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A Curriculum Mining Method for Clustering Study Modules and Assessing their Uniqueness

Benjamin Matthies
FH Münster, benjamin.matthies@fh-muenster.de

Julian Koch
South Westphalia University of Applied Sciences, koch.julian@fh-swf.de

Kathrin Maassen
University of Duisburg-Essen (Graduate), kathrin.maassen@uni-due.de

André Coners
South Westphalia University of Applied Sciences, coners.andre@fh-swf.de

A CURRICULUM MINING METHOD FOR CLUSTERING STUDY MODULES AND ASSESSING THEIR UNIQUENESS

Research in Progress

Benjamin Matthies, Münster University of Applied Sciences, Münster, Germany, benjamin.matthies@fh-muenster.de

Julian Koch, South Westphalia University of Applied Sciences, Hagen, Germany, koch.julian@fh-swf.de

Kathrin Maassen, University of Duisburg-Essen (Graduate), Duisburg-Essen, Germany, kathrin.maassen@uni-due.de

André Coners, South Westphalia University of Applied Sciences, Hagen, Germany, coners.andre@fh-swf.de

Abstract

Curriculum development can pursue several pedagogical goals. One is to design a curriculum that is attractive in comparison with other competing universities. To contribute to such a comparative assessment and, thereby, to the targeted development of curricula, the idea of a curriculum mining method is presented. Here, study modules are divided into homogeneous groups by means of a document clustering procedure. The generated knowledge improves the comparative assessment of curricula in two ways: First, depending on the context, it can be used to assess either the extent of the "uniqueness" of a module or its "consecutiveness" with other modules. Second, by supplementing the modules with metadata (e.g., region), a competitive analysis is provided in terms of modules offered by competing institutions. An exemplary case study demonstrates how this improves the evaluation of a specific IS curriculum. In conclusion, the current limitations and next steps of the research project are summarized.

Keywords: Curriculum Mining, IS Curriculum, Study Modules, Document Clustering.

1 Introduction

Curriculum development has a long history in Information Systems (IS) research (see Swanson et al., 1979) and is subject to constant review and change (Arbaugh and Hwang, 2015; van den Akker, 2007). In fact, it is a complex task to make a curriculum up-to-date, well-composed, and attractive (Mills et al., 2012). This involves, e.g., that the study contents have a relevant topicality, that the individual learning outcomes are well coordinated, and that the workload is realistic (Rawle et al., 2017).

Since the Bologna Reform in 1999, curriculum contents are documented in detail in the form of study modules, forming a module handbook of a study program (Pietzonka, 2014). This way, module handbooks serve to provide well-documented information for students, lecturers, and others involved in the study program (Huisman et al., 2012). This includes, e.g., information on learning objectives, learning contents, workloads, or examination requirements. Due to their largely standardized content structure, study modules can also be compared with each other more easily. In this context, a cross-university comparison of modules can be of particular value in terms of "competitive" analysis. The basic reasoning here is that a comparison with other (competing) curricula supports the critical evaluation of the own curriculum, which in turn facilitates the targeted curriculum development. To contribute to such a comparative assessment and, thereby, to the targeted development of curricula, the idea of a respective curriculum mining method is presented in this paper. The distinctive feature of this particular mining approach is that the focus is not on the exploration of new curriculum content (in terms of topic modeling and the extraction of relevant teaching content), but instead on the exploration of content structures within and across curricula per se. This can be achieved through the grouping and comparison of homogeneous study modules across, e.g., universities or regions.

The research goal is to develop and practically evaluate a *Curriculum Mining Method* (CMM) for the presented context. In this regard, this paper describes our current and further planned work. To conduct the research process in a focused manner, we have defined two guiding research questions (RQ).

RQ1: How must a curriculum mining method be designed (in terms of procedures and tools) to enable comparisons across curricula at the module level?

RQ2: What are the practical implications of using the method for curriculum design?

To this end, we modeled specific text mining procedures within the framework of a Design Science approach (see Hevner et al., 2004) to develop a method for comparing curricula at a study module level. In this context, our research on CMMs can be divided into two parts: First, the design of a CMM (referring to RQ1), which is presented in the form of a process model with integrated analytical methods (see Section 3). Second, the IS domain-specific implementation and evaluation of the CMM (referring to RQ2). For this purpose, an IS curriculum is used and exemplarily analyzed in the context of a case study (see Section 4). In this exemplary case study, one selected IS Master's program from Germany is compared with all available Bachelor's programs in terms of module content. The generated knowledge improves the comparative assessment of curricula in two ways: First, depending on the context, it can be used to assess either the extent of the "uniqueness" of a study module or its "consecutiveness" with other modules. As an interpretive viewpoint, "uniqueness" can be defined as follows: *the degree to which an individual module or a curriculum as a whole distinguishes itself from a comparison group in terms of content*. "Consecutiveness", on the other hand, is: *the degree to which an individual module or a curriculum as a whole exhibits comparability and therefore connectivity to a comparison group in terms of content.* Second, by supplementing the modules with metadata (e.g., region), a more focused competitive analysis is provided in terms of modules offered by directly competing institutions. The case study exemplarily demonstrates that such an explorative comparison of module content can discover clusters of teaching concepts previously unknown in this form. Furthermore, it is discussed how this knowledge can subsequently be used to assess a curriculum.

2 Research Background

The growth of digital teaching and the broad availability of learning data have led to the birth of a discipline known as *Educational Data Mining* (EDM) (see, e.g., Aldowah et al., 2019; Dutt et al., 2017; Peña-Ayala, 2014; Romero & Ventura, 2020). As a subfield of EDM, *Curricular Mining* (CM) is an emerging research area that draws increasing attention because of its potentials to support data-based decision-making around curriculum design (Aldowah et al., 2019; Daniel, 2015; Dutt et al., 2017; Slater et al., 2017; Viberg et al., 2018). This is done by applying different analysis approaches, such as text mining methods (see Miner et al., 2012), on the growing amount of publicly available curricular data. In particular, CM is often used to investigate the textual curriculum content and to generate insights into different elements, such as learning outcomes or relevant teaching content (see, e.g., Rawle et al., 2017). In addition, to gain even broader insights for targeted curriculum design, systematic CM is often extended by means of triangulation through a multifactorial methodology (Dennehy et al., 2020; Slater et al., 2017). E.g., a common research approach is to assess the content of curricula by supplementing or contrasting it with complementary data, such as generated by content analysis of teaching/learning assessments from e-learning environments (Romero et al., 2008) or secondary data such as job advertisements (Debortoli et al., 2014; Dutt et al., 2017; Ferguson, 2012).

However, most studies in the CM context focus exclusively on exploring potentially relevant teaching content, but not on systematically comparing already existing teaching content. In addition, there is as well a lack of studies examining large or even comprehensive collection of module handbooks in a certain field (as in this study consisting of > 4,250 study modules). One of the few comparable studies is the analysis by Föll and Thiesse (2021), which summarized 3,700 distinct modules from IS study programs. Additionally, there are no known studies that compare study modules for the purpose of competitive analyses in the higher education landscape. Building on these research gaps, our research can make valuable contributions by demonstrating a new approach to comparative analysis of curricula.

3 Curriculum Mining Method

Following the idea of Design Science Research (Hevner et al., 2004), the goal of this research project is to design a *Curriculum Mining Method* (CMM) for solving a relevant problem in higher education practice. In this context, the specific problem to be solved is to improve the content-based comparison of individual study modules in particular and, building on this, to support subsequent assessment of curricula in general (see Sections 1 and 2). A procedure is proposed (see Figure 1) to guide this analysis in a structured way. The procedure model is based in its main characteristics on the established ***CR****oss* ***I****ndustry* ***S****tandard* ***P****rocess for* ***D****ata* ***M****ining* "CRISP-DM" (Wirth & Hipp, 2000), which has been adapted regarding the specific examination of curricula. CRISP-DM is an abstract reference model designed for adaptation and is particularly well suited for the purpose of this solution because, especially in the first two phases, a focus can be placed on working with the curricula collections. Along these phases, appropriate techniques and analyses are incorporated. The phases and incorporated solutions are outlined in more detail below and demonstrated in Section 4 using an exemplary case study. At various points in these phases, iterations are also possible (e.g., between phases 2 and 3).

(1) Curricula Collection: Phase 1 focuses on compiling a database that is appropriate for the purpose of the analysis. Since the mining approach aims at a clustering and a subsequent comparison of curricula, two collections are required: a curriculum to be examined (A) and reference curricula suitable for comparison (B1 - Bn).

(2) Curricula Understanding: Phase 2 has the purpose to explore relevant relationships and structures in the curricula, to determine any quality deficiencies in the documentation, or to identify useful subsets in the curricula. These insights will be used for data preparation.

(3) Data Preparation: Phase 3 includes all data preparation activities to create the final database that can be used for further text analysis. The data pre-processing involves basic steps (e.g., tokenization, normalization, substitution) commonly used in the text mining context (see Miner et al., 2012) to transform a textual curricula collection into a statistically analyzable term-document-matrix (TDM).

(4) Modeling: Phase 4 involves the modeling and execution of a document clustering procedure. This includes the basic calculation of similarities between the curricula modules using an appropriate similarity index. On this basis, hierarchical clustering of modules can be performed, and the modules with the most similar (matching) content (A <=> B) can be extracted.

(5) Evaluation: Phase 5 involves the evaluation of whether the results are plausible and really provide the quality to support the assessment of the curriculum under investigation. This may involve a manual coding process, i.e., reading and interpretively comparing of potentially matching modules.

(6) Curriculum Assessment: Phase 6 involves the usage of the insights gained to examine the curriculum to be evaluated critically (e.g., with regard to desired unique selling points of the modules) and to identify potential for optimization (e.g., with regard to teaching content)

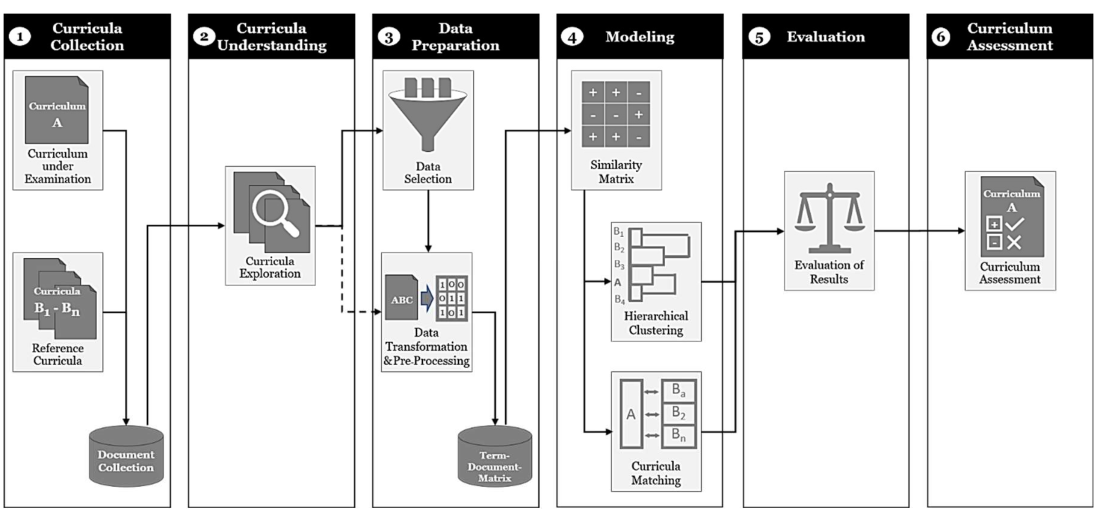

Figure 1. Curriculum Mining Method (CMM)

4 Case Study

The proposed CMM was initially tested and evaluated by means of an exemplary case study. This case aims at the comparative evaluation of a Master's program with Bachelor's programs in order to assess its composition of modules. On the one hand, this involves the consecutive fitting of the Master's modules into previous studies (i.e., consecutiveness) and, on the other hand, their uniqueness.

Starting with the **(1) curricula collection** (see Table 1), the curriculum under examination (A) is an Information Systems (IS) Master program offered at a University of Applied Sciences (UAS) in Germany, consisting of 17 modules. The reference curricula ($B_1 – B_{89}$) are represented by a collection of 89 IS Bachelor programs in Germany (4,234 Bachelor modules in total). In order to achieve a comprehensive analysis, an appropriately comprehensive curricula collection was compiled, including all types of universities (UNI and UAS) as well as public and private institutions. For the purpose of this analysis, a separation of UNI and UAS, i.e. in particular a focused analysis of only the study programs of UASs, was deliberately refrained from. The central argument for this is that a comprehensive competitive analysis should be achieved. Since students can change university types during the transition from a Bachelor's to a Master's program (e.g., from UNI to UAS), the analysis should also include both university types and thus also consider the competitive offer of UNIs in the assessment.

<table>
<tr><th></th><th>Curriculum under Examination (A)</th><th colspan="16">Reference Curricula (B)</th></tr>
<tr><td>Course of Studies</td><td>IS (Master)
[17 / 100%]</td><td colspan="16">IS (Bachelor)
[4.234 / 100%]</td></tr>
<tr><td>Type of University</td><td>UAS
[17 / 100%]</td><td colspan="8">UNI
[1.537 / 36%]</td><td colspan="8">UAS
[2.697 / 64%]</td></tr>
<tr><td>University (n = 89)</td><td>UAS #1
[17 / 100%]</td><td>UNI #1
[56 / 4%]</td><td colspan="2">UNI #2
[27 / 2%]</td><td colspan="2">UNI #3
[57 / 4%]</td><td>...</td><td colspan="2">UNI #29
[27 / 2%]</td><td colspan="2">UAS #1
[36 / 1%]</td><td>UAS #2
[45 / 2%]</td><td colspan="2">UAS #3
[41 / 2%]</td><td colspan="2">...</td><td>UAS #60
[31 / 1%]</td></tr>
<tr><td>Region (n = 16)</td><td>R #10
[17 / 100%]</td><td colspan="2">R #1
[117 / 3%]</td><td colspan="2">R #2
[118 / 3%]</td><td colspan="3">R #3
[385 / 9%]</td><td colspan="2">R #4
[602 / 14%]</td><td colspan="3">R #5
[52 / 1%]</td><td colspan="2">...</td><td colspan="2">R #16
[171 / 4%]</td></tr>
<tr><td>Type of Institution</td><td>public
[17 / 100%]</td><td colspan="8">private
[379 / 9%]</td><td colspan="8">public
[3.855 / 81%]</td></tr>
</table>

Notes:
- Dataset description:
  - Type of University: Research University (UNI) = 29; University of Applied Sciences (UAS) = 60
  - Region (R) = 16
  - Type of Institution: public = 83; private = 6
- Information in square brackets → [number of modules / percentage of all modules in the group]

Table 1. Curricula collections (A & B) and assignment of the analyzed modules.

The publicly available module handbooks were downloaded from the universities' websites via a web crawler, the texts extracted and stored in a structural database. The curricula collection was supplemented with relevant meta-data (i.e., type of university, region, and type of institution). By this means, this multidimensional collection can be further filtered for focused analyses if necessary (i.e., in the sense of slicing and dicing the data).

The **(2) curricula understanding** phase involves a screening of the curricula collection with regard to the structural and content characteristics of the collected modules (e.g., their completeness or language).

In the **(3) data preparation** phase, the textual curricula collection was limited to relevant content and prepared for statistical analysis using Natural Language Processing (Manning & Schutze, 1999). The following procedures were carried out with the tool *WordStat 7*. First, in an initial filtering process, the curricula collection was reduced to explicitly relevant content. Since the focus is on learning content, the descriptions of "learning objectives" and "learning content" were selected, which are obligatory according to the Bologna reform (see Chaparro, 2016). Other irrelevant documentation, e.g., sections on literature recommendations, were excluded. Furthermore, since this initial case study focused on a collection of German-language curricula, occasional modules in other languages were excluded. Second, various additional approaches are possible and necessary in data pre-processing (see Miner et al., 2012). In this case study, basic steps were performed, such as tokenization, i.e. extraction of word components in the textual document collection. Subsequently, a normalization (i.e., unification of almost identical words) and a stop-word removal were performed. To further unify the database, a lemmatization process was applied to transform varying word forms into their dictionary (base) form, thus reducing variation in the data.

In the **(4) modeling** phase, the modules of the curricula were grouped according to their homogeneity. The goal is to identify the position of (A) the curriculum under examination (i.e., in particular of its modules) in the body of (B) all reference curricula and their modules. For this purpose, a document clustering procedure is applied. Document clustering is the process of dividing text documents into appropriate clusters, i.e., documents within a group have high content-related similarity (see Popat et al., 2017). Therefore, in this study, the goal is to determine patterns in curricula, i.e., finding meaningful structures of similarity between modules and grouping them into a cluster. Document clustering procedures determine similarity measures or distance metrics to define the similarity or dissimilarity between documents. By grouping the documents in such a way that the most similar documents within the group can be found, a respective intra-similarity score will be increased. Common similarity measures are metric distances, cosine measures, or extended Jaccard similarity (Huang, 2008). In this study, a cosine similarity measure based on TF-IDF (Term Frequency-Inverse Document Frequency) values was used (see Popat et al., 2017). On this basis, a hierarchical clustering analysis was then performed by grouping objects into a tree-like data structure called a dendrogram (Figure 2). It represents a sequence of nested clusters which is thus suitable for determining the position of a specific module in the ensemble of all modules examined. Here, the silhouette coefficient is a measure of the quality of a clustering, indicating the degree of differentiation from other clusters.

Referring to the example case, more than 600 clusters with more than 4.200 modules have been built in total (after several iterations of evaluation and optimization). This acceptable result was narrowed down in several iterations with different numbers of clusters, evaluating in particular the silhouette coefficients and expressiveness of the cluster compositions. Exemplarily, Figure 2 shows two clusters, namely "Algorithms & Data Structures" and "Software Engineering & Requirements Specifications" (the titles in German were translated). These clusters contain two exemplary analyzed modules (A #3 & #7). Focusing on the cluster "Algorithms & Data Structures" (left side, Figure 2), it can be seen that it consists of 40 modules with a silhouette coefficient of 0.301, indicating a comparatively lower differentiation from other clusters. At first glance, the examined Master's module A #3 thus seems to have substantial content overlaps with at least 39 other Bachelor's modules. The second cluster, "Software Engineering & Requirements Specifications" (right side, Figure 2), consists of only five modules in total and a higher silhouette coefficient of 0.553 and hence, a better degree of differentiation. The examined Master's module A #7 can only be found rarely in other Bachelor modules and thus shows a certain uniqueness. Of course, for a comprehensive evaluation of the whole Master program under examination, all built clusters have to be examined (this demonstration is limited to two extreme modules to show the difference in interpreting the results).

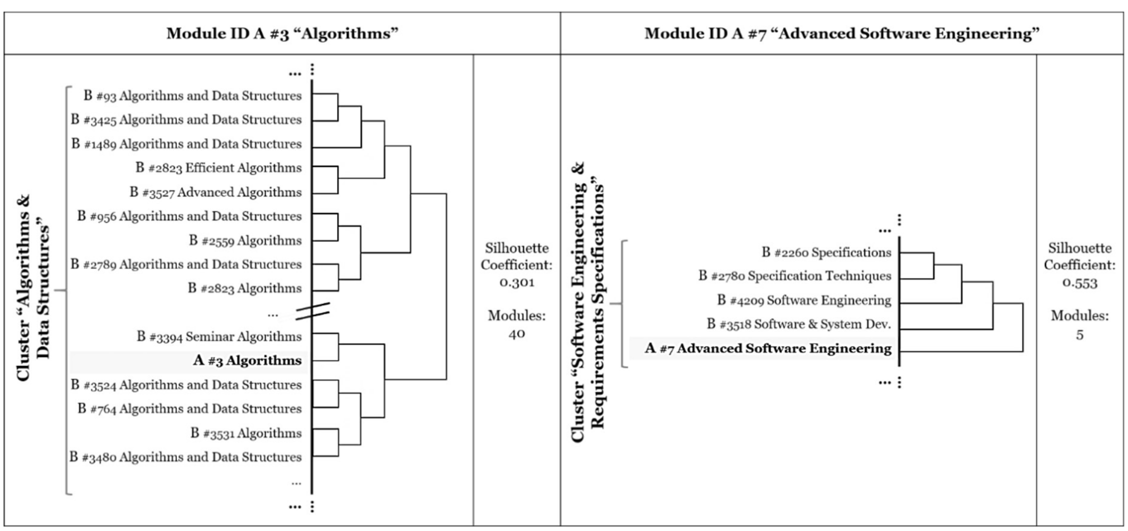

Figure 2. Hierarchical clustering of modules (excerpt of two exemplary modules).

In combination with the hierarchical clustering results, the matrix of similarities between modules can be used to allow an enriched analysis (see Table 2). The module IDs (B) were supplemented with further meta-data (e.g., university, region). Hence, it is possible to generate more accurate insights into comparable modules offered by other universities. This enables benchmarking in the sense of competitor analysis, e.g., on a regional level, which plays an important role in German university competition.

Curriculum under Investigation (A)								
Algorithms [ID A #3]	Adv. Software E. [ID A #7]	Reference Curricula (B)						
Similarity	Similarity	ID	Module	University	Type of University	Type of Institution	Region
0.4020	-	B #3394	Seminar Algorithms	UNI #11	UNI	public	R #9
0.3830	-	B #3194	Algorithms and Data Structures	UAS #58	UAS	public	R #4
0.3740	-	B #4213	Data Structures and Algorithms	UNI #29	UNI	public	R #10
0.3640	-	B #3852	Algorithms	UNI #20	UNI	public	R #7
0.3410	-	B #888	Algorithms and Data Structures	UAS #18	UAS	public	R #12
...	...	...	...	...	...	...	...
-	0.3330	B #2780	Specification Techniques	UNI #9	UNI	public	R #15
-	0.2850	B #3518	Software & System Development	UNI #14	UNI	public	R #4
-	0.2780	B #4209	Software Engineering	UNI #29	UNI	public	R #10
-	0.2720	B #2260	Specifications	UAS #47	UAS	private	R #16

Table 2. Matching of modules (excerpt of two exemplary modules).

In order to get an in-depth impression of the clustered modules, the **(5) evaluation** was based on a manual rating process. The potentially matching modules of a cluster were read and interpretatively evaluated with respect to their actual content similarity. This coding procedure was initially performed by an experienced senior researcher and subsequently evaluated by a second researcher. Differences were corrected by consensus.

To measure the quality of the clustering, typical evaluation measures of classification analysis were adapted (Precision and Recall). An example of the procedure: the cluster "Algorithms & Data Structures" contained 50 modules grouped as homogeneous (incl. the module ID A #3 to be compared). 90% of these modules (Precision: 0.900) actually have significantly comparable teaching content (5 modules have only partially comparable or non-comparable content). Thus, the clustering is precise in reliably grouping truly homogeneous modules. However, a further evaluation of all modules included in the curricula collection has revealed that in addition to the originally clustered modules, there is a larger number of other modules (51) that are very comparable in terms of teaching content and could also be assigned to the "Algorithms & Data Structures" cluster. Therefore, the clustering is not complete and has left about 60% of other potentially relevant modules unconsidered (Recall: 0.414). There are several explanations for this incompleteness, such as the large linguistic variation in the modules' documentation (see also Section 5). Comparable results were generated by a screening of the cluster "Software Eng. & Requirements Spec." (Precision: 1.000; Recall: 0.571).

In the **(6) curriculum assessment** phase and depending on the purpose of applying CMM, different interpretative directions are possible regarding the assessment of the curriculum under examination. In general, the design of Master's degree programs is a challenging task. On the one hand, they should be unique and specialized (or advanced) in a particular field of research, but at the same time easily accessible to students from other universities, i.e., well connected in content to the majority of Bachelor's degree programs. E.g., if a Master program should be fundamentally different from a Bachelor program to provide an in-depth and specialized study to complete the academic education, it is necessary that the majority of modules of the Master program are clearly different from the content of Bachelor programs and thus form a unique selling point. Since universities, e.g. of a specific region, compete with each other, another approach might be that in some Master's modules, contents of Bachelor programs are deliberately repeated to form a consecutive and well-connected program for students from other universities. These two interpretive directions can be understood as "uniqueness" vs. "consecutiveness."

Building on this discussion, Table 3 presents an exemplary evaluation of "uniqueness" and "consecutiveness." The first can be understood as the degree of providing a stand-alone offering in a comparison group (i.e., by region, university type, and institution). The second can be understood as the degree of comparability in terms of content and thus connectivity with a comparison group (see definitions in Section 1). These two interpretive directions can be expressed by the percentage of universities (i.e., curricula) that offer a comparable module and can be interpreted as follows: the smaller the percentage, the more pronounced the "uniqueness"; the higher the percentage, the more pronounced the "consecutiveness." The corresponding interpretation can be illustrated by means of the case study (see Table 3): On the one hand, if the "uniqueness" of a Master program is focused, it is necessary that Master modules are found only in very small clusters. This applies to the module ID A #7 "Advanced Software Engineering," which is part of a small cluster with only four other modules. Focusing on the competition between universities, an even deeper analysis is possible. In this regard, the available meta-data can be used to define specific comparison groups for the analysis (in this example: region, university type, and institution type). First, the IS-Master program is located in region #10. With reference to the module "Advanced Software Engineering" (ID A #7), one other university of region #10 offers such a designed module in the corresponding cluster. In relation to the total of 11 universities in region #10, this results in 18% (medium) "uniqueness" (= 2 out of 11 universities in region #10 offer a comparable module). Second, with a focus on university type (UAS), this module appears to be a very unique offering (2 out of in total 60 UASs in Germany offer a comparable module = 3.4% = "+" rating). On the other hand, if a Master's program aims to repeat some basics of a Bachelor's study program, it may make sense that certain Master modules are linked to larger clusters of Bachelor's study programs. In the sense of "consecutiveness", this could apply, e.g., to the module ID A #3 "Algorithms," which belongs to a larger cluster of 40 modules and is also widespread in a regional comparison with a percentage of 63.6% (= 7 out of 11 universities in region #10 offer such a module in the corresponding cluster = rating of "-").

Modules (exemplary)	**Uniqueness**			
	No. of Modules in the Cluster	by Region	by Type of University	by Type of Institution
ID A #3 “Algorithms”	40	-	o	-
ID A #7 “Adv. Software Engineering”	5	o	+	+

Notes:
+ = strong uniqueness (< 10 % of modules in the sub-sample) o = medium uniqueness (11 – 35%) - = weak uniqueness/ strong consecutiveness (> 35%)

Table 3. Assessment of the Module Positioning.

5 Conclusion

In this paper, a *Curriculum Mining Method* (CMM) is proposed to improve the content-based comparison and assessment of curricula by adapting the standard process CRISP-DM (referring to RQ1). This method relies on text mining procedures that extract patterns from textual module documentations to identify relationships within an extensive database of curricula. It was demonstrated that juxtaposition with comparable (competing) study modules supports critical evaluation of the own curriculum, which can ultimately improve its (re-)design. In this context, the method can evaluate the "uniqueness" or "consecutiveness" between curricula and hence is practical support for curricula design. To demonstrate the idea behind the method and, particularly, to show the potential of mining curricula collections, a case study was developed and possible indications of exemplary results were outlined (referring to RQ2).

5.1 Implications

The most immediate implications of the presented approach address the practical design and management of study programs. The presented case study demonstrated how a curriculum under examination (A) can be evaluated to reference curricula (B) by extracting and interpreting the built clusters. More precisely, modules of the curriculum under examination were found in in small clusters (i.e., the content of the module description matched only with few Bachelor modules), but also relatively large clusters (i.e., the module description matched with a bunch of Bachelor modules). It was discussed that the interpretation of these results clearly depends on the strategy of the study program ("uniqueness" vs. "consecutiveness"). E.g., if the Master's program is designed for students from other universities, and hence good connectivity (i.e., "consecutiveness") is focused, it may make sense that some modules of a Bachelor's program are repeated and thus located in large clusters. On the other hand, if a Master's program has a clear differentiation strategy, a larger portion of the study modules should have a clear "uniqueness." However, the CMM can also be used for other purposes in curricula design and is not limited to the presented case study. Basically, whenever a "unique" or "consecutive" study program shall be developed, it is insightful to assess the position of a curriculum in the higher education landscape (in the sense of a competitive analysis). Another use case is the crediting of modules from students of other universities, for which the adequate comparability of modules must be assessed.

The contributions to research are twofold. First, it is one of the core topics in higher education research to explore the differences as well as commonalities between different university types (see Society for Higher Education Research, 2018). Module handbooks are increasingly used as a data source for this purpose (see, e.g., Föll and Thiesse, 2021). To this end, the proposed CMM would be an analytical solution for such investigations, esp. to explore structures in teaching content across universities. Second, from a theoretical perspective, the factors "uniqueness" and "consecutiveness" provide new interpretative perspectives that have not been used before for the comparative analysis of cross-university curricula.

5.2 Limitations

This paper demonstrates the idea of a CMM, which is still under development. The case study results have highlighted the current limitations of the approach, which need to be addressed in the further course of the project (see also the following section). The quality of the generated clusters does not yet has a practical level. Clusters are not yet clearly enough separated from each other. In addition, a sufficient proportion of all potentially homogeneous modules is not yet clustered. In this regard, the wide variation in the amount and style of module descriptions, as well as their content, is one of the biggest challenges in their automated document clustering. One possible cause for this could be characteristic differences between university types and their teaching content, which could lead to such variations (see Section 5.1). This is to be addressed in the further course of the project.

5.3 Outlook

As this research project is still in its early stages, there are several paths for further developing the CMM. According to the Design Science Research Methodology Process (Peffers et al., 2007), this project is currently still in the first iteration of the phases "Design & Development" and "Evaluation." Further research can be structured according to the procedure of the CMM:

- *Curricula Collection*: The demonstrated curricula collection is limited to general IS programs. Expanding the collection to include further specialized programs (e.g., Data Science) is the next step. In addition, the study is currently focused on IS curricula in Germany, which will be expanded in the future to internationalize the database. Likewise, the integration of further meta-data (such as a further distinction between Technical Universities (TU) and the non-technical Universities) is useful for more in-depth analyses. This is a currently ongoing process.
- *Curricula Understanding*: The extent and quality of individual module descriptions varied widely. Therefore, a comprehensive, descriptive study of these documentation practices will enhance the understanding of module handbooks for their analysis. This should also include a comparative study of the characteristic differences between university types.
- *Data Preparation*: The variation in the module descriptions significantly impacts the quality of the results. This data source has its own peculiarities that require special handling. The preparation of this particular textual database thus opens up further questions to be investigated, e.g., suitable pre-filtering based on descriptive measures (e.g., on the extent or style of documentation).
- *Modeling*: The case study merely demonstrates one possible clustering approach. An application and comparative evaluation of other alternative clustering methods (e.g., Doc2Vec clustering) should be conducted. In addition, the complementary use of topic modeling might provide deeper understanding of module contents by extracting key thematic concepts and comparing them across curricula.
- *Evaluation*: The quality of the clustering procedure must be further optimized. The elimination of weaknesses (e.g. through more targeted preparation of the database) is to be further elaborated.
- *Curriculum Assessment*: A specific criteria-based decision-making framework must be developed for the assessment and targeted development of curricula. This includes, e.g., the incorporation of the generated similarity scores as a basis for the formulation of metrics-based assessment strategies.

To further evaluate the general contribution of the presented method, a comparative action research study is planned that will, e.g., examine a curriculum design process with and without applying the CMM.

References

Aldowah, H., Al-Samarraie, H., and Fauzy, W. M. (2019). "Educational Data Mining and Learning Analytics for 21st Century Higher Education: A Review and Synthesis," *Telematics and Informatics* 37, 13-49.

Arbaugh, J. B., and Hwang, A. (2015). "What are the 100 most cited articles in Business and Management Education Research, and what do they tell us?" *Organization Management Journal* 12 (3), 154-175.

Chaparro, T. S. (2016). "The European Association for Quality Assurance in Higher Education (ENQA).: Mission, importance and main action lines," *Education and Law Review* (13), 1-7.

Daniel, B. (2015). "Big Data and Analytics in Higher Education: Opportunities and Challenges," *British Journal of Educational Technology* 46 (5), 904-920.

Debortoli, S., Müller, O., and vom Brocke, J. (2014). "Comparing Business Intelligence and Big Data Skills," *Business & Information Systems Engineering* 6 (5), 289-300.

Dennehy, D., Conboy, K., Babu, J., Schneider, J., Handali, J., vom Brocke, J., Hoffmeister, B., and Stein, A. (2020). "Adopting Learning Analytics to Inform Postgraduate Curriculum Design," in *Proceedings of the International Working Conference on Transfer and Diffusion of IT*, 218-230.

Dutt, A., Ismail, M. A., and Herawan, T. (2017). "A Systematic Review on Educational Data Mining," *IEEE Access* 5, 15991-16005.

Ferguson, R. (2012). "Learning Analytics: Drivers, Developments and Challenges," *International Journal of Technology Enhanced Learning* 4 (5-6), 304-317.

Föll, P. and Thiesse, F. (2021). Exploring Information Systems Curricula. *Business & Information Systems Engineering* 63 (6), 711-732.

Hevner, A. R., March, S. T., Park, J., and Ram, S. (2004). "Design Science in Information Systems Research," *MIS Quarterly* 28 (1), 75-105.

Huang, A. (2008). "Similarity Measures for Text Document Clustering," in *Proceedings of the 6th New Zealand Computer Science Research Conference*, Vol. 4, 9-56.

Huisman, J., Adelman, C., Hsieh, C.-C., Shams, F., and Wilkins, S. (2012). "Europe's Bologna Process and its Impact on Global Higher Education," *SAGE Handbook of International Higher Education*, 81-100.

Manning, C. and Schutze, H. (1999). *Foundations of Statistical Natural Language Processing*. MIT Press.

Marín-Marín, J.-A., López-Belmonte, J., Fernández-Campoy, J.-M., and Romero-Rodríguez, J.-M. (2019). "Big Data in Education. A Bibliometric Review, " *Social Sciences* 8 (8), 223.

Mills, R. J., Velasquez, N. F., Fadel, K. J., and Bell, C. C. (2012). "Examining IS curriculum Profiles and the IS 2010 Model Curriculum Guidelines in AACSB-Accredited Schools," *Journal of Information Systems Education* 23 (4), 417-428.

Miner, G., Elder IV, J., Fast, A., Hill, T., Nisbet, R., and Delen, D. (2012). *Practical Text Mining and Statistical Analysis for Non-Structured Text Data Applications*. Academic Press.

Nieveen, N. and Folmer, E. (2013). "Formative Evaluation in Educational Design Research," in *Design Research*, Plomp, T. and Nieveen, N. (eds.), (153), 152-169.

Peffers, K., Tuunanen, T., Rothenberger, M. A., and Chatterjee, S. (2007). "A Design Science Research Methodology for Information Systems Research," *Journal of MIS* 24 (3), 45-77.

Peña-Ayala, A. (2014). "Educational Data Mining: A Survey and a Data Mining-Based Analysis of Recent Works," *Expert Systems with Applications* 41 (4), 1432-1462.

Pietzonka, M. 2014. "Die Umsetzung der Modularisierung in Bachelor- und Masterstudiengängen," *Zeitschrift für Hochschulentwicklung* 9 (2), 78-90.

Popat, S. K., Deshmukh, P. B., and Metre, V. A. (2017). "Hierarchical Document Clustering Based on Cosine Similarity Measure," in *Proceedings of the ICISM*, 153-159.

Rawle, F., Bowen, T., Murck, B., and Hong, R. (2017). "Curriculum Mapping Across the Disciplines: Differences, Approaches, and Strategies," *Collected Essays on Learning and Teaching* 10, 75-88.

Romero, C. and Ventura, S. (2020). "Educational Data Mining and Learning Analytics: An Updated Survey," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 10 (3), e1355.

Romero, C., Ventura, S., and García, E. (2008). "Data Mining in Course Management Systems: Moodle Case Study and Tutorial," *Computers & Education* 51 (1), 368-384.

Slater, S., Joksimović, S., Kovanovic, V., Baker, R. S., and Gasevic, D. (2017). "Tools for Educational Data Mining: A Review," *Journal of Educational and Behavioral Statistics* 42 (1), 85-106.

Society for Higher Education Research (2018). *Warum eine Gesellschaft für Hochschulforschung?* [*Why a society for higher education research?*]. Gesellschaft für Hoschulforschung GfHf. https://www.gfhf.net/home/ziele/ (visited on June 7, 2021).

Swanson, T., Hatch, R., Lane, L., and Sondak, N. (1979). "Curriculum Development in Information Systems," *ACM SIGCSE Bulletin* 11 (1), 202-206.

van den Akker, J. 2007. "Curriculum Design Research," *Introduction to Educational Design Research* 37.

Viberg, O., Hatakka, M., Bälter, O., and Mavroudi, A. (2018). "The Current Landscape of Learning Analytics in Higher Education," *Computers in Human Behavior* 89, 98-110.

Wirth, R., and Hipp, J. (2000). "CRISP-DM: Towards a Standard Process Model for Data Mining," in *Proceedings of the 4th International Conference PADD*, London, UK.