Metadata Analysis of Open Educational Resources

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ABSTRACT

Open Educational Resources (OERs) are openly licensed educational materials that are widely used for learning. Nowadays, many online learning repositories provide millions of OERs. Therefore, it is exceedingly difficult for learners to find the most appropriate OER among these resources. Subsequently, the precise OER metadata is critical for providing high-quality services such as search and recommendation. Moreover, metadata facilitates the process of automatic OER quality control as the continuously increasing number of OERs makes manual quality control extremely difficult. This work uses the metadata of *8,887* OERs to perform an exploratory data analysis on OER metadata. Accordingly, this work proposes metadata-based scoring and prediction models to anticipate the quality of OERs. Based on the results, our analysis demonstrated that OER metadata and OER content qualities are closely related, as we could detect high-quality OERs with an accuracy of **94.6**%. Our model was also evaluated on *884* educational videos from Youtube to show its applicability on other educational repositories.

CCS CONCEPTS

• **Applied computing** → **Education**; **E-learning**; **Computer-managed instruction**; **Digital libraries and archives**.

KEYWORDS

Open Educational Resources, OER, Metadata Analysis, Exploratory Analysis, Prediction Models, Machine Learning

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1 INTRODUCTION

Open Educational Resources (OERs) play a key role in informal education these days. There are many OER repositories (e.g., MIT[1], Khan Academy[2]) hosting and launching millions of OERs under Creative Common license[3] on a daily basis. However, the lack of high-quality services, such as OER search and recommendation systems, limit the use of OERs [3, 20, 22]. In order to provide such services, high-quality metadata that describe OERs thoroughly and reliably are essential [19]. Although most of the OER repositories are using standardized metadata definitions (e.g., IEEE Standard for Learning Object Metadata (LOM) [6] and Learning Resource Metadata Initiative (LRMI) [1]) to improve open educational services, the lack or low-quality of metadata still limits the performance of these initiatives [7, 11].

Furthermore, from a learner point of view, OERs vary in terms of a large number of important features, like levels of education, topics or vocation. OERs also come in large numbers of different formats and languages. Therefore, it has become inevitable these days to put more emphasis on assessing and controlling the quality of OERs, in which OER metadata should play a prominent role. If OER metadata is created as generic part of the OER quality control processes, automatic metadata analysis may significantly improve the evaluation of OERs. This is not the case currently, as very often only manual methods are used to validate both the quality of OER content and metadata [18], which are time consuming and unscalable solutions [11]. Although, there are some attempts to automatize quality assessment of metadata [11, 23], these only focus on defining criteria and metrics to evaluate the existing OER metadata [2, 10, 17] without building an intelligent model or models to predict the quality of OERs based on metadata.

Based on our assumption that the quality of OER metadata has tight relationship with the quality of OER content, in this paper we show our steps towards the exploratory data analysis on an OER data-set from *SkillsCommons*[4], which provides insights about: (1) the quality of metadata in existing OERs; (2) the effect of quality control on metadata quality; (3) building a machine learning model based on OER metadata to predict the quality of OERs; and finally, (4) we evaluated our proposed models by using the metadata of *884* OERs from *YouTube*, to demonstrate the general nature of our proposed approach, by applying it to different types of educational resources and repositories.

The article is organized as follows: Section 2 discusses the state-of-the-art of assessing the quality of OER metadata and also OER content using metadata. Section 3 explains our steps when it comes to data collection, analysis, and the proposed approach of metadata scoring and prediction of OER quality. Section 4 shares the results

[1]https://ocw.mit.edu/

[2]https://www.khanacademy.org/
[3]https://creativecommons.org/
[4]http://skillscommons.org

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of applying our model on Youtube educational videos in order to validate our proposed approach. Finally, Section 5 discusses our results and Section 6 drives the conclusion and showcases our future work on this topic.

2 RELATED WORK

Most of the literature about OER metadata quality focused on metadata records and their data values [15]. In this section, we review the related body of OER metadata literature, in terms of: (1) research defining dimensions and metrics for metadata, and (2) approaches that improve the quality of metadata.

2.1 Defining Dimensions and Metrics for Metadata

Currently, the following dimensions have been proposed to determine the quality of OER metadata: *completeness, accuracy, provenance, consistency, coherence, timeliness*, and *accessibility* [2]. Ochoa and Duval [10] have defined a set of calculated metrics based on the dimensions, which have been widely reused by researchers addressing OERs' metadata quality [4]. Moreover, they evaluated the metrics regarding *completeness and accuracy* on *425* OERs from the ARIADNE Learning Object Repository [11]. Palaez and Alarcon have evaluated the completeness and consistency of OERs metadata based on Ochoa and Duval's metrics [10] and the standardized domain values (e.g., language should be according to *ISO 639-111* language standard) [14].

2.2 Improving the Quality of Metadata

To have high-quality metadata, some methods have been developed in order to help authors and experts in providing metadata for OERs. A process for improving the metadata quality of OERs was developed to support domain experts with metadata creation; the process introduces qualitative methods (e.g., online peer review of metadata) and tools (e.g., metadata quality assessment grid) in the various phases when it comes to populating metadata in OER repositories [13]. Furthermore, a higher level of metadata quality analysis was applied to help metadata creators to assess and improve the quality of metadata [15]. They exploit linked open data to discover and analyze connectivity between metadata records. Accordingly, they used network statistics (e.g., density of graph) to calculate the relationship between the metadata records in terms of their attributes (e.g. subject) and values. Their study was applied on six large digital library collections and they discussed several improvements that can help users find related resources.

2.3 Lessons Learned

Based on the state-of-the-art, although there are several attempts regarding assessing and improving OER metadata, most of these efforts are either conceptual [17], or focusing only on a few dimensions [8, 16]. Furthermore, currently there is no scalable solutions available [11], which limits the capability of existing approaches, when it comes to OER metadata quality assessment and improvement [5]. Therefore, it is clear that there is a significant need for improving the discoverability, usability, and reusability of OERs with the help of intelligent metadata quality assessment [5]. Subsequently, a recently brief preliminary analysis was conducted on the current state of OER metadata in order to establish a quality prediction model [19]. As a result, we conclude that: it is worthwhile and timely to analyse OER metadata and build metadata-based quality prediction models which not only improve OER-based services, but also facilitate the quality control processes of OERs.

For the above mentioned reasons, in this paper, we attempt to follow-up, extend and evaluate the OER metadata quality prediction model suggested by [19], by using a video based OER data-set, consisting of educational videos from *Youtube*. This was done in order to show the scalability and the generalizability of the proposed approach. Accordingly, the main objectives of this paper are:

(1) Executing exploratory data analysis on metadata acquired from extensive volumes of OERs.
(2) Plotting metadata quality and quality control processes in our OER data-set.
(3) Building and Evaluating a metadata-based quality prediction model for OERs.

3 DATA COLLECTION AND RESEARCH METHOD

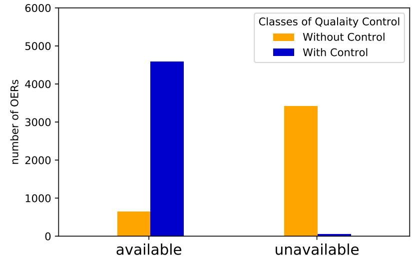
3.1 Data Collection

We have used two data-sets to analyze the OERs metadata and evaluate our model. The *SkillsCommons* data-set was used to analyze and train our machine learning model and the *YouTube* data-set was used to evaluate our prediction model.

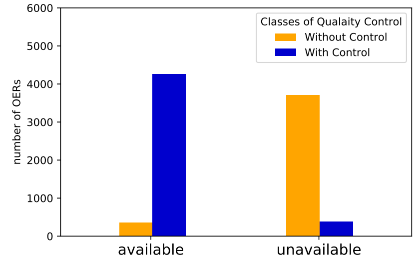
3.1.1 SkillsCommons. For analyzing the OERs metadata and building the quality prediction model, we retrieved all search results for the terms *Information Technology* and *Health Care* via the SkillsCommons platform API and built our OER metadata data-set [19]. The data-set contains *8,887* OERs metadata[5]. The OER metadata in our sample included the following fields: *url, title, description, date of availability, date of issuing, subject list, target audience-level, time required to finish, accessibilities, language list, and quality control* (i.e., a categorical value that shows if a particular OER went through a quality control or not). It should be mentioned that the *quality control* field means manual quality control, and it has been set to **with control** if an OER had at least one inspection regarding the Quality of Subject Matter, and at least one inspection regarding the Quality of Online/Hybrid Course Design, otherwise it is set to **without control**.

3.1.2 Youtube. To evaluate our proposed model, we selected 16 topics, which are defined by [21] as *Information Technology* related search keywords. In addition, we randomly selected another 16 topics from [12] as *Health Care* related search terms. Afterwards, for each of the 32 selected topics in the areas of *Information Technology* and *Health Care*, top videos in Youtube search results were collected[6] using *Pafy* python library[7]. In a Youtube search, the number of top videos appearing in search results depends on the search query topic, and therefore, we can be confronted by different number of videos as top results. However, we collected at least 10

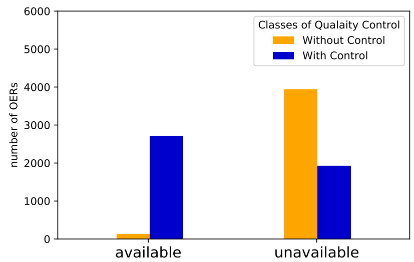
[5]Our *SkillsCommons* data-set is available on: https://github.com/rezatavakoli/ICALT2020_metadata
[6]Our *Youtube* data-set is available on: https://github.com/rezatavakoli/LAK21_metadata
[7]https://pypi.org/project/pafy/



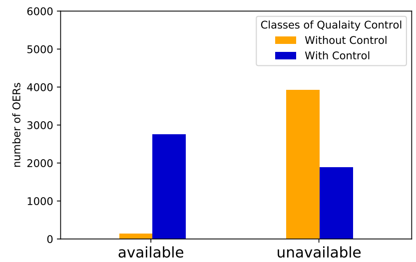
(a) *Level* metadata



(b) *Language* metadata



(c) *Time Required* metadata



(d) *Accessibilities* metadata

Figure 1: Analyzing metadata availability with respect to manual quality control

videos per each search term. At the end, *884* Youtube educational videos were collected for our evaluation step[8]. The video metadata includes the following fields: *url, title, description, number of dislikes, length, number of likes, rating, subject list*, and *number of views*.

3.2 Exploratory Analysis of OER Metadata

As a point of departure, we used our Skillscommons data-set to explore the availability of different OER metadata elements (i.e., level, language, time required, accessibilities) based on their quality control categories ("with control" or "without control"). The results of the analysis are summarized in Figure 1:

- *Level* refers to the learners' expertise or educational level in relation to a specific OER. Figure 1a illustrates how the quality control increases the availability of level metadata.
- *Language* refers to the available language versions of an OER. Figure 1b illustrates the effect of quality control in increasing the availability of language metadata.
- *Time Required* refers to the expected duration needed to complete an OER. Figure 1c shows that it is more likely that OERs with quality control have this type of metadata.
- *Accessibilities* defines the accessibility guidelines supported by an OER. Figure 1d illustrates how quality control increases availability of the accessibility metadata.

To clarify, in each chart, bars on the left show the number of OERs including the particular metadata field, and bars on the right show the number of OERs missing that particular metadata field. Moreover, blue bars are related to the number of OERs with quality control, and orange bars show the number of OERs without quality control. For example, in the left chart of *Level* metadata, you can see more than 4,000 OERs have passed through quality control and also contain Level metadata. At the same time, around 3,000 OERs did not go through quality control, and also do not contain the Level metadata. The plots in Figure 1 show a clear improvement in OER metadata quality (i.e., availability) in the OERs which have passed through quality control. Therefore, this improvement can be interpreted as a result of quality control processes. However, as Figure 2 shows, the proportion of manual OER quality control has been decreasing over the last years in our data-set. We believe that the growing number of OER providers and contents are among the main reasons for this negative change in the proportion of manual OER quality control.

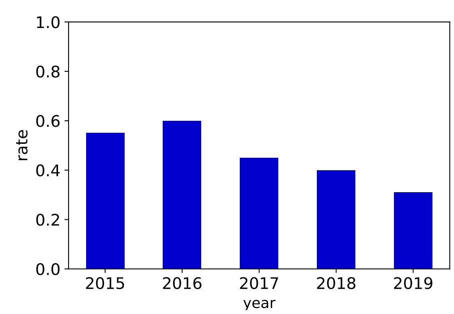
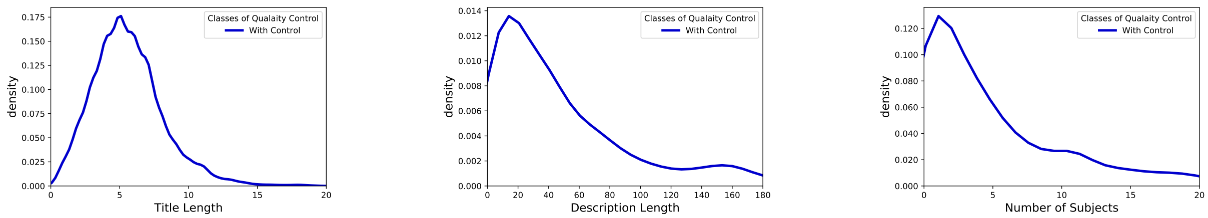


Figure 2: Proportion of manual OER quality control

As results of our exploratory data analysis, (1) we can use the OER metadata subset with already existing quality control to define quality benchmarks for metadata elements, and (2) it is desirable to define a method to facilitate the automatic assessment of OER

[8] For the current version, we used openly available videos, but we disregarded the type of license for our analysis.



(a) Length of *Title* (word count) **(b) Length of *Description* (word count)** **(c) Length of *Subject* (subject count)**

Figure 3: Metadata analysis of quality controlled OER elements

Table 1: OER metadata fields and importance [19]

Type	Importance Rate [0-1]	Normalized Importance Rate [0-1]	Rating Function [0-1]
Title	1	0.17	$\frac{1}{\lceil \lvert x-5.5 \rvert /2.5 \rceil}$
Description	1	0.17	$\frac{1}{\lceil \lvert x-54.5 \rvert /40 \rceil}$
Subjects	0.86	0.145	$\frac{1}{\lceil \lvert x-4.5 \rvert /3.5 \rceil}$
Level	0.98	0.165	If available: 1; else: 0
Language	0.92	0.155	If available: 1; else: 0
Time Required	0.58	0.098	If available: 1; else: 0
Accessibilities	0.59	0.099	If available: 1; else: 0

metadata quality, and consequently the assessment of OER content quality. Therefore, as the next step in our analysis, we focused on OERs with quality control and screened the remaining metadata elements (i.e., title, description, and subjects) of these OERs:

- *Title* refers to the title given to an OER. Figure 3a shows the distribution of title length (as number of words).
- *Description* refers to the content summary of an OER. Figure 3b illustrates the distribution of description length (as number of words).
- *Subject* refers to the subjects (topics) which an OER addresses. Figure 3c shows the distribution of subjects (as number of subjects).

The plots in Figure 3 show that these features have distributions similar to normal. Therefore, it is possible to fit a normal distribution on them and build a scoring model based on the distribution parameters.

3.3 OER Metadata Scoring Model

In order to build our scoring model, we started with the definition of the importance of each metadata field, and a rating function based on the quality controlled OERs. Thus, we defined the importance rate of each metadata field based on their availability rate (between 0 and 1) among quality controlled OERs [19]. For instance, we set the importance rate of the *description* field to 1 as this field was included in all quality controlled OERs, and we set the importance rate to 0.58 for the *time required* field since *58%* of quality controlled OERs included this metadata field. Accordingly, we normalised the calculated importance rates as *normalized importance rate*.

Moreover, we created a rating function for each field based on quality controlled OERs, in order to rate metadata values [19]. Regarding the fields *title, description*, and *subjects*, we fitted a normal distribution on their value length, as according to Figure 3, they have distributions similar to normal. Afterwards, to rate the metadata values based on the properties of controlled OERs, we used the reverse of Z-score concept [24] for each metadata value. Thus, the closer an OER *title/description/subject* length to the mean of the distributions of quality controlled OERs, the higher is the rate[9]. Regarding the four fields of *level, length, language,* and *accessibility*, we used a Boolean function, which assigns 1 when they have a value and assigns 0 otherwise. The output of these calculations is illustrated in Table 1.

Finally, to consider the defined benchmarks in evaluating the quality of OERs' metadata, we defined the following two scoring models [19]:

3.3.1 Availability Model [19]. OER availability score is calculated as follows: $norm\_import\_rate(k)$ is the *Normalized Importance Rate* of metadata field k. The output indicates the completeness of a given metadata in a weighted summation. The weights here are the normalized important rates. As a consequence, high availability score means that the metadata of a given OER consists of fields with significant importance. Consider an example, when a given $OER1$ has values for the following important metadata *title, description*, and *level*, while $OER2$ contains metadata for *subjects, language, time required*, and *accessibilities.* In our model $OER1$ gets a higher availability score than $OER2$.

$$avail\_score(o) = \sum_{k=availablefields} norm\_import\_rate(k) \quad (1)$$

3.3.2 Normal Model [19]. The normal score of an OER o we define this way: $norm\_import\_rate(k)$ is the *Normalized Importance Rate*

[9]It should be mentioned that when a field value is *equal to the mean* or *empty*, the rate will be 1 or 0, respectively.

of metadata field k, where *rating(o,k)* is the assigned rating to OER o regarding field k. This score is built on the rating function of metadata field k. As a result we can benchmark a given metadata to a predefined standard (In our case, we consider quality controlled OER metadata as the standard). This means that a given OER with similar metadata properties to a standard OER, will obtain a high normal score.

$$norm\_score(o) = \sum_{k=fields} norm\_import\_rate(k) * rating(o,k) \quad (2)$$

3.4 Predicting the quality of OERs based on their metadata

As the next step, we used our scoring models to build a machine learning model to predict the quality of OERs based on their metadata [19]. For this purpose, we extracted *4,651* OERs *with quality control* and classified them as high quality OER, while labelling the remaining *4,236* OERs as low quality OER. Subsequently, we trained a Random Forest classifier on the *SkillsCommons* data-set to build a model that makes a binary decision: high-quality/low-quality. We used *80%* of the data as a training set and the remaining *20%* as test set. As a result, the classifier achieved a *94.6%* F1-score when classifying OERs into one of the two above-mentioned categories[10]. Furthermore, we extracted the importance value (i.e. effect) of each feature on our classification model as: *Availability Score*: 0.32, *Normal Score*: 0.25, *Level Metadata Availability*: 0.23, *Description Length*: 0.10, *Title Length*: 0.05, *Subjects Length*: 0.05.

4 VALIDATION

In this section, we report the results of applying our scoring and prediction models on our *Youtube* data-set, including the metadata of *884* educational videos in *32* subjects in the areas of *Information Technology* and *Health Care*. First, we applied our scoring and prediction models on the data-set to classify the videos into two groups: *with control* (higher quality) and *without control* (lower quality)[11].

After classification, we got *477* videos *with control* and *407* videos *without control*. Then, we needed to identify a metric in their metadata to compare the two groups in order to check whether our model detects the groups of videos with higher quality or not. Therefore, we decided to focus on video *rating* feature as a quality indicator from the users' perspective, which is calculated based on *likes* and *dislikes*, and one of the most commonly used metrics of quality assessment of videos [9]. Finally, for each of the *32* subjects, we calculated the average of video ratings for each of the predicted groups (*with control* as higher quality and *without control* as lower quality). Table 2 shows the subjects, the difference of the average rating between the groups, and the difference sign which specifies whether our model predicted correctly and the "with control" group has higher ratings (shows with +) or not (shows with −).

[10]We implemented this classifier in Python. Our steps and results are publicly available on: https://github.com/rezatavakoli/ICALT2020_metadata

[11]In order to apply our model, we set our required fields based on the video properties. For instance, we set *level availability* based on the videos title, and set *length availability* to "available" as all videos have length metadata.

Table 2: Difference between videos rating of groups

Subject	Rating Difference	Difference Sign
bioethics	0.15	+
deep learning	-0.15	-
infectious disease	0.14	+
sleep disorder	-0.14	-
apache spark	0.13	+
data mining	0.10	+
allergies	0.09	+
vaccinations	0.08	+
women and nutrition	-0.08	-
data management	0.07	+
SQL language	-0.06	-
brain tumors	0.05	+
big data	0.05	+
cancer prevention	0.05	+
data cleaning	0.05	+
sun awareness	0.05	+
addiction	0.05	+
data visualization	0.04	+
psychology	0.03	+
neural network	0.03	+
apache hadoop	0.03	+
stress management	0.02	+
tensorflow	0.02	+
obesity care	0.02	+
python language	0.02	+
R language	0.02	+
statistics	0.02	+
text mining	0.02	+
machine learning	0.01	+
prostate cancer	0.01	+
eye care	0.01	+
smoking health risks	-0.01	-
Average	**0.05**	**+**

As per the results detected by our prediction model, the average rating in a group with higher quality has 0.05 higher video rating than the lower quality group. This is very reasonable considering the standard deviation of ratings in the data-set of *0.25*. To further elaborate, the maximum difference between around *80%* of the ratings is *0.25*. Therefore, dividing them into two groups with a rating difference of *0.05*, emphasizes that our classifier works well in this context. Additionally, in *27* out of *32* subjects (**84.3%**), where our model detected higher quality groups, they had higher ratings.

5 DISCUSSION

5.1 OER Metadata

Based on the exploratory analysis on our OER data-set, it is clear that there is a strong relationship between OER quality control and the metadata quality. Therefore, the more an OER passes the quality control process, the higher the chance of including high-quality metadata is. Accordingly, we can define benchmarks for metadata quality by analyzing the controlled OERs. On the other hand, using metadata quality as a proxy for OER content quality can be beneficial in developing automatic quality control processes for OERs. According to the analysis of quality controlled OERs, *Title* and *Description* metadata play a key role in publishing OERs, as all of the controlled OERs contain these two fields in their metadata. Moreover, more than *85%* of the controlled OERs include metadata regarding *Language* and *Level*, and *Subject* which shows the importance of these three fields in defining OERs.

5.2 Metadata Scoring

Analyzing the importance values in our quality prediction model reveals the effectiveness of our proposed scores for metadata, as the *Random Forest* model assigns the highest value to our *Availability Score* and *Normal Score* features. Therefore, these two proposed indicators illustrate the quality of OER metadata well and can be applied not only for metadata scoring, but also for OER content quality prediction.

5.3 Quality Prediction Model

The F1-score of our proposed prediction model (**94.6%**) shows that we can accurately predict the quality of OERs in *SkillsCommons* repository. Our validation step on *Youtube* data-set also supports the generalizability of our model, which can be applied in different repositories and various types of educational resources (e.g. videos, text-based). Moreover, according to the result of our validation step, as our prediction model detected the higher quality groups in *14* (out of *16*) *Information Technology* topics and in *13* (out of *16*) *Health Care* topics, the proposed *Random Forest* prediction model works well in different topic areas.

6 CONCLUSION AND FUTURE WORK

In this study, we used the metadata of a large OER data-set to analyse OER metadata quality and OER quality control processes. Based on our analysis, we created a prediction model to evaluate the quality of OER metadata and as a consequence OER content quality. We deem that our proposed model not only helps OER providers to revisit and think about the importance of the quality of their metadata, but also facilitates the process of OER quality control in general, which is essential according to the rapidly growing number of OERs. Applying our quality prediction model on the *Skillscommons* data-set showed that it can detect quality controlled OERs with the F1-score of **94.6%**. We also validated our approach in another context, by applying our scoring and prediction model to open educational videos on *Youtube*. The results show that our approach successfully detects videos with higher user rating values. The validation step indicates that our approach can be used on different OER repositories.

In the future, we plan to further validate our models by collecting more data from other knowledge areas and repositories. Moreover, we consider to progress towards improving the models by adding more metadata features such text-based analysis of title, description, and keywords.

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