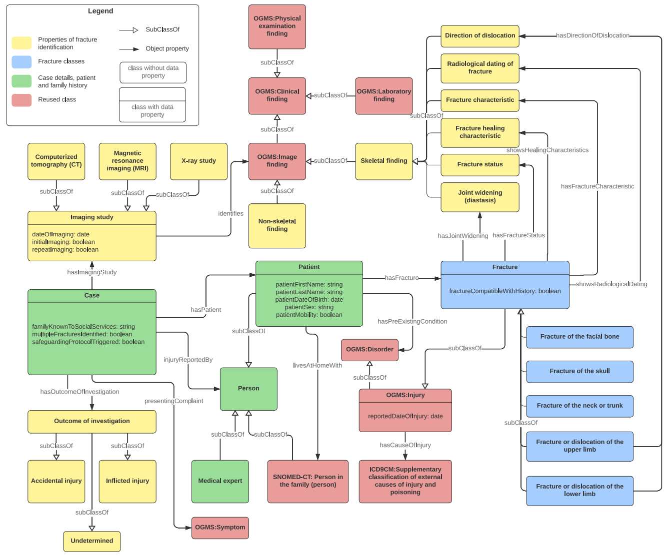

Fig. 1. ELECTRICA Ontology - main classes of the ontology. A higher resolution image is available at: `https://github.com/fatibaba/electrica/blob/main/ELECTRICAdatamodel.pdf`

the higher incidence of atlantoaxial instability and the unique developmental characteristics of their cervical spine.

The ontology also covers fractures of the upper and lower limbs, detailing fractures of bones such as the humerus, radius, ulna, femur, tibia, and fibula, down to the specific phalanges of the fingers and toes. Each class is hierarchically organised to detail the exact location and type of fracture, crucial for accurately documenting and analysing fractures in young children. This is particularly important in young children, where growth plate fractures can significantly impact future bone growth and overall development.

Fracture characteristics within ELECTRICA are detailed through the 'fracture characteristics' class, which includes subclasses such as 'buckle', 'greenstick', 'transverse', 'Oblique', and the various Salter-Harris types (Salter-Harris type 1 - 5) that are critical for understanding fractures that involve the growth plates. Some features, such as 'metaphyseal corner' fractures, are particularly indicative of potential inflicted injuries, as they are often associated with inflicted trauma in young children [13]. The ontology also includes classifications such as 'avulsion', 'comminuted depressed fracture' and others, each representing different patterns and severity of fractures.

We also captured additional features of fractures depending on the specific bone involved. For instance, the 'sutural diastasis' class is included for detailed documentation of skull fractures, where separation along the sutures can occur.

Similarly, the ‘direction of dislocation’ class is utilised for injuries involving dislocations in the upper or lower limbs, allowing for precise characterisation of the dislocation’s direction, such as anterior, posterior, superior, or inferior.

In addition to the detailed classification of fractures, we introduced classes for other key radiological findings that enhance fracture descriptions. The ‘radiological dating of fracture’ class categorises fractures by age, as determined through radiographic analysis, with subclasses like ‘0-2 weeks’, ‘2-4 weeks’, and beyond, aiding in understanding the injury’s timeline and healing process. Another vital class, ‘fracture healing characteristic’, includes subclasses such as ‘lamellar bridging bone of hard callus’ and ‘subperiosteal new bone formation’, which detail specific healing features and provide insights into the repair stage and quality.

To enhance the specificity of the ELECTRICA ontology, we introduced the ‘fracture status’ class to distinguish between possible and definite fractures, aiding in the differentiation of suspected and confirmed fractures. We also capture detailed patient and family history to provide comprehensive case context, utilising data properties such as ‘familyKnownToSocialServices’ and ‘safeguardingProtocolTriggered’. Other properties like ‘totalPreviousHospitalVisits’ track prior hospital visits, while ‘multipleFracturesIdentified’ documents cases with multiple fractures. To address pre-existing conditions affecting fracture susceptibility, the ‘hasPreExistingCondition’ object property links to the ‘disorder’ class, facilitating detailed medical condition documentation that aids in assessing the injury.

We leveraged existing ontologies to create a robust and interoperable ELECTRICA framework. BFO served as the upper-level ontology, structuring ELECTRICA and facilitating integration with OGMS, which also uses BFO. Following NHS England’s guidance, we aligned ELECTRICA with SNOMED-CT to enhance clinical data capture. Additionally, we incorporated the ‘causes of injury’ class and its subclasses from the International Classification of Diseases, Version 9 - Clinical Modification [5] to enrich injury causation details. This reuse and extension of established ontologies ensure ELECTRICA’s comprehensiveness and compatibility with healthcare systems, promoting interoperability and standard adherence.

We conducted a comprehensive evaluation of the ELECTRICA ontology, confirming its accuracy, consistency, and completeness through multiple validation methods. We executed SPARQL queries on sample annotated dataset, which effectively demonstrated the ontology’s capability to retrieve and represent the required information, aligning with the identified competency questions. Additionally, using the OntOlogy Pitfall Scanner! (OOPS!) and reasoners like Pellet and HermiT, we identified and resolved several issues including missing labels, minor hierarchical inconsistencies, and redundant classes, thereby ensuring the ontology’s robustness, user-friendliness, and logical consistency. We have documented the results of this validation in detail on the GitHub repository[9]. The evaluation process confirmed that ELECTRICA is robust and fit for purpose.

[9] The ELECTRICA GitHub repository

5 Future Work

With our initial ontology, we are currently using a web-based interface that allows clinicians, paediatricians, and emergency care staff to input historical cases and populate our ontology, thereby developing a comprehensive knowledge base. For example, a paediatrician treating a child with unexplained fractures could enter details such as the type of injury, patient age, and clinical history. This information would then be mapped onto relevant concepts in the ontology, such as specific injury types, mechanisms of trauma, and patient demographics, enriching the knowledge base with every case added. Although this process is currently manual and requires significant effort—thus far, we have a sample of 63 retrospective cases—we are working to extend our network of international paediatric radiologists who can contribute to this effort.

In the future, we plan to develop NLP models to automate case entry and scale up to larger datasets, improving the efficiency of ontology population. For instance, these NLP models could extract relevant information from clinical notes or radiology reports and automatically classify cases into our ontology. Once the ontology is populated with a larger volume of data, we will apply data science techniques to analyse the knowledge base and develop predictive models. These models could help clinicians identify patterns, predict the likelihood of certain injuries based on clinical history, or guide decision-making in paediatric emergency care.

Acknowledgments. The work described in this paper was funded by The Children's Hospital Charity funded ELECTRICA project (CA19008)

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article

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