Preprint of an article published in International Journal of Semantic Computing Vol. 0, No. 0
1–23
10.1142/S1793351X22400013

https://doi.org/10.1142/S1793351X22400013

AccTEF: A Transparency and Accountability Evaluation Framework for Ontology-based Systems

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Received (Day Month Year)
Revised (Day Month Year)
Accepted (Day Month Year)

This paper proposes a new Accountability and Transparency Evaluation Framework (AccTEF) for Ontology-based Systems (OSysts). AccTEF is based on an analysis of the relation between a set of widely accepted data governance principles, i.e., FAIR (Findable, Accessible, Interoperable, Reusable) and accountability and transparency concepts. The evaluation of accountability and transparency of input ontologies and vocabularies of OSysts addressed by analyzing the relation between vocabulary and ontology quality evaluation metrics, FAIR, and accountability and transparency concepts. An ontology-based knowledge extraction pipeline is used as a use case in this study. Discovering the relation between FAIR and accountability and transparency helps in identifying and mitigating risks associated with deploying OSysts. This also allows providing design guidelines that help accountability and transparency to be embedded in OSysts. We found that FAIR can be used as a transparency indicator. We also found that the studied vocabulary and ontology quality evaluation metrics do not cover FAIR, accountability, and transparency. Accordingly, we suggest these concepts should be considered as vocabulary and ontology quality evaluation aspects. To the best of our knowledge, it is the first time that the relation between FAIR and accountability and transparency concepts has been found and used for evaluation.

Keywords: FAIR data; Semantics; AI governance.

1. Introduction

Due to its ability in automation, AI has been extensively deployed in different fields, from education to finance and medicine. However, there are risks associated with AI, such as lack of accountability and lack of transparency [1, 2, 3, 4, 5, 6, 7]. Through transparency, AI outcomes and processes can be understandable and interpretable, which makes AI risk identification and mitigation possible. Transparency also allows the users to know about the possible adverse outcomes of the systems. This concept also incorporated in "The right to explanation" of the European General Data Protection Regulation (GDPR) [8].

Accountability deals with the responsibility over a system's behavior and potential risks, which is getting more important as the use of AI increases. For example, in a AI-based Clinical Risk Management (CRM) system, people who are affected by the system outcomes and actions have the right to know about the existence of the system, its possible adverse outputs, and if responsibilities are clear and policies and regulations are in place to prevent and handle them. AI and data governance are essential to overcome these risks.

AI governance mechanisms are used to minimize these risks while maintaining full benefits of the AI technology [9]. Data governance can be seen as a prerequisite for AI governance. It is used to control the data quality and compliance with relevant legal and ethical requirements to help trustworthy decisions by AI [10]. Accordingly, it is crucial to facilitate the Accountable and Transparent (accountability and transparency) deployment of AI, using governance frameworks [1]. However, data governance has been often overlooked in efforts to create accountability and transparency AI systems.

During recent years, semantics and knowledge graph techniques have been growing in popularity. Through these techniques, knowledge is structured, classified and made easier to process for machines by supporting formal logical models and rich, self-describing data and ontologies. This simplifies knowledge extraction, retrieval, and analysis. In this paper, a framework, titled AccTEF for evaluating transparency and accountability of ontology-based systems is proposed. Our use case is governance of Ontology-based Knowledge Extraction (OKE) for Clinical Risk Management (CRM). CRM has a great impact on the quality of clinical service. Accordingly, studying OKE governance in the CRM context gives a great opportunity to identify, analyze, and mitigate OKE risks in a critical setting to ensure responsible AI development and deployment.

We investigate answering the following question: "To what extent can accountability and transparency of OSysts be evaluated/measured?". To answer the research question, AccTEF is proposed. FAccT is based the minimum necessary properties list for accountable and transparent datasets, driven from the best practices and recommendations for FAIR semantic artifacts [11, 12] and important factors for accountability and transparency, derived from the literature. the minimum necessary properties list for accountable and transparent datasets is generated based on our analysis of the relation between FAIR and accountability and transparency. Then, FAIRness and accountability and transparency of the OKE pipeline is evaluated using AccTEF to see if the results support the relation between FAIR and accountability and transparency concepts.

FAIRness of one of the OKE pipeline's inputs is also evaluated using a set of best practices and recommendations for FAIR semantic artefacts [11, 12, 13, 14] and a set of automatic FAIR tools[a,b,c] [15, 16]. To assess the quality of the OKE pipeline resource, the quality of its input vocabulary is also evaluated using 26 quality evaluation metrics for SKOS vocabularies [17] and the QMM subjective method [18]. Then, the used metrics are mapped to FAIR principles and accountability and transparency to see if they can be used for evaluating accountability and transparency.

The contributions of this paper are as follows. An accountability and transparency evaluation framework, titled AccTEF is constructed for OSysts, based on an analysis of the relation between FAIR principles [19] and accountability and transparency concepts. We found that it is not possible to evaluate the accountability and transparency of vocabularies and ontologies using a set of vocabulary and ontology quality evaluation metrics [17, 18]. Accordingly, we suggest accountability and transparency of the ontologies and vocabularies should be evaluated as part of the ontology/vocabulary quality evaluation. This allows assessing governance-related issues before using semantic artefacts in creating ontology-based AI systems.

This paper is an expansion of our previous work [20] which was presented at the TransAI 2021 conference. In that paper, the relation between FAIR and accountability and transparency was analyzed, the quality and FAIRness of a SKOS vocabulary, titled "Hospital Adverse Incidents Classification Scheme" (HAICS) were evaluated, and a set of vocabulary and ontology quality evaluation metrics [17, 18] found unable to evaluate transparency and accountability. We expanded our previous paper [20] by further analyzing the relation between FAIR and accountability and transparency concepts for OSysts and their output linked data (Sec. 4.1.2), designing AccTEF (Sec. 4.1), evaluating the accountability and transparency of the OKE pipeline (Sec. 4.2), and the OKE pipeline (Sec. 3). In accordance with the added contributions, four sections have also been added to the related work, i.e., accountability (Sec. 2.1), transparency (Sec. 2.2), accountability and transparency evaluation (Sec. 2.3), OKE (Sec. 2.6).

The remainder of this paper is structured as follows. In Sec. 2, a concise Related Work is mentioned. Sec. 3 overviews the Use Case and Requirements. The Evaluation and Analysis is performed in Sec. 4. Finally, Conclusion is mentioned in Sec. 5.

[a] https://fair-checker.france-bioinformatique.fr/base_metrics
[b] https://fairsharing.github.io/FAIR-Evaluator-FrontEnd/#!/
[c] https://www.f-uji.net/index.php#

2. Related Work

AccTEF is an accountability and transparency evaluation framework based on the state of the art and FAIR principles. Accordingly, in this section the state of the art on accountability (Sec. 2.1), transparency (Sec. 2.2), accountability and transparency evaluation (Sec. 2.3), and FAIR principles (Sec. 2.4) are described. Also, since our use case includes an OKE pipeline and its input SKOS vocabulary, we describe SKOS and ontology quality evaluation metrics (Sec. ??) and approaches and the related work on OKE (Sec. 2.6).

2.1. *Accountability*

Accountability is defined as the state of being responsible for a system's behavior and potential risks [21]. A system is known to be accountable if it is reliable and its outcomes and actions are justifiable for stakeholders and users [22]. This requires identifying potential risks associated with using the system, building systems in a way that allows oversight, and mechanisms, laws, and regulations to handle adverse outcomes [22]. In different stages of AI production and deployment, responsible parties and stakeholders should supervise the process and the safety and quality of the AI-based services [5, 7].

Accountability is the fourth component of Reddy et al.'s governance model [5] which has been identified as the most challenging due to the involvement of a large and diverse group of stakeholders. Reddy et al. [5] recommend determining important stages of the AI-based systems lifecycle, where monitoring and evaluation is necessary, identifying relevant/accountable stakeholders at each stage, and building monitoring and evaluation mechanisms to ensure safety and quality of the systems.

Similarly, Raji et al [23] suggest an auditing framework to be operated within the AI system development life-cycle, internally by a dedicated team. They suggest internal audit as a way to generate complementary information needed for external audit. The audit team leads other stakeholders, e.g., developers, managers, etc. to contribute to the audit. The framework includes five stages, i.e. Scoping, Mapping, Artifact Collection, Testing and Reflection (SMACTR). In each stage of the audit, a set of documents is created which yields an overall audit report, to assess if the AI system creation and deployment processes meet policies and principles, including internal and external ethical expectations. This way, it is possible to predict system-level risks and help to design mitigations [24]. However, one of the weaknesses of internal audits is that taking an independent view is challenging.

There are also techniques to audit automated decisions after deployment. Shneiderman suggests an independent process, including planning oversight, continuous review, and retrospective analyses to hold algorithms accountable [25]. Kroll et al. [26] also emphasize that accountability is achieved by design. They argue that existing computational techniques that can communicate partial information about secret processes, can be used to continuously audit AI systems. In this way, accountability and oversight can still function, without disclosure. Software Verification, cryptographic commitments, zero-knowledge proofs, and fair random choices are the computational techniques that have been reviewed as suitable techniques to ensure accountability.

Accordingly, the literature confirms that adequate documentation and metadata generation, creating suitable laws and regulations, and accountability by design are sufficient to create accountable AI. In this research, important accountability factors are identified from literature [5, 22, 27, 28] to build an accountability assessment checklist. We also study the accountability concept in the context of OSysts to find necessary metadata to enhance OSysts accountability.

2.2. *Transparency*

Transparency means understandability and interpretability of the AI systems processes and outcomes for humans [29]. GDPR affirms "The right to explanation" and restricts automated decision-making [8]. Transparency is also necessary for accountability [2, 3]. Since currently nonlinear Machine Learning (ML) algorithms, e.g., LSTMs and kernel-based methods are so popular and their outcomes are not easily interpretable [1, 2, 3, 4, 5, 30, 31], most of the current research around transparency is done for complicated ML algorithms. Generally, the current solutions can be classified into four groups, as follows.

Interpretable Explanations. To achieve transparency, several studies have suggested using XAI, while being less accurate [32, 33, 34]. XAI turns a complicated model into a mathematically interpretable one. The issue is that XAI does not consider whether the explanations are practically understandable for humans [35, 36, 37]. There are also some methods that work as a proxy explainer over "black box" models [33], such as sparse linear classifiers, discretization methods such as decision trees and association rule lists, and instance/case-based models. The weakness of linear models is that when the model does not optimally fit the training data, they may optimise the error using spurious features which are usually difficult to interpret for a human. Besides, explanations will often not be useful if the model is large and complicated.

Fully-informed Consent. Fully-informed consent is part of the GDPR [5, 8], through which relevant information about the AI-based application is given to the users by means of a Plain Language statement that they sign freely and independently.

Auditing or Risk Assessment An auditing strategy assesses the inputs and outputs of the decision process assuming the decision process itself as a black box. Some studies suggest ongoing or prospective auditing to evaluate the systems' performance [5, 7]. However, auditing is the least powerful of a set of available methods for understanding their behaviors [38].

Transparency and Openness of the Algorithm's Source Code, Inputs, and Outputs The issue with this approach is that it exposes the system to strategic gaming and sharing sensitive data, e.g. healthcare and finance data, against privacy preservation. Also, openness does not work for algorithms that change by time and for those with random elements [2].

Transparency has different aspects which might need a mix of different methods to be applied. Burrell [34] characterizes three types of opacity in algorithmic decision-making and suggests solutions for each: (1) intentional opacity (solution: legislations such as GDPR in EU), (2) illiterate opacity (solution: stronger education programs and independent experts' advice), (3) intrinsic opacity/interpretability problem (solution: using alternative machine learning models that are easy to interpret by humans, however less accurate).

Since the OKE pipeline does not involve machine learning algorithms, in search for a more general solution, we have mostly focused our research on the last two approaches.

2.3. *Accountability and Transparency Evaluation*

There are a few checklists to measure accountability and transparency, regardless of the techniques that are used in building systems. Shin [29] claims to use a 27 measurements checklist on a 7-point scale for seven criteria, i.e., fairness, accountability, transparency, explainability, usefulness, convenience, and satisfaction, to evaluate user perceptions of algorithmic decisions. However, the checklist itself is not publicly available and it was not retrievable neither from the presented references nor from contacting the author. In another work, Shin et al. [39] have proposed a survey with accountability and transparency among its variables. But it cannot be independently used and needs other approaches to measure these criteria.

Jalali et al. [27] evaluated the transparency of reports for 29 COVID-19 models using 27 binary criteria. This criteria has been adopted from three transparency checklists [40, 41, 42] which are checklists of reproducibility and transparency indicators of scientific papers and reports. In this paper, the transparency assessment checklist by Jalali et al. [27] has been modified for the transparency evaluation purpose.

2.4. *Data Governance: FAIR Principles*

The goal of data governance is to have fair, accountable, and transparent AI [43]. It is being used to control the data quality and compliance with relevant legal and ethical requirements and guarantee trustworthy decisions by AI [43]. Accordingly, to have an accountability and transparency OKE system, it is important to check the compliance of its sources, i.e., data, ontologies, and vocabularies with a set of widely accepted data governance principles. For this purpose, we consider FAIR (Findable, Accessible, Interoperable, Reusable) principles [44]. These principles have initially been proposed by a multidisciplinary group from academia, industry, and funding agencies to enhance usability of scholarly digital resources for humans and machines. Since their emergence in 2016, FAIR principles have gained a wide acceptance [45, 46] and several tools in the form of metrics [47], questionnaires [47, 48, 49, 50], checklists [51, 52], and semi-automated evaluators [53] have been suggested to evaluate the *FAIRness* of digital resources.

In addition to the general FAIRness evaluation methods and metrics, there has been some work particularly around FAIRness of semantic artefacts. "D2.2 FAIR Semantics: First recommendations" [11] is an effort towards a practical solution for making semantic resources FAIR. It includes 17 preliminary recommendations (P-Rec.) related to one or more of the FAIR principles and 10 best practice recommendations (BP-Rec.) to improve the global FAIRness of semantic artefacts. Cota [12] presents guidelines and best practices for FAIR ontologies on the Web, which have been suggested with the help of standard practices and pointing to existing tools and frameworks. Generally, best practices and recommendations suggest moving towards template and content pattern unification to achieve uniformity in semantic representations. They also suggest having a set of agreed-on metadata/annotations to reach transparency and accountability in semantic definitions and usage. In this research, the relation between FAIR and accountability and transparency is analyzed and based on that a metadata evaluation checklist for OSysts (Sec. 4.1.2) is built using the best practices and recommendations for FAIR semantic artifacts[d] [11, 12].

2.5. *SKOS/Ontology Quality Evaluation Metrics and Approaches*

Ontology evaluation approaches can be divided into eight groups, i.e., rule-based, evolution-based, criteria-based, application-based, data-driven, evaluation by humans, gold-standard-based, and task-based [54]. In this research, we focus on the criteria-based approaches which are application-independent and are not as expensive as gold-standard-based and human-based approaches. There are different criteria-based models for ontology evaluation. Ivanova and Popov [55] classify these ontology evaluation approaches, methods, and metrics into three main groups, domain presentation quality, domain model quality and correctness criteria, and usability and usefulness criteria. Ontology evaluation frameworks by Duque-Ramos et al. [56] and Gangemi et al. [57] are well-known frameworks [58] that divide ontology evaluation criteria into three dimensions: structural, functional, and usability. There are also different tools for automatic evaluation of ontologies, such as OntoMetric [59], TOMM [60], Protege [61], and OntoKeeper [62].

Since, HAICS is a SKOS vocabulary which does not have object and data properties, a lot of ontology quality evaluation metrics are not suitable for evaluating HAICS. However, there are some subjective methods that can be used for evaluating both SKOS vocabularies and OWL ontologies. Silva-Lopez et al. [18] suggest a

[d]We define a semantic artifact as linked datasets, ontologies and vocabularies, or OSysts.

quantitative model of minimalist verification techniques (QMM) based on the ontology design principles, mentioned in Gruber [63], Kohler [64], and Wiesner and Marquardt [65]. Based on QMM, if the ontology is compliant with a principle, one point is assigned to it, which is adjustable based on how it fulfils the criteria.

There are some quality evaluation metrics for evaluating SKOS vocabularies. Mader et al. [66] identify 15 potential quantifiable quality issues in SKOS vocabularies and classify them in three categories, labelling and documentation issues, structural issues, and linked data specific issues. They also formalized and implemented the issues in an open source quality assessment tool, called qSKOS. As a continuation of this work, Suominen and Mader [17] define 26 quality issues and update qSKOS accordingly. In this study, QMM [18] and the 26 SKOS vocabulary quality evaluation metrics by Suominen and Mader [17] are used for analysis.

2.6. *OKE*

OKE emerged from the early 2000s. In 2003, Arani et al. [44] used an ontology of artists and artifacts coupled with WordNet[e], and an entity recognizer, to extract named entities and their relations from web documents. Hiekata at al. [67] proposed an ontology-based knowledge extraction method for shipyard fabrication workshop reports. Their proposed method converts the report into a weighted graph in which subjects are the problems, objects are the component names, and the link between them shows the number of times this problem has been detected in a particular component. This allows human experts to generate recommendations simply by looking at the result graphs. Pradhan et al. [68] present an ontology-based metadata extraction approach to prepare documents containing metadata for SPARQL querying. First, Wikipedia contents are annotated and extracted. Then, metadata is created in RDF format from the contents based on annotations. In another study [69], an ontology-based representation of urban heat island mitigation strategies has been proposed. First, terminologies are conceptualized and their relations are established. Then, terminologies and their relations are integrated to form the representations.

In this paper, the existing ontology-based knowledge extraction techniques are used to build the OKE pipeline as the use case. Similar to above-mentioned approaches, in this research relevant vocabularies and ontologies are used to map the knowledge from an semi-structured format (CSV) to linked data in RDF format. This way, knowledge will be queryable and its retrieval will be simplified.

3. Use Case and Requirements

In this research, our use case is the OKE from clinical Adverse Incident Reports (AIRs) to help generate annual safety reports. This is one of the important clinical risk management activities in our partner hospital in Ireland, based on which

[e]https://wordnet.princeton.edu

safety improvement recommendations are made. Accordingly, such a system needs to be accountable and transparent for non-expert users in order to be trustworthy. AIRs are database records that have been exported to CSV files. They contain a mix of descriptive free text fields and structured data about date, time, exact occurrence place of an adverse incident in SJH, and people who are involved in that incident. OKE extracts distilled risk knowledge from a high number of AIRs and simplifies generating the ASR for humans. For this purpose, an OKE pipeline has been built (Figure 1) by mapping AIRs (in CSV format) to knowledge graphs (in RDF format). This has been done by using the structure of the AIRs, given to us by our partner hospital in Ireland, the R2RML-F tool [70], and related vocabularies and ontologies. Through this process, raw data turns into classified and machine-readable knowledge. This pipeline is a part of an ongoing research on AI governance for clinical risk management.

For the purpose of OKE, HAICS was created, which is a SKOS vocabulary. HAICS consists of 213 SKOS concepts and 188 semantic relations, representing a classification scheme for hospital adverse incidents. This vocabulary has been created using data from our partner hospital in Ireland, Simple Knowledge Organisation System (SKOS), and the R2RML-F tool [70]. Since HAICS is a SKOS vocabulary, without objects and data properties, in our experiments we need to choose the quality evaluation metrics accordingly. We use QMM [18], the SKOS vocabulary quality evaluation metrics by Suominen and Mader, and the qSKOS tool [17] to evaluate HAICS.

4. Evaluation and Analysis

In this section, AccTEF is described. Then, the accountability, transparency, and FAIRness of the OKE pipeline is evaluated using AccTEF and FAIR principles. The evaluation results are used to assess the relation between FAIR principles and accountability and transparency concepts. Finally, HAICS FAIRness and quality

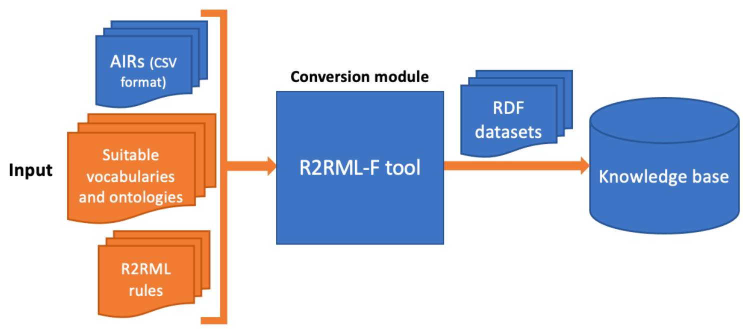

Fig. 1. An overview of the OKE pipeline for AIRs.

are evaluated using the best practices and recommendations for FAIR semantic artifacts [11, 12, 13, 14] and a set of vocabulary and ontology quality evaluation metrics [17, 18]. Based on the results, we indicate ways to improve the transparency and accountability of OSysts.

4.1. *AccTEF Framework*

To evaluate accountability and transparency of OSysts, and identify their related risks, an accountability and transparency evaluation framework, named AccTEF, has been designed (Figure 2). AccTEF incorporates both data and system evaluation components. The former includes a metadata checklist, while the latter includes transparency and accountability checklists. Scores from the two checklist are normalized and averaged to obtain a final accountability and transparency score. AccTEF's checklists are described as follows.

4.1.1. *Accountability and Transparency Checklists*

We adapted Jalali et al. [27] transparency assessment checklist, both available and suitable for our work, for the system transparency evaluation in AccTEF (Table 1). Some of the questions might not be applicable to some systems. For the OKE pipeline, questions three, four, five, seven, eight, nine, ten, 14, 15, 19, 20, 22, 26, and 27 are not applicable. Accordingly, by assigning one point to each question, the total transparency grade for our OKE pipeline is 14.

Important factors for the accountability assessment purpose are identified from the literature: "reliability", "transparency and justifiability of outcomes and actions", "auditability, oversight, monitoring, and verification", "Risk assessment", "responsibility", "controllability", "policies and procedures, Response and enforcement", and "training and awareness" [5, 22, 27, 28]. They give a holistic overview of the accountability concept and allows evaluation and related risks identification. An accountability assessment checklist, including 13 questions is created accordingly (Table 2). One point is assigned to each question.

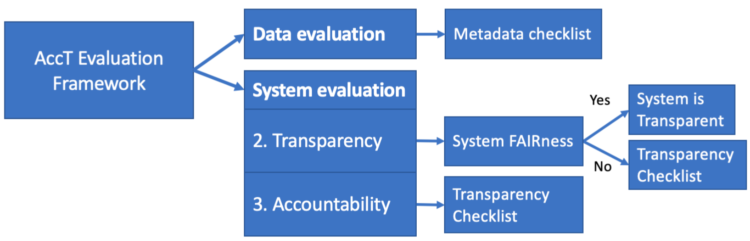

Fig. 2. An overview of the AccTEF framework.

Table 1. Transparency assessment checklist [27].

Number	Questions
1	Is the modeling method clearly denoted?
2	Are the model mechanisms described?
3	Are modeling assumptions discussed?
4	Are parameters clearly defined?
5	Are data assumptions disclosed?
6	Are targeted users defined?
7	Is any type of sensitivity/uncertainty analysis reported?
8	Is sensitivity of outcomes to data uncertainty/assumptions reported?
9	Are potential biases of the data disclosed?
10	Is model calibration (parameter estimation) reported?
11	Is there discussion about system limitations?
12	Are sources of funding disclosed?
13	Are dates of the modeled period defined?
14	Are parameter values (known/assumed constants) reported?
15	Does the specified data retrieval method work?
16	Are all data resources (longitudinal data) reported?
17	Are potential conflicts of interest disclosed?
18	Are model questions reported?
19	Is the quality of simulated data fit to historical data reported?
20	Are estimated model parameters reported?
21	Is the software used identifiable?
22	Are all data (longitudinal) provided?
23	Is there a high-level visualization of the model?
24	Are any codes reported?
25	Is there documentation for the codes?
26	Is model evaluation/testing (other than fit to data and sensitivity analysis) reported?
27	Is sensitivity of outcomes to model formulation assumptions reported?
28	Is there metadata for the data used?

4.1.2. *The Metadata Checklist: The Relation between FAIR Principles and Accountability and Transparency Concepts*

As pointed out by Janssen [10], the goal of data governance is to have fair, accountable, and transparent AI. FAIR, as well known data governance principles, contribute to this goal by enhancing the transparency of locally produced digital resources [71]. Accordingly, FAIR principles contribute to transparency and accountability concepts by emphasizing on findability and accessibility of digital objects, such as ontologies and linked data [19]. Best practices and recommendations for FAIR semantic artifacts [11, 12] emphasize on

- "P-Rec. 1 & 2: Globally unique, persistent and resolvable identifier for semantic artefact, their content, versions, and metadata should be provided" [11];
- "P-Rec. 3: Use a common minimum metadata schema to describe semantic artefacts and their content" [11];
- "P-Rec. 8: Define human and machine-readable persistency policies for semantic artefacts metadata" [11];

Table 2. Accountability assessment checklist.

Accountability factors	Questions
Reliability	Is the system reliable? Does the system do what it has been designed for?
Transparency and justifiability of outcomes and actions	Is the system process and outcomes understandable and interpretable? Are the system's actions justifiable for the users and stakeholders? Is suitable (a set of defined minimum required metadata based on the system and application) metadata available?
Auditability, oversight, monitoring, and verification	Are important stages of the system creation process where monitoring and evaluation is necessary determined? Is the system auditable? Does it allow oversight? Are there evaluation mechanisms in place to ensure safety and quality of the system?
Risk assessment	Are potential risks associated with using the system identified?
Responsibility	Is a list of provenance metadata identified and made available? Have accountability roles for system's potential risks identified and explicitly declared?
Controllability	Are requirements that the system needs to follow in order to be compliant with stakeholders' laws and regulations identified? Are suitable control measures for handling the system's potential risks determined and explicitly declared?
"policies and procedures", "Response and enforcement"	Are suitable policies and mechanisms to reinforce control measures determined?
Training and awareness	Are training in place for stakeholders to make them aware of the risks, control measures, and policies?

- "P-Rec. 16: The semantic artefact should be clearly licenced for machines and humans" [11];
- "P-Rec. 17: Provenance should be clear for both humans and machines" [11];
- "Ontology Metadata: license (recommend a CC-BY); creator, contributor, creation date, previous version; namespace URI and version IRI; prefix, title, description, a citation" [12].

Based on accountability and transparency concepts definitions, it can be inferred that by being FAIR, suitable metadata provided for semantic artifacts convey some aspects of accountability and transparency: data transparency, auditability, responsibility, and policies and procedures. Therefore, being FAIR enhances the transparency and accountability of the semantic artifacts by reinforcing the use of appropriate metadata and suggesting suitable ways to enhance findability, accessibility, and reusability. A closer look at the accountability and transparency, and FAIR concepts shows that a FAIR linked dataset, ontology, or vocabulary is both accountable and transparent. For an OSyst, FAIRness guarantees transparency but not full accountability. Also, while being FAIR guarantees transparency, being non-FAIR does not imply the non transparency of the semantic artifact. Accordingly, there is a relation between FAIR and accountability and transparency; FAIRness test can be a part of transparency evaluation. In addition, based on the recommended metadata for FAIR semantic artifacts, we studied DCAT[f] properties and selected corresponding properties as the minimum necessary properties for transparent and accountable linked datasets. A checklist was built based on this list to evaluate the accountability and transparency of linked datasets (Table 3). One point is assigned to each of the data properties if the information is valid and verifiable.

Table 3. The metadata checklist.

Properties	Questions	Points	Total
dct:title	Is the title of the dataset explicitly declared?	1	2
dct:description	Is there a description of the dataset?	1	
dct:issued	Is the issue time of the dataset explicitly declared?	1	2
dct:modified	Is the modification date of the dataset explicitly declared?	1	
dct:identifier	Is the dataset identifier explicitly declared?	1	2
dcat:landingPage	Is the landing page of the dataset explicitly declared?	1	
dct:license	Is the dataset license explicitly declared?	1	3[a]
dct:rights	Are the dataset attribution rights explicitly declared?	1	
dct:accessRights	Are the dataset access rights explicitly declared?	1	
dct:creator	Are the dataset creators explicitly declared?	1	5
dct:contributor	Are the dataset contributors explicitly declared? (If the dataset has no contributors, creators are mentioned as the contributors)	1	
dct: publisher	Is the dataset publisher explicitly declared?	1	
prov:wasAttributedTo	Is the dataset explicitly attributed to an agent (a/an person/organisation)?	1	
dcat:contactPoint	Are contact points provided?	1	
prov:wasDerivedFrom	Is the source of the dataset explicitly declared?	1	1
		Total	15

[a]If the rights are expressed via ODRL policies (odrl:hasPolicy), this property can be used instead of dct:rights, dct:license, and dct:accessRights, depending on the information it covers.

[f]https://www.w3.org/TR/vocab-dcat-2/

4.2. *Accountability and Transparency Evaluation of the OKE Pipeline*

The transparency and accountability of the pipeline has been evaluated using AccTEF (4.1). There is no metadata provided which according to the evaluation method, reduces the accountability and transparency score by one third. Table 4 and Table 5 illustrate transparency and accountability questions for which OKE has scored zero.

Table 4. OKE transparency assessment.

Number	Questions	Answers	Points
11	Is there discussion about system limitations?	No	0
13	Are dates of the modeled period defined?	No	0
28	Is there metadata for the data used?	No	0
			11

Accordingly, normalized scores for metadata, transparency, and accountability of the OKE system are approximately 0, 79, and 39, which gives the total accountability and transparency score of 39. Based on the results, there are risks associated with using the system, which root from:

- Lack of suitable metadata;
- Lack of requirements analysis;
- Lack of evaluation mechanisms to ensure safety and quality of the system, prior to the introduction of AccTEF;
- Lack of suitable control measures for handling the system's potential risks and suitable policies and mechanisms to reinforce control measures;
- Lack of training for stakeholders to make them aware of the risks, control measures, and policies.

FAIRness of the OKE output (RDF-AIRs) is evaluated by comparing its features to FAIR principles (Table 6). FAIRness of the RDF-AIRs is also evaluated using three automated FAIR tools, FAIR Checker, FAIR Evaluator [15], and F-UJI [16] (Table 7). This has been done to find similarities in found risks and FAIRness evaluation results that validate the relation between FAIR and accountability and transparency. According to the results, RDF-AIRs dataset is not FAIR, which validates the transparency and accountability results.

4.3. *HAICS FAIRness*

The FAIRness of HAICS has been evaluated by assessing the alignment of its features with FAIR best practices and recommendations [11, 12, 13, 14]. Through the evaluation, FAIRness limitations were found in HAICS, as reported in Table 8.

Table 5. OKE accountability assessment.

Accountability factors	Questions	Answers	Points
Transparency and justifiability of outcomes and actions	Is suitable (a set of defined minimum required metadata based on the system and application) metadata available?	No	0
Auditability, oversight, monitoring, and verification	Are there evaluation mechanisms in place to ensure safety and quality of the system?	No	0
Risk assessment	Are potential risks associated with using the system identified?	No	0
Responsibility	Is a list of provenance metadata identified and made available? Have accountability roles for system's potential risks identified and explicitly declared?	No	0
Controllability	Are requirements that the system needs to follow in order to be compliant with stakeholders' laws and regulations identified?	No	0
	Are suitable control measures for handling the system's potential risks determined and explicitly declared?	No	0
"policies and procedures", "Response and enforcement"	Are suitable policies and mechanisms to reinforce control measures determined?	No	0
Training and awareness	Are training in place for stakeholders to make them aware of the risks, control measures, and policies?	No	0
		5 over 13	

Finding and mitigating these limitations help enhancing transparency and accountability of the vocabulary through targeted expansion of its metadata and increasing its findability, accessibility, and reusability. It also contributes to the transparency and accountability of the ontology-based AI systems relying on HAICS.

According to Table 8, we aim to improve the findability of HAICS by publishing it in a semantic repository and adding annotations to its HTML file. To make it more accessible and reusable, we will make it available in other formats, such as RDF-XML and add previous version, version IRI, and last modification sections to its metadata. In this way, by being FAIR, the vocabulary will be linked to by other vocabularies as well. While these are simple interventions, they contribute to the transparency and accountability of the AI systems based on HAICS.

Table 6. RDF-AIR FAIRness evaluation.

To be Findable:		
F1	(meta)Data are assigned a globally unique and persistent identifier	Yes
F2	Data are described with rich metadata	No
F3	Metadata clearly and explicitly include the identifier of the data it describes	No
F4	(Meta)data are registered or indexed in a searchable resource	Yes
To be Accessible		
A1	(Meta)data are retrievable by their identifier using a standardized communi-cations protocol	Yes
A1.1	The protocol is open, free, and universally implementable	Yes
A1.2	The protocol allows for an authentication and authorization procedure, where necessary	Yes
A.2	Metadata are accessible, even when the data are no longer available	No
To be Interoperable:		
I1	(Meta)data use a formal, accessible, shared, and broadly applicable language for knowledge representation	Yes
I2	(Meta)data use vocabularies that follow FAIR principles	No
I3	(Meta)data include qualified references to other (meta)data	Yes
To be Reusable:		
R1	Meta(data) are richly described with a plurality of accurate and relevant at-tributes	No
R1.1	(Meta)data are released with a clear and accessible data usage license	No[a]
R1.2	(Meta)data are associated with detailed provenance	No
R1.3	(Meta)data meet domain-relevant community standards	-[b]

[a] No license has been provided.
[b] There is no domain relevant community standards for linked data for CRM.

Table 7. RDF-AIR FAIRness evaluation using automatic tools.

FAIR elements	FAIR Checker[a]	FAIR Evaluator [15]	F-UJI [16]
Findability	12.5 %	1.8	1.7
Accessibility	40 %	2.5	0.3
Interoperability	0 %	0.7	0.4
Reusability	0 %	0.2	0.1

[a] https://fair-checker.france-bioinformatique.fr/base_metrics

4.4. *HAICS Quality*

One of the data governance aspects is data quality evaluation [72]. It is important to check the quality of vocabularies and ontologies before using them to avoid issues

Table 8. HAICS FAIRness limitations.

Principles/ Best practices	FAIRness limitations
D2.2 FAIR Semantics	• BP-Rec. 5: Define workflows between different formats, • P-Rec. 4: Publish the semantic artefact and its content in a semantic repository.
BP-FAIR	• Metadata: Add "previous version" and "version IRI", • Visualization: Recommendation is UML, • Publication on the Web, – Accessibility in multiple interoperable formats, – Publish the ontology in a semantic repository and add annotations to its HTML file.
5-star by Vatant	** last modification
5-star by Janowicz et al.	***** The vocabulary is linked to by other vocabularies

related to the lack of accountability and transparency to be propagated in systems that are using the resources. Accordingly, in this paper, the quality of HAICS has been evaluated to check if the quality evaluation metrics under study can cover FAIR, and accountability and transparency concepts. Quality evaluation metrics should be chosen considering the fact that HAICS is a SKOS vocabulary without object and data properties. For this reason, 26 quality evaluation metrics for SKOS vocabularies [17] and QMM [18] have been used to evaluate HAICS (Tables 9 and 10). Compliance with most of the SKOS metrics, except "Extra Whitespace in Labels", "Disjoint Classes Violation", and "Invalid URIs", has been checked using the qSKOS tool [17].

According to Table 9, HAICS has failed in six of the 26 SKOS evaluation metrics. There are two similar concepts in different levels of the hospital adverse incident categories and subcategories, which is the reason why "Overlapping Labels" and "Cyclic Hierarchical Relations" have been detected in the vocabulary. The HAICS hierarchy has been created using unidirectional "Narrower" relations, in which the reverse direction, i.e., "broader","hasTopConcept", and "topConceptOf" relations, are assumed to be inferable. For this reason, "Unidirectionally Related Concepts", "Unmarked Top Concepts", and "Omitted Top Concepts" have been detected in the vocabulary.

According to table 10, HAICS scored poorly in four of the QMM metrics. Since two of the 213 definitions in HAICS are similar, there are slight redundancies in

Table 9. HAICS quality evaluation using 26 SKOS vocabulary quality metrics.

Category	Criterion name	Results
Labelling and Documentation Issues	Omitted or Invalid Language Tags	Pass
	Incomplete Language Coverage	Pass
	Undocumented Concepts	Pass
	Overlapping Labels	Fail
	Missing Labels	Pass
	Inconsistent Preferred Labels	Pass
	Disjoint Labels Violation	Pass
	Extra Whitespace in Labels	Pass
Structural Issues	Orphan Concepts	Pass
	Disconnected Concept Clusters	Fail
	Cyclic Hierarchical Relations	Fail
	Valueless Associative Relations	Pass
	Solely Transitively Related Concepts	Pass
	Omitted Top Concepts	Fail
	Unmarked Top Concepts	Fail
	Top Concepts Having Broader Concepts	Pass
	Unidirectionally Related Concepts	Fail
	Relation Clashes	Pass
	Mapping Clashes	Pass
	Disjoint Classes Violation	Pass
Linked Data Specific Issues	Missing In-links	Pass
	Missing Out-links	Pass
	Broken Links	Pass
	Undefined SKOS Resources	Pass
	HTTP URI Scheme Violation	Pass
	Invalid URIs	Pass

definitions. Also, in some of the concepts, the underline operator has been used to separate different words while some others have been written in the form of camel case. This results in inconsistencies in operators' use. Finally, the vocabulary is particularly related to the hospital adverse incidents, which makes it less generalisable and causes the "minimum ontological commitment" metric to be less than 1.

4.4.1. *Do the Studied Ontology and SKOS Vocabulary Quality Evaluation Metrics Point Out FAIR, Accountability and Transparency Issues?*

Reusability is a common element between FAIR principles and the QMM. Besides, "reusability" metric itself partially covers findability and accessibility aspects of FAIR principles, since a resource needs to be findable and accessible in order to be reusable. "Adaptability" and "reuse of available resources" metrics imply interoperability. Minimalist, coherence, flexibility, and standardization categories of the metrics are closely related to interoperability and reusability principles, since they are

Table 10. QMM results for HAICS.

Verification technique	Design principle	Complies	Total
Minimalist	Clarity	+1	8.49
	Intelligibility	+1	
	Homogeneity	+1	
	Non-subjective definitions	+1	
	Intelligible definitions	+1	
	Definitions not redundant	+0.99	
	Compounds terms	+1	
	Consistency in operators use	+0.5	
	Documentation	+1	
Coherence	Coherence	+3	3
Flexibility	Extensibility	+1	4
	Customization	+1	
	Opening	+1	
	Adaptability	+1	
Standardization	Minimal encoding trend	+1	3
	Simple tools	+1	
	Reuse of available resources	+1	
Redundancy	Concise terminology	+0.99	1.99
	Terminological moderation (curating data to make it more concise by time)	+1	
Efficiency	Minimum ontological commitment	+0.5	1.5
	Efficiency	+1	

assessing ontologies' clarity and transparency. Some metrics, i.e., "non-subjective definitions", "intelligible definitions", and "documentation" from the minimalist and the coherence categories are also related to accountability and transparency. The reason is that objective and clear definitions, and good documentation not only allow transparency, but also prevent biased output of the OSysts by encouraging correct usage of terms in the ontologies and vocabularies. They also allow accountability through enhanced transparency.

Flexibility and standardization categories of QMM metrics are mostly relevant to accountability and transparency, since an extensible, customizable, and adaptable ontology which is open access and has minimal encoding bias, enhances transparency and as a result, accountability. Low level of redundancy in definitions and terms allows accountability and transparency and facilitates reuse. Finally, efficiency, i.e., simple and minimal axioms and simple and easily processable ontology structure, facilitates accountability and transparency, interoperability, and reusability.

Among SKOS quality evaluation metrics, "Linked data specific issues" metrics affect accountability and transparency since they affect findability and accessibility of the vocabulary. Two categores, “Labelling and Documentation Issues” and “Structural Issues”, affect reusability and interoperability. “Linked Data Specific Issues” metrics affect FAIRness, since it directly affects findability and reusability.

Although ontology and SKOS vocabulary quality evaluation metrics partially overlap FAIR principles, they do not fully cover them. Accordingly, we suggest considering accountability and transparency, and FAIR as the important quality evaluation aspects of semantic artefacts to help with both AI and data governance. We also suggest targeted expansion of the ontologies metadata and increasing findability and accessibility of ontologies based on FAIRness best practices and recommendations [11, 12, 13, 14] to increase their accountability and transparency.

5. Conclusions

In this paper, our focus has been on evaluating and improving accountability and transparency of OSysts. We analyzed the relation between FAIR principles and the accountability and transparency concepts. We found that a FAIR linked dataset, ontology, or vocabulary is both accountable and transparent and for an OSyst, FAIRness guarantees transparency. This shows that the accountability and transparency of ontologies and vocabularies, i.e., OSysts inputs, can be evaluated by evaluating their FAIRness. It also shows that the transparency of OSysts can be evaluated using FAIR principles. Accordingly, an accountability and transparency evaluation framework for OSysts, titled AccTEF, was proposed. AccTEF consists of three checklists: accountability, transparency, and metadata. The transparency checklist is a modification of an existing checklist proposed in [27]. The accountability checklist has been built based on important factors of accountability extracted from the literature. The metadata checklist has been built based on the best practices and recommendations for FAIR semantic artifacts [11, 12]. It gives a minimum set of necessary metadata for accountable and transparent linked datasets. Experiments on our use case, i.e., the OKE pipeline, support the relation between FAIR principles and accountability and transparency concepts (Sec. 4.2).

Furthermore, FAIRness and quality of HAICS, as one of the OKE's input vocabularies, were evaluated based on the best practices and recommendations for FAIR semantic artifacts [11, 12, 13, 14] and a set of vocabulary and ontology quality evaluation metrics [17, 18]. Based on the results, we suggest enhancing accountability and transparency of vocabularies and ontologies through targeted expansion of their metadata. We also found that the transparency and accountability of ontologies and vocabularies cannot be evaluated using the studied quality evaluation metrics. Accordingly, we suggest considering accountability, transparency, and FAIR as the ontology/vocabulary quality factors, which allows for assessing governance-related issues before using semantic artefacts in creating OSysts.

Accordingly, our research question “To what extent can accountability and transparency of OSysts be evaluated/measured?” has been answered by designing

AccTEF and proposing FAIR as a way to evaluate the accountability and transparency of ontologies, vocabularies, and linked datasets as the inputs and outputs of OSysts. This research is limited in the set of ontology quality evaluation metrics that were analyzed due to the limitation of SKOS vocabularies in having no data and object properties. As next steps, we plan to expand our case study to include OWL ontologies and analyze more ontology quality evaluation metrics. We also plan to modify AccTEF by assigning different points to different questions based on their importance for our use case. It is also important to have different checklists for the input and the output of the OKE pipeline.

Acknowledgements

This work was conducted with the financial support of the Science Foundation Ireland Centre for Research Training in Digitally-Enhanced Reality (d-real) under Grant No. 18/CRT/6224 and the ADAPT Centre for Digital Content Technology which is funded under the SFI Research Centres Programme (Grant 13/RC/2106_2) and is co-funded under the European Regional Development Fund. For the purpose of Open Access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript version arising from this submission.

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