Battalogy: Empowering Battery Data Management through Ontology-driven Knowledge Graph

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Abstract

Developing a battery ontology to represent battery management knowledge is crucial in the new sustainable and green energy era. As battery production revenue is projected to exceed 300 billion US dollars annually by 2030, researchers are exploring new battery materials, models, standards, and manufacturing processes. AI and ML methods are being employed to manage battery manufacturing and enhance performance. Data representation techniques and formats are important for enhancing the expressiveness of battery data and improving battery quality. This paper presents an ontology for creating a battery knowledge graph to address data interoperability challenges and share battery data among different actors. The battery ontology includes various types of knowledge, such as domain knowledge, battery applications, and core battery-specific knowledge. The ontology was evaluated through competency questions and usability tests. It aims to enhance battery production and design by facilitating efficient communication and data exchange between battery management systems and applications. This research has significant societal, economic, and environmental impacts as it contributes to developing more efficient and sustainable batteries.

Keywords

Ontology, Semantic model, Battery ontology, Battery data management

1. Introduction

Batteries are essential resources in the new era of sustainable and green energy. Designers, engineers & industries need cheaper, safer and more energy-efficient batteries [1]. According to the World Economic Forum battery production revenue will grow to more than 300 billion US dollars annually by 2030 [2]. In the past few years, a lot of research has been conducted in battery cell failures of materials including electrodes [3, 4, 5, 6, 7, 8, 9, 10, 11]. Some of the methods for live delamination detection in battery cell material include the electrical resistance methods [12, 13], electrical potential methods [14, 15], electromagnetic damage detection method [16, 17], hybrid electromagnetic method [18, 19], self-sensing electrical resistance-based damage detection method [20, 21, 22]. Today, more research topics are being pursued to develop and

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produce large, high-performance, sustainable batteries. Battery data can play a key role in developing new battery materials, models, battery standards, manufacturing processes and battery ecosystem [23]. Lithium-ion batteries are the most advanced technology in the battery ecosystem [24].

Advances in AI and ML methods are used to manage battery manufacturing and improve insights into anatomy to improve performance and to target measures of errors and safety parameters in the production and designing of green batteries [25]. With the help of AI and ML methods, we can manage battery production, improve performance, and minimize errors and safety concerns. The utilization of these technologies in the production and designing of green batteries has enabled us to create batteries that are not only environment-friendly but also efficient in their performance [26].

Data representation techniques and formats play a crucial role in enhancing the expressiveness of data. With the help of various data representation techniques, we can transform the raw data into a more structured and meaningful format that can be easily processed and analyzed [27]. These techniques include but are not limited to data modelling, data visualization, and data compression. By implementing these techniques, we can gain valuable insights into battery production and performance, which can help us in improving the overall quality of batteries [28]. One of the challenges in battery manufacturing is the integration of data from different sources. Various laboratories and factories are producing batteries online and locally, generating large amounts of battery data. As diverse sources generate and handle data in distinct ways, datasets may differ in terms of their formats, metadata, or terminologies and be handled differently [1]. Therefore, integrating data from various sources becomes a significant challenge. This is where the concept of data interoperability comes into play.

Data interoperability refers to the ability of different systems, devices, and applications to communicate, exchange data, and use information effectively. This can be achieved by using common data-sharing standards and paradigms [29]. A variety of data representation techniques and formats can be entertained to enhance the expressiveness of the data. This characteristic helps to improve the data interoperability challenges from various data sources with common data-sharing standards and paradigms in different contexts of Battery ecosystems. This knowledge-sharing phenomenon helps to build common vocabulary or taxonomies that help to facilitate the end users, knowledge workers, domain users and potential customers to retrieve relevant information according to their needs and demands in a specific context. Collaborative knowledge-sharing plays a crucial role in addressing data interoperability challenges. We can facilitate information retrieval for end users, knowledge workers, domain users, and potential customers by sharing knowledge and building a shared vocabulary or taxonomy.

The utilization of AI and ML methods, data representation techniques, and collaborative knowledge-sharing approaches can significantly improve battery production and design. By addressing the challenges of data interoperability, we can enable effective communication and exchange of data between different systems, devices, and applications. The standardization of terminologies and the use of common data-sharing standards can improve the efficiency of battery manufacturing and design [29]. The battery research generates more data which needs to be managed and utilised in a better way for sustainable batteries and large-scale production. Data interoperability refers to integrating different source data to ensure that different systems and applications create and exchange a clear meaning of data. Implementing reliable approaches for the interoperability of battery data is essential to fully exploit advanced techniques in battery research and development [1].

Ontologies can play an important role in semantic interoperability between enterprise applications to exchange information. An ontology is an explicit specification of a conceptualization and can be used to build conceptual models to represent the specific domains semantically [30]. Semantic interoperability is the ability to exchange data with unambiguous and shared meaning. Ontologies ensure that exchanged information between different systems and applications is understandable [31]. Ontologies can be used to address data interoperability problems by providing a common vocabulary or a set of agreed-upon terms and concepts for different data sources to use. This facilitates the exchange of information between different systems and enables data to be shared more easily and effectively. Ontologies can be used to define relationships between concepts, establish taxonomies and classifications, and provide semantic annotations for data.

In this paper, we present an ontology which has been developed to represent battery data. This ontology has been developed to incorporate battery knowledge to use in practical applications and create a knowledge graph for the battery management system. This ontology is a first step towards developing an ontology-based framework to utilize battery data and share knowledge between battery actors to solve the data interoperability issue. The primary data was given in textual format and knowledge extraction was done manually and validated by battery domain experts.

The rest of the paper is organised as follows. Section 2 discusses the previous work about the field. Section 3 presents the ontology development method. Section 4 describes the battology developed to represent the battery knowledge. Section 5 presents the results and evaluation of the ontology. The discussion is concluded with future work in section 6.

2. Related Work

This section presents principles and methods for data integration, data integration techniques, and data representation and integration with ontologies in battery space and its landscape. This section presents principles and methods for data integration, data integration techniques, and data representation and integration with ontologies in battery space and its landscape.

2.1. Principles and Methods of Data Integration

Designing a data integration system is a trivial task combining data residing at different sources and providing the user with a unified view of these data [32]. From a data integration perspective, the sources contain real data, while the global schema provides a reconciled, integrated, and virtual view of the underlying sources. Two basic approaches have been proposed. The first approach, called global-as-view, requires that the global schema is expressed in terms of the data sources. The second approach, called local-as-view, requires the global schema to be specified independently from the sources and the relationship between the global schema [32]. The phenomenon of data integration can be achieved by deploying various methods such as manual integration, middleware integration, application-based integration, uniform access user interface, and creating a common database at different levels of abstraction. Manual data integration is the extensive process of integrating all different data sources without any automation. Middleware data integration is an abstraction layer used to integrate different applications and transfer data through this layer to different data sources. Application-based integration is a method where software applications are responsible for locating, retrieving and integrating data from different sources and interlinked systems [33, 34]. A uniform access user interface relates to the ability to integrate data from multiple dispersed sources and present it uniformly. Creation of the common database approach requires all data of interest to be manually migrated to the new data repository [35]. Developing uniform data access does not require manual data integration, migration of data, or additional storage space. Semantic heterogeneity of the source data repository itself is a trivial task and a difficult job to develop uniform data access. So in this study, we present an ontological framework as a solution to address data heterogeneity solution for battery data management using semantic web techniques such as ontologies and knowledge graph techniques [36, 37].

2.2. Data Integration Techniques for Battery Data Management

The phenomenon of data integration can be achieved using different semantic techniques, programming languages and standards with common exchange protocols and different data formats to support data across several data sources [38]. These techniques provide a semantic layer that serves to facilitate and allow machines to read, understand and interpret data which comes from different data repositories [39]. This layer is responsible for sharing and reuse across diverse applications and systems, converting structured and semi-structured web documents and unstructured data in the form of tacit knowledge, especially competence models, into a unified form of data that allows the expression of basic semantics in a way machines can process and understand [39, 40]. The machine-readable data can be produced through the creation of a schema comprising marked and interlinked characteristics such as defined terms, properties and formal relationships of various sources [41]. Semantic techniques, especially ontologies, provide definitions for the rules of representation and the establishment of relationship hierarchies, and this allows for the contextualization of data points by linked data through the supply of additional information on data [42]. A wide of semantic technologies and standards are used to develop the integration layer using different data integration techniques such as Unicode and URI Layer [43], RDF (Resource Description Framework) model [41], RDFS (Resource Description Framework Schema) [40], Ontology Layer [44] and developed conceptual model using ontology-driven language RDF, OWL [45], Cryptography layer and Unifying Logic Layer [43]. In this study, we utilize some of the above-mentioned techniques to address the wicked challenge of data integration and interoperability issues in battery management and its landscape.

2.3. Data Representation and Integration with Ontologies in Battery Management

In data, the ecosystem comprises a wide array of complex heterogeneous data sources and their semantic interoperability issues, such as Meaning, Granularity, Temporal, and Structural, can be achieved by using ontologies and ontology standards, including RDF, OWL and SPARQL [46], especially in battery management landscape [1]. Modern battery management targets affordable, high-performance, and sustainable battery design; these endeavours are held back by the lack of common battery and vocabulary standards, as well as machine-readable tools to support interoperability. A battery ontology offers an effective means to unify battery-related activities across different fields, accelerate the flow of knowledge in both human-and machine-read-able formats, and support the integration of artificial intelligence (AI) in battery development [1]. However, ontologies have been applied with great success in life science but have already developed some ontologies in battery management which are real contributions in battery and material science. These ontologies, such as EMMO (Elementary Multiperspective Material Ontology) is, supported by European Materials Modelling Council (EMMC) [1] and use RoMM vocabulary that is used as a basis for the model data (MODA) template and Li-Ion battery Ontology [47] in battery management [48]. In developing domain-oriented ontologies in the battery management space, a number of methods have been put forward for building ontologies or models. Ontology 101 proposes a very simple but practical guide for building an ontology using an ontology editing environment, such as Protege [49]. METHONTOLOGY contributes with a general framework for ontology development, which defines the main activities that people need to carry out when building an ontology, and outlines three different processes: management, technical, and supporting [50]. Similarly, the OTK Methodology is focused on application-driven ontology development [51, 52]. In this study, we utilize collaborative methodology for the development of domain-oriented ontology and models using ontology design patterns (ODPs) for battery management and resolving data integration and interoperability issues [53].

3. The Battery Ontology and Development Method

In this section, we describe how our ontology was developed along with basic battery concepts and battery domain knowledge.

3.1. Ontology Development

The field of Ontology Engineering (OE) develops ontologies that can be further refined, updated, and extended by adding new knowledge [54]. The development of an ontology is a complex process that includes different activities to define, develop, and maintain the ontology. Different methods have been suggested to develop an ontology. However, we do not have one specific or standard ontology development methodology in the field of OE. The ontology development process depends on the purpose, domain, and application of ontologies to determine what activities are to be involved in it.

Methontology [50] suggested the ontology lifecycle based on the experiences of the authors of ontology development. The suggested framework consists of six phases: *specification, conceptualization, formalization, integration, implementation, and maintenance.* These phases are supported by the lifecycle suggested by planning, acquiring knowledge, documenting, and evaluating.

Ontology Development 101 [49] provides guidelines and proposes the different steps to develop an ontology: *determining the domain and scope, reusing existing ontologies, enumerating important terms, defining classes and class hierarchy, defining the properties, defining the facets,* and *creating instances*. [55] proposed a methodology for ontology development to support the Semantic Web application which contains four phases: *Requirements analysis, Development of ontology, implementation* and *evaluation and maintenance* of the ontology. An agile methodology has also been proposed to develop ontology by adopting the specific agile principles and practices from software engineering [56]. The agile methodology proposes four phases: *pre-game, development, post-game,* and *support activities*.

A variety of different ontology development methods and approaches such as Methontology [50] and Ontology Development 101 [49] can be found in the literature related to Ontology Engineering. Almost all methodologies focus on manual ontology development where Ontology Engineers alone or along with domain experts are involved in creating ontology from scratch or reusing existing ontologies in the ontology development process [57]. The ontology development process can be categorized into four main phases: Pre-development, Development and Implementation, Evaluation, Maintenance and Enrichment of an ontology. Each phase can have different activities depending on requirements, domain, and application of the ontology.

- The pre-development phase specifies the requirement, purpose and scope of the ontology. Generally, Ontology Engineers and Domain Experts are involved in the Pre-development process for specification and acquisition of knowledge.
- The development and implementation phase identifies and defines ontology elements such as concepts, properties, instances and axioms. This phase performs different activities, including building the conceptual model of an ontology, and defining concepts, instances and their relations in an ontology. Ontology Learning research mainly focuses on this phase to automate the ontology development process.
- The Evaluation phase analyses and checks if the developed ontology fulfils the needs and represents the required knowledge to achieve the defined purpose of the ontology. Competency Questions (CQs) are mainly used to evaluate an ontology by finding answers to predefined questions. Ontology Experts along with Domain Experts define CQs for evaluating an ontology. Reasoners, such as Pellets and Fact++, are used to check the consistency of an ontology in the evaluation.
- The Maintenance and Enrichment phase updates the developed ontology according to the evaluation's results and adds new knowledge to the ontology if it is necessary.

The general ontology development process has been applied to develop the battery ontology. The ontology developers develop the initial draft of the ontology in the pre-development phase. In this phase domain resources about the battery are explored for acquisition and specification of the ontology. In the Development and implementation phase, ontology developers conceptualize and implement the ontology. The development tool used was the Protégé. Pellet reasoner [58] was used to check the consistency of the ontology. Ontology developers along with domain engineers worked in pairs for the evaluation phase to improve and enhance the ontology. The development and evaluation phases have been repeated several times. Figure 1 shows the general process applied during the battery ontology development.

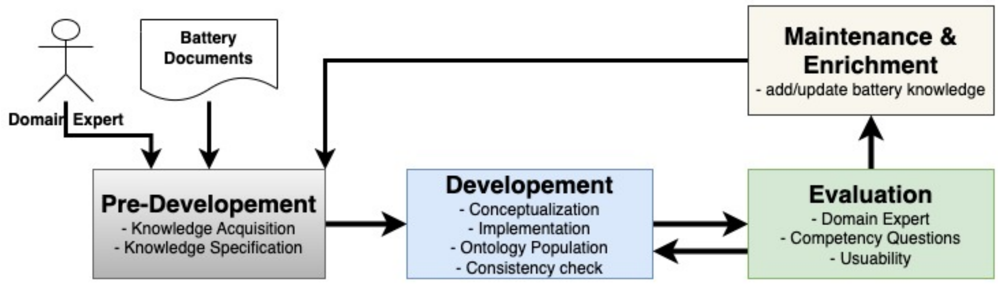

Figure 1: The Ontology Development Process

3.2. Batteries and their characteristics

There are different types of batteries such as Primary and secondary. Each battery has different characteristics and can be used in many other applications. Each battery is made of material. Different batteries have different characteristics. The most common characteristics of a battery can be as follows:

- **Voltage** - The voltage of a battery is a measure of the potential difference between its terminals and is expressed in volts (V). Different types of batteries have different nominal voltages, and the voltage of a battery can vary during charge and discharge cycles.
- **Cycle Life** - The number of times a battery can be charged and discharged before its performance deteriorates. Cycle life measures a battery's durability and is an important factor for applications where a battery will be used repeatedly over its lifetime, such as in electric vehicles.
- **Specific Energy** - Specific energy is the amount of energy a battery can store per unit of mass or volume. High specific energy allows for a longer driving range on a single charge in applications where energy density is important, such as electric vehicles. A higher specific energy indicates a more energy-dense battery in a smaller and lighter package.
- **Specific Power** - Specific power is a measure of a battery's power output per unit mass or volume. It is a key metric for applications where size and weight are important considerations, such as in portable electronics and electric vehicles. A higher specific power indicates a more powerful battery in a smaller and lighter package.
- **Safety** - How safe the battery is to handle, use, store and transport. Batteries can pose a safety risk if they overheat, catch fire, leak, or explode and therefore are designed with safety features such as overcharge and short-circuit protection.
- **Performance** - As a measure of battery performance, we refer to the voltage, capacity, and energy output of the battery over its lifetime. Several factors can negatively impact the performance of a device over time, such as ageing, repeated charging and discharging, and exposure to extreme temperatures. A battery's performance can vary according to its operating conditions and usage pattern. Higher-performing batteries will provide a more reliable and consistent output of power over time.
- **Life Span** - The lifespan of a battery refers to the number of cycles it can undergo before it no longer functions effectively or reaches the end of its usable life. A battery's lifespan is

determined by various factors, including its type, design, manufacturing quality, operating conditions, and usage patterns.

- **Charge Limit** - The charge limit of a battery refers to the maximum amount of energy that can be stored in the battery without causing damage. Overcharging a battery beyond its charge limit can cause permanent damage to the battery, shorten its lifespan, and reduce its performance.
- **Self Charge or Discharge Rate** - The rate at which a battery can be charged and discharged safely without affecting its performance or lifespan.

4. Overview of Battery Ontology

Figure 2 shows a holistic view of the battery management ontology that contains different entities involved in the process and the relations between them for making real-time synergy and realization. The main objective of ontology is to represent the core knowledge about the battery domain and its characteristics in terms of use in different applications. This ontology includes three types of knowledge: 1) a meta-model of the battery domain and 2) the domain knowledge of the battery applications, and 3) core battery-specific knowledge.

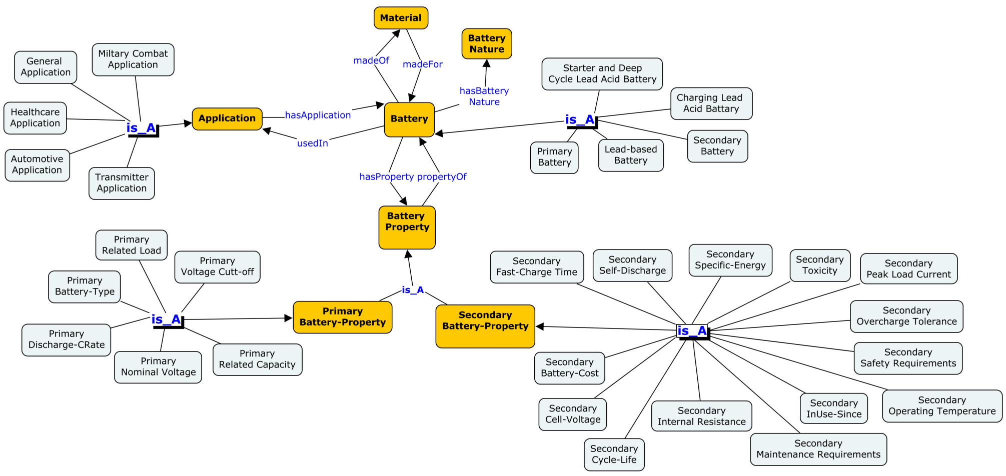

Figure 2: Holistic view of Ontology-based Implementation of the Battery management model

It describes different small taxonomies, including primary batteries, secondary batteries, primary battery properties, secondary battery properties, and applications. Taxonomy is a classification system used in knowledge management (KM) to organize and categorize information. It involves creating a hierarchical structure that groups related concepts based on their characteristics, attributes, or relationships. In KM, taxonomy can be used to maintain a hierarchical information structure that is easy to navigate and understand, making it easier to find the information needed.

It explains the working mechanism between different taxonomies and follows a triplet pattern (e.g., subject, predicate, object). For instance, Battery is used in various applications such as military combat, healthcare, automotive, transmitter and general applications. Similarly, the

Battery entity is made of the Material entity (e.g., Lithium Nickel Manganese Cobalt Oxide (LiNiMnCoO2)). It also creates some association links with primary and secondary battery properties such as primary-related load, primary voltage cut-off, primary-related capacity, nominal-voltage, discharge-CRate, and battery type. It can also be applied to secondary battery properties such as secondary battery toxicity, peak load current, safety requirements, overcharge tolerance, operating temperature, maintenance requirements, in-use since (time), internal resistance, fast-charge time, specific energy, cycle-life, cell-voltage, battery-cost, self-discharge.

The following success scenario in figure 3 explains the true demonstration of these properties, which describes primary batteries' properties' associations with battery instance and their instance values for better understanding and realization.

Success Scenario: In the context of battery management, the primary battery is a subclass of battery and its instance, such as Alkaline-Manganese, which linked up with different entities instances to make the personalized KGs. The instance Alkaline-Manganese and its association with other entities. For example, the primary battery is assigned to Alkaline-Manganese and creates an association with battery properties. Here, the semantic relational expression follows a triplet structure (e.g., subject, predicate, object: Node ⟶Node)

For instance, there is a relationship between the concept of "Primary-Battery" and the concept of "Battery-Properties", referring to "hasPrimary_NominalVoltage". Thus the "Primary Battery" is known as the domain, and the "Battery-Properties" is known as a range with the model which reflects the value of this triplet, such as "Nominal Voltage-9Volts".

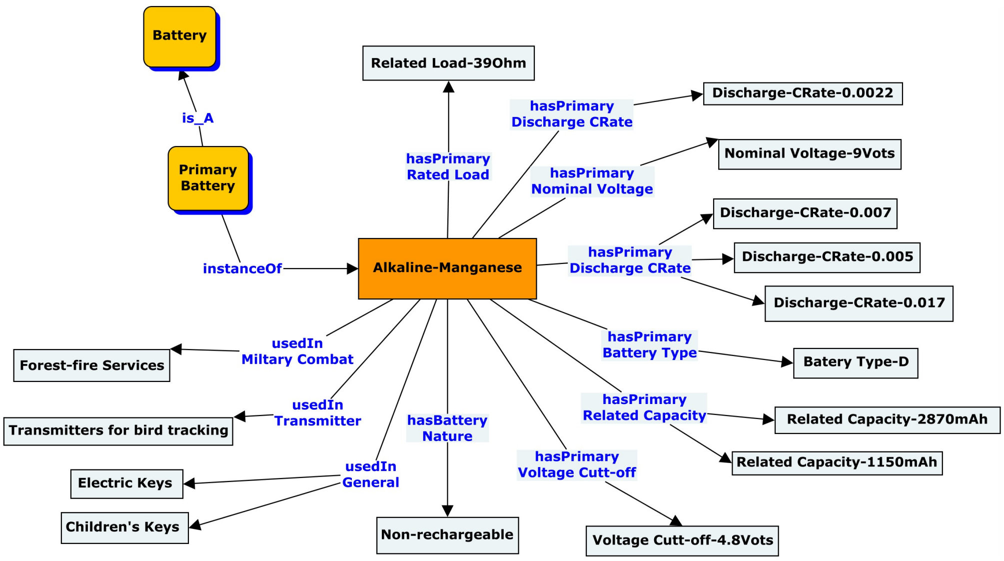

Figure 3: Knowledge graph (KGs) (Ontological Model) of Primary Battery

5. Evaluation of the Ontology

This section describes different evaluation and testing strategies in this research work. The ontology evaluation aims to develop a battery ontology model (Battology) that depicts the contextual knowledge of various batteries with different materials involved. It is used to manage the diverse nature of the data representation and its manageability in battery management, which is a challenging task, especially in the automotive industry. This Battology is served as a basis for developing personalized KGs for specific focal group and their usages.

This section targets to evaluate the Battology on different levels; structural, semantic-relational and lexical evaluation.

- **Structure Evaluation** In this phase, the hierarchical structure of the Battology has been assessed concerning the correctness of the *is_a* relationship as to whether the given concept **A** is a particular type of the given concept **B**. For instance, *Alkaline-Manganese* is an instance of *Primary Battery* which is a subclass of *Battery*, and this classification of the battery can be seen in Battology (see figure-3).
- **Semantic Relational Evaluation** In this phase, the Battology is evaluated for holding semantically correct relations between these concepts and these relations are associated with *Object Properties* and *Data Properties* in the ontology-based editors (e.g., Protege, Topbraid Composer, etc.). Here, the semantic relational expression follows a triplet structure (subject, predicate, object: Node–>Node). For instance, there is a relationship between the concept of *Battery* and the concept of "*Application*", referring to *hasApplication.* Thus, the Battery is known as the domain, and the Application is known as a range within the Battology.
- **Lexical Evaluation** The purpose of this section is to examine some attributes of the Battology regarding its expressiveness, completeness, and clarity of the annotation of a given Battology related to the battery and its manageability. Participants and domain experts were asked whether the relationship is confirmed in the Battology in the second information session using several competence questions (CQs).

5.1. Evaluation by CQs

We have used a DL Query Tab in Protege 5.0 to verify CQs. They help to confirm that the knowledge repository is in the form of Battology or KGs and has enough information to answer these questions, which are related to battery-related information. The following table-1 shows an example of CQs with a DL query and presents the results of executing the DL query in the Protege editor.

5.2. Modelling workshop/Information Session

During the modelling workshop, we presented a holistic view of the domain model design artefact (Battology) that explains how domain experts with different assigned roles and competencies initiate different processes and perform different activities to achieve the Battology goals. The session also shows how the CQs can be used to retrieve information. We have also

Competence Questions	DL Query	Result
Which specific batteries are used in what applications?	Battery and usedIn Value pacemakers_for_heart_patients	• Alkaline-Manganese
What basic properties are associated with in batteries manufacturing?	Battery-Property and propertyOf value Alkaline-Manganese	• Primary-Batttery-Type-9V • Primary-Batttery-Type-AA • Primary-Nominal-Voltage-1.5Volts • Primary-Volage-cutt-off-4.8Volts • ...
What batteries are made of what material?	uery:Battery and madeOf value LiCoO2	• Lithium-Cobalt-Oxide
What type of batteries and their nature?	Battery and hasBattery_Nature value Non_rechargeable	• Alkaline-Manganese
What batteries are used in what applications or made of material?	(Battery and usedIn value Miltary_Combat) or (Battery and madeOf value LiCoO2)	• Alkaline-Manganese • Lithium-Cobalt-Oxide

Table 1
Evaluation of Ontology through CQ and DL query. The result column shows the instances of the classes used in the queries. A few of the results are shown in the second row where return results are a long list of properties related to Alkaline-Manganese Primary Battery

exemplified Battology related to battery management and its data portability and its dissemination among different components of batteries with standard formats to resolve the data interoperability challenges to some extent. The data interoperability factor can be addressed by using the data rendering options and its versatility of data representation in the form of RDF/XML, OWL/XML and JASON-LD.

5.3. Evaluation of Usability

The evaluation of the usability of an ontology is important when the ontology is going to be used by application and domain experts who are normally not ontology experts. The evaluation of the usability of a product or system is something that goes back in time. In 1986, Brooke developed a questionnaire, the System Usability Scale (SUS) [59]. During the years since then, it has been demonstrated that the SUS applies to a wide range of systems and types of technology and that it produces similar results as more extensive attitude scales that are intended to provide deeper insights into a user's attitudes to the usability of a system. SUS also has a good ability to discriminate and identify systems with good and poor usability [60]. In this work we make use of the version of SUS introduced in [61].

	Statement of evaluate of the ontology	AE	DE	OE
1	In my opinion, I could make a valuable contribution to this ontology	4	5	3
2	I found the ontology unnecessarily complex	1	2	2
3	It is easy for me to understand the ontology model	5	4	5
4	I would need more theoretical support to understand this ontology	1	4	3
5	In the ontology, I found that a variety of concepts were well incorporated	4	4	4
6	There were too many inconsistencies in this ontology	1	1	3
7	I would imagine that most domain experts would understand this ontology very quickly	5	4	5
8	I find the ontology very cumbersome to understand	1	2	2
9	It is my confidence that I understand the ontology conceptualization	5	4	5
10	I needed to ask a lot of questions before I could understand the conceptualisation of the ontology	1	1	2

Table 2
Ontology usability evaluation (AE: Application Engineer, DE: Domain Engineer, OE: Ontology Engineer, score: 1=strongly disagree, 2=disagree, 3=no preference, 4=agree, 5=strongly agree

The ontology usability is important before its use in an application by domain experts and application engineers. The developed ontology was evaluated by a domain expert in the battery domain, and an application engineer who was involved in developing and using ontologies and Knowledge graphs in different applications. An ontology expert who is actively involved in ontology development and research in the semantic web. It is possible to get reliable results with a sample of 8-12 users [62]. A more extensive evaluation is planned with the development of an application using Battalogy.

In the table 2, questions are positioned as defined in SUS which are a combination of positive and negative forms. The questions at odd positions are all in positive form and the even positions are all in negative form to avoid biases. The goal is to have respondents read each statement and try to reflect on whether they agree or disagree with it by alternating positive and negative statements.

The SUS scores indicate that the usability results for the application Engineer were 95, the Domain expert was 77.5 and the ontology engineer had a result of 75. The sus score is calculated as described in [59]. This implies that the usability of the ontology from the application experts' point of view was very positive while the usability of ontology from domain and ontology experts' point of view needs to be improved. Figure 4 shows the sus score with a percentile rank based on interpretation given by [63].

The SUS score of 95 suggests that the ontology model is highly usable, with users finding it easy to learn, efficient to use, and overall providing a good user experience. This is particularly important for an ontology model, which is designed to help users navigate complex knowledge structures and make sense of large amounts of information. The high percentile score of 99.8%

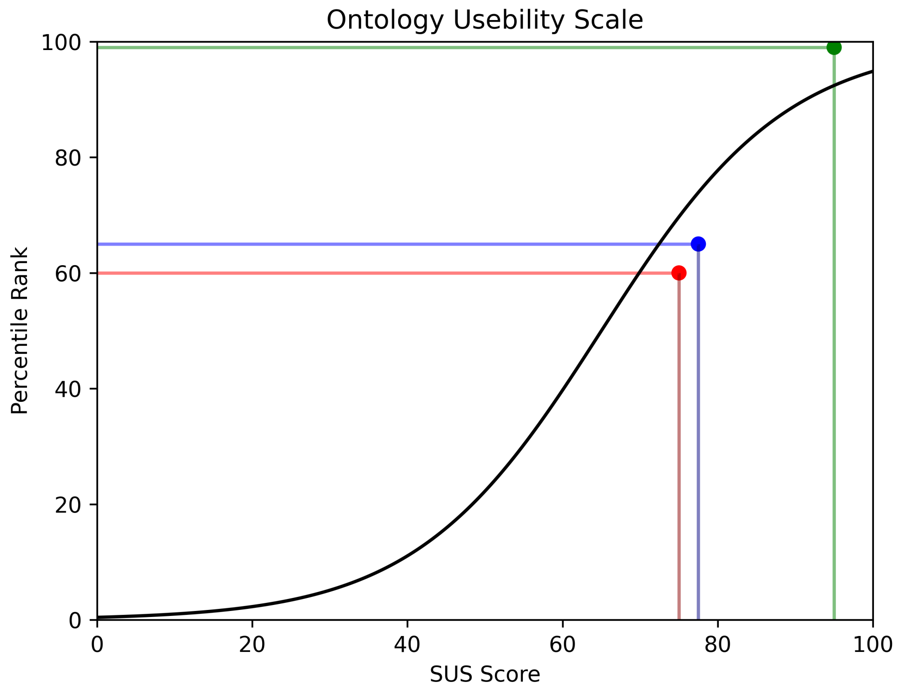

Figure 4: Percentile ranking of SUS scores [63]. (green line: AE evaluation, blue line: DE evaluation result and red line: OE evaluation result

indicates that the ontology model performs exceptionally well compared, which is a positive finding.

However, the SUS scores of 77.5 and 75 suggest that there are areas of the ontology model that could be improved to better meet the needs and expectations of users. For example, users may have encountered difficulties in navigating the ontology or in finding specific information. These results indicate that usability issues need to be addressed to provide a better user experience.

Overall, these results suggest that the ontology model has some strong points in terms of usability, but also some areas for improvement. By addressing the usability issues identified in the study, the ontology model could be made even more user-friendly and effective in supporting knowledge representation in the domain. The overall feedback was given that the ontology model well integrated most concepts and no inconsistencies were found and the ontology model can be improved by adding more knowledge about the domain by adding more instances and relations between them. The ontology was the first version and authors have planned to add more knowledge about the domain and linked with existing ontologies within the battery domain.

6. Conclusion and Future Work

This research focuses on developing a battery ontology for representing battery data and addressing data interoperability challenges in the battery domain. The ontology development process follows different methodologies such as Methontology and Ontology Development 101. The battery ontology includes various concepts and properties related to batteries, their characteristics, applications, and materials. The ontology is evaluated using structural, semantic relational, and lexical evaluations, as well as through competence questions and usability evaluation using the System Usability Scale (SUS). The ontology expects to facilitate better data representation, knowledge sharing, and interoperability in the battery domain.

Future work in this area could involve further refinement of the battery ontology and expanding it to include more specific concepts and properties related to different types of batteries and their applications. Additionally, the ontology could be integrated into existing battery management systems to improve data exchange and interoperability. Further evaluation and testing of the ontology's usability with domain experts and application users could also be conducted to ensure its effectiveness in real-world scenarios. Overall, the development of the battery ontology has the potential to contribute to advancements in battery research, development, and manufacturing for sustainable and green energy.

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