An overview of analytics for curriculum understanding and optimization in Higher Education

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ABSTRACT: The use of Curriculum Analytics (CA) helps teachers, learners, as well as other institutional stakeholders to make evidence-based decisions at the program level to improve student success and reduce dropouts. This paper presents the first insights of a systematic literature review on Curriculum Analytics at Higher Education Institutions to determine 1) existing CA solutions proposed in the literature for Higher Education; 2) how such solutions have been used; and 3) the maturity of those solutions. Based on the review's findings, the paper presents limitations of the studies and proposes recommendations for future research in this field.

Keywords: Curriculum Analytics; Learning Analytics; Higher Education; Systematic Literature Review

1 INTRODUCTION

Higher Education Institutions (HEIs) -including universities, colleges, professional and teacher-training schools, junior colleges, and institutes of technology- are in pressure to evolve their strategies to increase student success and completion rates (Tinto, 2005). Many different factors may influence student success and dropout at the personal and institutional level, e.g. student choices, educational goals, personal reasons, the curriculum quality or the institutional support (Tinto, 2005).

Among the different strategies to overcome these issues, especially during the last decade, HEIs have used Learning Analytics (LA) solutions in order to offer different insights related to learning and teaching activities. While many LA solutions have focused on the improvement of teacher and learning strategies, improvements at the curriculum level are also necessary to address problems that go beyond the classroom context (Gottipati & Shankararaman, 2018). To target this need, Curriculum Analytics (CA), a subfield of LA, can be used to raise awareness and inform curriculum-related decision-making among program managers and directors (Ochoa, 2016).

While many reviews have been done in the field of LA in the last few years (e.g., Sclater et al., 2016; Mangaroska & Giannakos, 2018; Vieira et al., 2018; Larrabee et al., 2019; Romero & Ventura, 2020; Ifenthaler & Yau, 2020), none of them have focused on the area of CA. In fact, little is known about how CA tools facilitate the improving curriculum (Hilliger et al., 2020). Thus, a review of existing CA solutions would help to better understand the current state and existing gaps. Therefore, the purpose of this article is threefold: 1) to identify existing CA solutions proposed in the literature for higher education; 2) to understand how they have been used; and 3) to assess the maturity of those solutions.

2 RELATED WORK ON ANALYTICS FOR LEARNING DESIGN

Within the field of LA, several authors have highlighted the importance of connecting learning design and analytics (e.g., Lockyer et al., 2013; Rodríguez-Triana et al., 2015; Bakharia et al., 2016). While this connection could have benefits for both sides, in this paper we pay special attention to how analytics solutions can inform learning design decisions (Hernández-Leo et al., 2019), more concretely in relation to the curriculum. Evenmore, while the term *curriculum* could refer to lessons, seminars, workshops, courses and degree programs (Fraser and Bosanquet, 2006), we will focus on course and degree programs.

As reported in the review done from Mangaroska & Giannakos (2018) on LA for learning design, most of the papers remained at the learning activity level or focused on analysed teaching practices not specifically connected with the curriculum. On the contrary, the number of papers related to curriculum-related decision-making are very scarce. The recent LA review conducted by Ifenthaler & Yau (2020) shows in general how existing LA solutions facilitate study success in HEIs. However, the data-based decision to improve study success at the different course and program levels is not explicitly stated in the current reviews (Greer et al., 2016). Further, there is a paucity of evidence on how students' success depends on different curriculum aspects (Hilliger et al., 2020). Thus, there is a need for further understanding of the state of art in CA, especially, raising awareness about the contributions done so far, the stakeholders involved, and the maturity of the solutions. In summary, it is necessary to understand how CA stands regarding the rest of the LA field.

3 METHODOLOGY

As justified in the previous sections, the purpose of this paper is to address the following research questions: *1) What are the existing CA solutions proposed in the literature for HE settings?; 2) How have CA solutions been used?;* and *3) What is the level of the maturity of those solutions?* To answer these questions, we have carried out a systematic literature review following the guidelines provided by Kitchenham and Charters (2007).

As part of the review design, we selected six popular databases related to technology-enhanced learning and LA, namely: ACM Digital-Library[1], IEEE XPLORE[2], ERIC[3], ScienceDirect[4], Wiley[5]. These databases have been selected based on the past systematic reviews in this field (e.g., Schwendimann et al., 2016; Mangaroska & Giannakos, 2018; Ifenthaler and Yau, 2020). To identify the papers related to our research goals, we looked for papers where the core contribution was about curriculum

[1] http:// dl.acm.org/dl.cf
[2] http://ieeexplore.ieee.org/ Xplore/home.jsp
[3] https://eric.ed.gov
[4] http://www.sciencedirect.com
[5] https://onlinelibrary.wiley.com

analytics, or use a data mining, institutional, learning or educational analytics solution to improve the curriculum or curricula. Thus, we used the following query: *"Curriculum Analytics" OR "Curricula Analytics" OR (("Institutional analytics" OR "Learning Analytics" OR "educational analytics" OR "data mining") AND ("curriculum" OR "curricula"))*.

While conducting the review, we queried the databases in between January 24th to 26th 2021 and yielded 4418 entries in total (see Figure 1). Since each database used different search engines and filtering criteria, we ran a script to automatically select those papers where the query terms appeared either in the title, abstract or keywords in order to have an homogenous dataset. After removing duplicates, we assessed all papers to comply with the inclusion and exclusion criteria presented in Table 1.

Figure 1: Stages of the systematic literature review

Table 1: Inclusion and exclusion criteria

Criteria	Description
Core contribution	The core contribution was about curriculum or curricula analytics, or use a data mining, institutional, learning or educational analytics solution to improve the curriculum or curricula.
Type of curriculum	The review covered studies at the course or program level. Thus, studies focused only on lessons were excluded.
Context	The article targeted HE.
Publication type	Short paper contributions such as conference posters and abstract-only publications were excluded.
Accessibility	The full text was available.
Versioning	In case of several publications about the same contribution, the most "mature" was taken into consideration for the review.
Language	Publications were written in English.

Out of 375 papers, 48 satisfied the inclusion and exclusion criteria, and were part of the systematic review (see Appendix A). For each paper, we extracted the following aspects:

- *Type of contribution*: including type of publication (e.g., reports, conference or journal papers) and type of research contribution (e.g., models, tools, frameworks, etc).
- *How the contribution was used:* including target stakeholders of the analysis results (e.g., students, teachers, curriculum designers or researchers), the granularity of the curriculum (e.g., course or program), the key purpose of the study (understanding vs. optimizing), supported curriculum aspects, as well as the data sources, data gathering and analysis techniques.
- *Maturity of the contribution*: including stakeholders involved, type of evaluation (e.g., proof of concept, expert evaluation, authentic case study, etc.), and focus of the evaluation (e.g., usability, accuracy, adoption, …).

The outcome of the coding process is summarized and can be consulted as additional material[6]. The following section reports on the first results from the review.

4 RESULTS

Out of 48 reviewed papers, 50% were journal and 50% conference papers. When reporting the results we used aggregated numbers since there are studies which have more than one way of supporting curriculum, data sources, data gathering techniques, data analysis techniques etc. This section reports on the results following the research questions.

RQ1) What are the existing CA solutions proposed in the literature for HE settings?

We grouped papers based on the type of research contribution tagged by the authors. Out of 48 papers, 28% of the papers proposed *processes* to assess entire course materials, evaluate curriculum coherence . *Models* were the core contribution of 24% papers, including linear regression models for predicting the placement of students, explicit learner models, models for students results prediction, and planning course registration model. *Frameworks* followed the list of more frequent contributions (20%), structuring course-adapted student LA, critical dimensions of LA, or curriculum assessment. The 17% of the papers presented *tools* which provide a visual based analysis to discover the strengths and weaknesses of the curriculum, and help the curriculum committee for continuous curriculum improvement. Next, 9% of the papers focused on *methods.,* e.g. to study the levels of curriculum importance and student satisfaction. Finally, 2% of the papers presented *architectures* for areas covered in the system such as architecture for game based learning. This architecture helps curriculum designers to understand the impact of such a learning method to the curriculum compared to the traditional teaching-learning process.

[6] Paper codification: https://tinyurl.com/y3dd2md2

RQ2) How have CA solutions been used?

LA Purpose. Attending to SOLAR's LA definition[7], LA may have two purposes: understanding or optimising learning and the environments. In this review, 46 papers (95.8%) focused on understanding the curriculum, and 2 papers (8.3%) went one step further taking actions to improve it. Some of those steps are adopting the curriculum to the dynamic changes in the industry and helping students identify the optimal curricula based on the students' educational history.

Curriculum support. In terms of the *granularity* of the curriculum, most of the papers (41, 85.4%) referred to programs while 6 (12.5%) of them focused on courses (only one paper the granularity of the curriculum was not stated (2.1%). In terms of the kind of proposed solution, Figure 2 provides an overview of the main aspects of the curriculum that the reviewed papers tried to address.

Figure 2: Types of curriculum support

For instance, some of these papers aimed at *assessing* course materials, the coherence of the program, the student preferences and academic needs on the curriculum, the curriculum's alignment with the industry expectations, the student learning processes, or to what extent the students have achieved the needed competencies based on the current curriculum.

Other papers tried to *identify new ways of improving teaching practices* (eg., looking at curriculum-level factors that affect retention and student outcomes, the difficulty level of the curriculum from the student perspectives, academic gaps and overlaps in the curriculum), to *identify good practices among students* (e.g., best study path students must traverse to acquire higher results), or to identify what resources are necessary for the improvements, to offer a better

[7] SOLAR's LA definition: *LA is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs*). https://www.solaresearch.org/about/what-is-learning-analytics/

curriculum and a more personalised learning experience. Figure 3 shows the relationship between the CA solutions (RQ1) and type of curriculum support. According to the results, we can see that most of the studies have provided different processes, models, tools and methods for analyzing program structure.

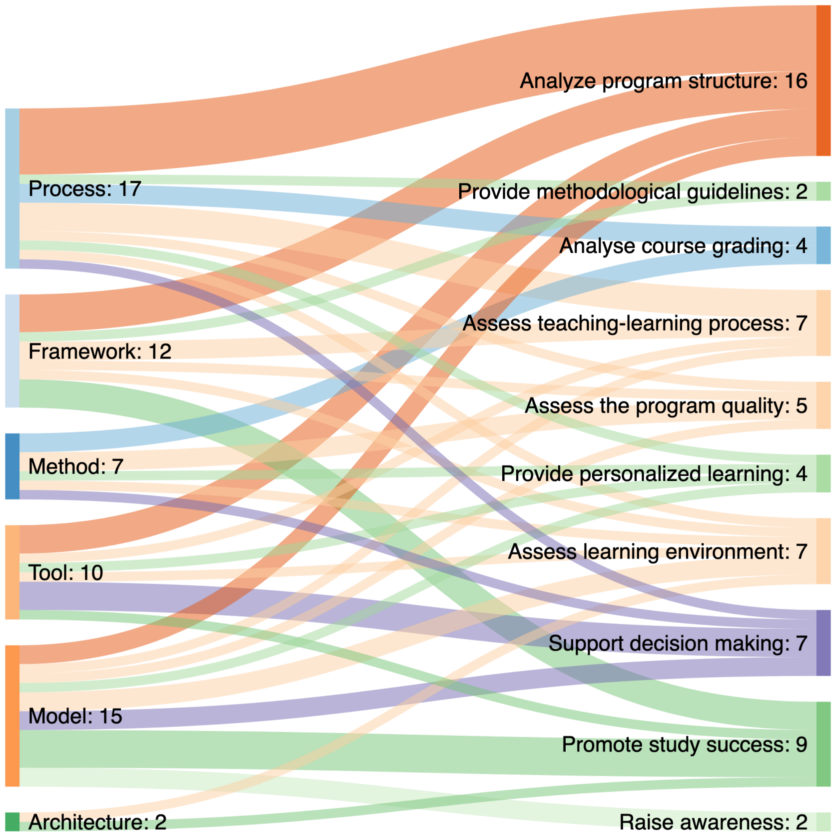

Figure 3: Relationship between types of curriculum support and CA solutions

Target users. The intended target users of the selected studies were curriculum designers 27 (56.3%), students 14 (29.2%), administrators 13 (27.1%), teachers 10 (20.8%), program curators 6 (12.5%), and researchers 1 (2.1%). As Figure 4 shows, it should be noticed that there were several studies which addressed different users in their proposals. The total size of each stakeholder group is represented on the left barplot. The bottom plot represents every possible intersection, and their occurrence is shown on the top barplot.

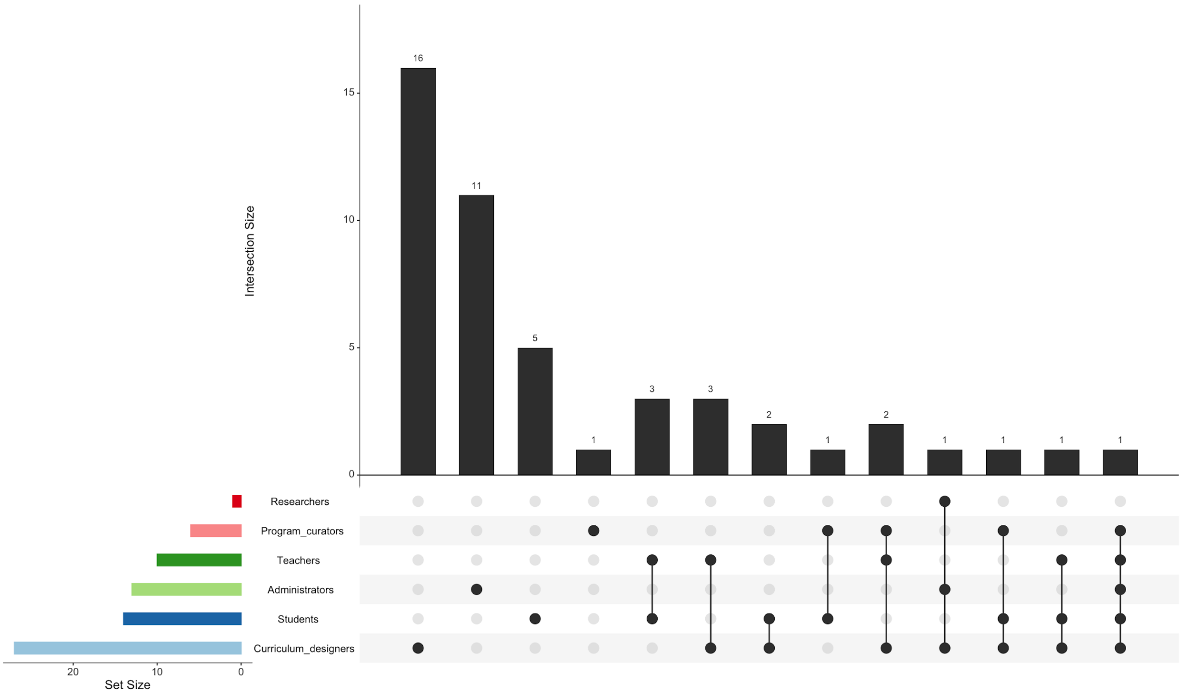

Figure 4: The target users of the paper contributions

Data sources. The analysis of data sources used in the studies shows that interestingly, 11 (22.9%) papers did not use or report the data sources of their studies. Among those mentioning the data sources, even if not all the data sources were reported, most of them used already-existing data from the learning ecosystem: 16 (33.3%) from institutional management system, 6 (12.5%) from learning management systems (e.g., Moodle or Blackboard), 6 (12.5%) other learning tools (e.g., chat or student feedback tools, YZU virtual classroom, clinical log. In addition, 3 (6.3%) papers used the university website as a data source and other 3 (6.3%) papers extracted data from non academic websites (e.g., Job bank, The library of congress, or LinkedIn). Finally, it is noteworthy that 12 papers (25%) collected ad-hoc data directly from the stakeholders.

Data gathering and analysis techniques. For *data gathering*, out of 44 papers mentioning the techniques used, the most common option (29 papers) was to extract content from a document storage (e.g., documents related to learning/course designs in a learning management system or data from a web page), followed by those using activity tracking and log data (10 papers). In addition, some authors used surveys (5) and interviews (3). Nonetheless, it should be noted that in several papers, only some of the data gathering techniques were mentioned.

In terms of *data* used in the analysis, 25 papers (52.1%) used academic information from the students, 19 (39.6%) learning or course designs, 6 (12.5%) used content downloaded from non academic websites (e.g., job requirements and forum data), 4 (8.3%) activity traces, 5 (10.4%) other personal data, and 4 (8.3%) relied on learning content generated by the students. Only 2 (4.2%) papers did not collect any data.

Finally, Figure 5 provides an overview of the *analysis techniques* used in the reviewed papers. As we can see, while there is a wide variety of techniques, text mining and descriptive statistics are the most prominent ones.

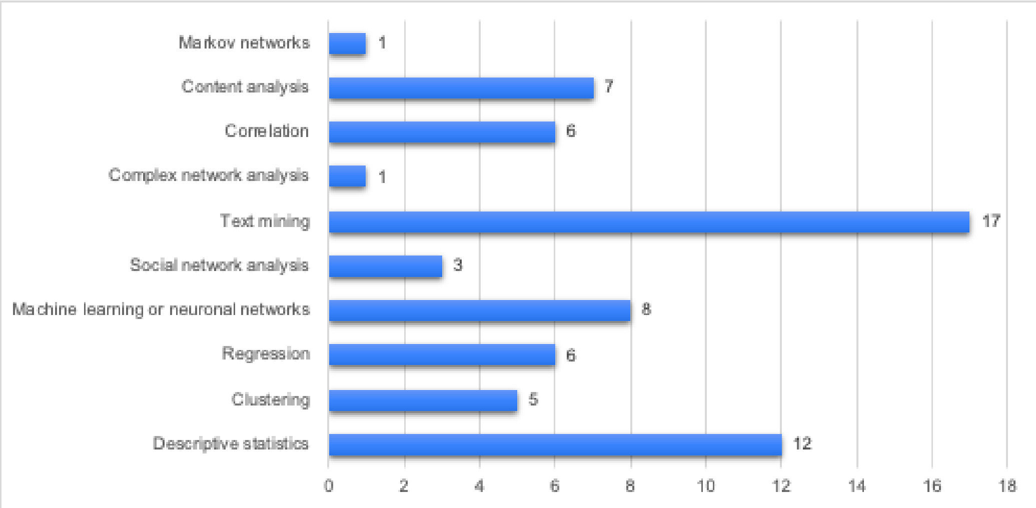

Figure 5: algorithms or techniques used to analyze data

RQ3) What is the level of the maturity of those solutions?

Out of 48 studies only 20 have conducted evaluation. Regarding user involvement, only 8 papers were evaluated with stakeholders, which included students (4 paper), teachers (1 paper), curriculum designers (1 paper), career counsellor (1 paper), and program curators (1 paper). In terms of the type of evaluation, 13 papers evaluated their contributions with already existing data from a real setting, 3 in authentic settings, 1 with a proof of concept, 1 with focus groups, and 1 with experts. For one of the papers, the kind of evaluations was not stated. Finally, regarding the purpose of the evaluation, 12 papers focused on the accuracy, 2 on the usability, 2 on the effectiveness, 1 on the feasibility, 1 on the adoption, and 1 on the performance of the solution.

5 DISCUSSION, CONCLUSIONS AND FUTURE WORK

According to the international and European reports, student success and dropouts constitute a significant concern. Many HEIs are trying to improve teaching practices and the student learning process to address dropouts. However, along with improving teaching strategies, it is necessary to improve the curriculum as well (Gottipati & Shankararaman, 2018) since continuous curriculum improvement provides better results for students and higher education programs (Pistilli and Heileman, 2017). To support that need, this review signals first insights to improve the curriculum through analytics, extending the current works (Ifenthaler & Yau, 2020) by putting more emphasis on the curriculum analytics aspects.

Coming back to the research questions addressed in this paper, the results show the variety of existing *CA solutions proposed in the literature* for HE settings, including theoretical proposals (e.g., such as processes, models, methods, frameworks, and architectures) and practical ones (i.e., tools). However, when we look at how these solutions were used in relation to the curriculum, most of them aimed at understanding it, and just a couple of papers reached the level of optimizing it. Furthermore, the maturity level of those solutions is, in most of the cases, in a very early stage. In fact, only 16.67% of the papers were evaluated with stakeholders and only 6.25% reported evaluations taking place in authentic settings. Thus, further work needs to be done until the adoption of those solutions.

While the presented results do not come without limitations (e.g., due to the query, the selection of databases, bias and inaccuracy in data extraction as it was performed only by one author, or lack of information reported in the papers), based on these results and in connection to the related literature, this paper proposes the following guidelines for the future CA agenda:

- *Theoretical grounding.* In line with the synergies between learning design and analytics, it is important to emphasize that there should be a theoretical ground behind the CA solutions that help stakeholders in the decision making (Macfadyen et al., 2020).
- *Wider variety of CA studies:* At the moment, most of the CA studies focus on analyzing program structure, such as providing the best program path to follow for the desired job or finding the best curriculum path for successful graduation. Further, most of those studies are limited to processes. Very few studies focus on analyzing the curriculum in reflecting faculty teaching and student learning. The available studies are linked to individual students and actions, such as reflecting on their own core competencies corresponding to the covered curriculum. Thus, there is a need for CA tools to understand and improve also other curriculum aspects (e.g., competence-based curriculum assessments).
- *Increase stakeholder involvement*: While Ochoa (2016) presented CA as a solution addressing mainly program managers and directors, in this review we have seen that, while not extensively, other stakeholders such as students, teachers and administrators were taken into account. Still, in order to promote adoption, it would be necessary to further engage the different stakeholders by the CA solutions during the design, deployment and assessment of the proposed solutions (Rodríguez-Triana et al., 2018; Tsai et al., 2018). This would help to better satisfy the stakeholders needs and to adjust the solutions to their practice.
- *Benefit from visualisations:* Even though most LA studies relate to the development of visualisations (Gašević et al., 2017; Wise et al., 2014), the selected CA papers lack it. In addition, we found that many reviewed studies provide solutions without incorporating them into learning environments, such as learning or institutional management systems. To cover this gap, visualizations could play a helpful role to introduce analytics inhelp to integrate into different learning environments for when improving curriculum improvement. More concretely, dashboards are one possible solution to provide institutional stakeholders with a real-time picture of the situation (Schwendimann et al., 2016).
- *Benefit from multimodal analytics:* Compared to the other LA reviews (e.g., Ifenthaler & Yau, 2020; Romero & Ventura, 2020), the data sources, data gathering techniques and data analysis techniques are limited in variety. Also, the number of studies including different data

sources is scarce. For example, combining stakeholders' feedback, teacher data (observation data, teacher traces), student behavioural data, and course metadata could help to get a broad understanding of the current teaching and learning practices. This points out that the MMLA field may be of great help in order to understand multiple factors conditioning the curriculum.

- *Move from understanding to optimizing.* Most of the CA solutions identified in this review focused on understanding. To move one step forward towards the optimization, if we want to facilitate informed-decision making about the curriculum (Hilliger et al., 2020), it would be necessary to increase the actionability of the CA solutions, e.g., prompting and supporting the interpretation and reflection on the data, and explicitly connecting the retrieved evidence with the decisions that the targeted stakeholders have to make. Also, most of the tools are still in the prototyping phase or implemented on a very small scale. Furthermore, a clear relationship between program outcomes improvement has not been established. In other words, there is still limited research on how program curators accept, interpret and use CA to improve the program outcomes.
- *Further evaluation.* While CA's ultimate goal is to improve student success and reduce dropouts (Mendez et al., 2014), there is still little evidence on that regard. To address this gap, there is a need for more thorough evaluations, including authentic settings and longitudinal studies that show the impact of the solutions in practice. Also, HE institutions would highly benefit from studies that report on the CA solutions from different perspectives (e.g., such as performance, effectiveness, accuracy and usefulness), enabling also comparative studies. For that goal, it would be necessary to define a common framework for CA evaluation.

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APPENDIX A - LIST OF REVIEWED PAPERS

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