TOWARDS MINIMUM VIABLE EDUCATION ANALYTICS

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Abstract

Analytics has been in focus on education in the recent years. The majority of the work has been on study and learning analytics where the actions and the results come from students. The data is collected in the learning environment and analyzed to track the learning and the progress. Based on this, for example, needs for intervention from the teacher for individual students can be identified. In addition to the study and the learning analytics, other areas of analytics such as environmental, biometric, and behavioral have also been identified.

However, there are still additional related areas of analytics applicable in education. For example, while current analytics focus on the actions of the student, they focus less on the actions of the teacher and the interactivity between the student and the teacher. For example, the workflow and teacher's activities related process and teaching analytics have not been studied in educational setting to the same extent as study, learning, environmental, biometric, and behavioral analytics.

In this sense, it can be argued that the current focus on analytics in education is mainly on the low hanging fruits (quick benefits) at the expense of the whole. Also, compared with other domains, the teaching process is typically not that well - or even at all - defined, which may be one of the reasons behind the current focus. Therefore, there is a need for a clearer picture of the education related analytics such as for a holistic model describing the taxonomy of education analytics and providing insight on the scope and applicability of different analytic areas.

In this paper, we present a model for education analytics with a taxonomy of different areas of related analytics. In addition, we discuss the scope and applicability of the different areas. Our focus in this paper is on minimum viable analytics that should be implemented first, but we also present ideas for the next steps after achieving the minimum viable level. We base this part on existing literature of different areas of analytics from which we form a synthesis, the education analytics model, as a result.

Moreover, for the minimum viable analytics, we present an ongoing case study in K12 level schools where developing education analytics is a part of digitalization of education and its processes in a developing economy. The case is described, and early case experiences and observations are analyzed providing a practical example on applying the education analytics model when taking the first steps towards building a minimum viable education analytics. The case also illustrates the importance of the minimum viable approach, since the case was started just before the COVID-19 pandemic that resulted in a disruption where the digitalization overall needed to be implemented very quickly due to the education moving into remote work and distance learning.

Keywords: digitalization, education analytics, learning analytics, developing economy, K12 level schools, case study.

1 INTRODUCTION

Analytics has been in the focus of education in recent years. However, there still are areas of analytics applicable to education that have not received much attention. While current analytics focus on the actions of the student, they focus less on the actions of the teacher and the interactivity between the student and the teacher. For example, the workflow and teacher's activities related process and teaching analytics have not been studied in an educational setting to the same extent as study, learning, environmental, biometric, and behavioral analytics.

In this sense, it can be argued that the current focus on analytics in education is mainly on the low-hanging fruits (quick benefits) at the expense of the whole. Also, compared with other domains, the teaching process is typically not that well defined—or even defined at all—which may be one of the reasons behind the current focus. Therefore, a clearer picture of education-related analytics is needed, such as for a holistic model to describe the taxonomy of education analytics and provide insight on the scope and applicability of different analytic areas.

Also, when digitalizing education, in addition to the education analytics model as a whole, it is important to understand where to start. Therefore, in this paper, we study the following research question:

RQ1: What are the minimum viable education analytics when digitalizing education?

To answer this question, we present a model for education analytics with a taxonomy of different areas of related analytics. In addition, we discuss the scope and applicability of these areas. Our focus is on the minimum viable analytics that should be implemented first, but we also present ideas for the next steps after achieving the minimum viable level.

Moreover, for the minimum viable analytics, we present an ongoing case study in K12 schools where developing education analytics is part of the digitalization of education and its processes in a developing economy. The case also illustrates the importance of the minimum viable approach since the case was started just before the COVID-19 pandemic, which resulted in a disruption where digitalization needed to be implemented very quickly due to education moving into remote work and distance learning.

2 BACKGROUND AND MOTIVATION

Reliable analysis requires reliable data, and through digitalization, more data are available than before [1]. Digitalization is a phenomenon that affects all industries [2], and education is not an exception. However, although digitalization has been studied in the education process, e.g., from an expert point of view [3], a comprehensive approach to developing education analytics is rare. In the existing literature, the term "education analysis" is rarely mentioned, and when it is, it normally refers to learner-focused learning analytics (as defined in [4], for example).

In the education domain, most of the work related to analytics has been on the actions and results of students [4]–[6]. The data are collected in the learning environment and analyzed to track the learning and the progress [7], [8]. These can be considered as pedagogic outcomes and can be compared to pedagogic goals and objectives; for example, the need for intervention from the teacher for individual students can be identified and the pedagogical behavior modified [5]. In addition to the study and learning analytics, other areas such as environmental and biometric analytics have also been identified [9].

Most often, the analytics in education has been called learning analytics (such as in [4]–[9]), although it sometimes covers both learning (for example, learning results) and studying (for example, materials viewed or tasks completed). This difference has been recognized, and combined with the additional identified areas, learning analytics has been divided into study, learning, biometric, environmental and teaching analytics [9]. Also, the big data in education analysis focuses on learning and uses the term "learning analysis" [10], [11].

In addition, it seems that learning analytics is clearly separated from institutional analysis (see, e.g., [12]). We see this separation as problematic. The main purpose of institutional analysis is to improve services and business practices and processes [10], while learning analytics intends to enhance and improve student success [12]. Distinguishing the two means that actions related to student learning fall outside of the institutional processes and their development.

This raises a question: Isn't supporting learning the core purpose of the education institutions? It is worrying if institutions see management as a self-sufficient part of an organization without any connection to teaching and learning, and only this part is analyzed with institutional analysis.

One reason for this kind of distinction comes from the history: institutional analysis is rooted in enterprise resource planning (ERP) systems, where resource and finance management have been stressed a lot, and analysis has been seen as a tool for management [13]. According to Mitra and Mishra [14], ERP systems have been applied in education as well, but they are mainly used for student admission, course enrollment, student data management, course management, library systems, alumni management, and research networks [14]. It seems that ERP systems, although they are process management tools, are not yet used in teaching process or learning process management nor analysis.

Learning analytics, in turn, is more connected to the pedagogical discussions and have been considered a tool for teachers. However, regardless of this different background, there is no need to maintain this separation. On the contrary, it is important to understand that these analytics are not isolated, but the phenomena that they analyze are interrelated and intertwined: resource management affects the teachers' possibilities, and learning outcomes reflect overall functioning of the whole organization, not only the pedagogical choices that teachers make.

Learning analytics is a good tool for the operational level, but other levels and relevant stakeholders must be understood as well (see Fig. 2 in Chapter 4). When all levels and stakeholders of education are accounted for, we speak of education analytics. Education analytics gives the “big picture” of education in society, including both learning analytics and institutional analysis; however, it is more than the two combined, as described in more detail in Chapter 4.

Having this holistic picture is important, and in the world of ever-accelerating change, its importance is growing all the time: the education premises valid today are not guaranteed to be valid tomorrow. Societies are changing. It has been estimated that, due to digitalization and automation, a remarkable share of jobs is vanishing [15], and new types of skills and knowledge are needed [16]. There is a growing need for solutions that support personalized learning [17]. In addition, new kinds of pedagogical approaches and education software is being developed all the time. It is also worth noting that education is rather often one of the cost-saving targets when public finances are balanced. All these changes have effects that should be measured and analyzed.

3 METHODOLOGY

We apply a constructive approach [18] here to develop an education analytics model based on the motivation presented in Chapter 2. This means that we form a synthesis based on the existing literature and the identified areas of analytics in the education domain. The scope of the model in relation to the levels and stakeholders in the educational domain is also built using the same approach.

Following the constructive approach, we also recognize the connection of our model development to two key methodological principles: the minimum viable principle [19] and the creating usable data with minimal effort principle [20]. The minimum viable principle, often associated with the lean approach and used, for example, in agile information systems development [19], emphasizes iterative and incremental development. Since data form the basis in analytics, minimum viable analytics should also follow the fundamentals of creating the usable data with minimal effort [20], especially the following two basic ones: 1) what data are relevant must be understood, and 2) the origin of data must be understood.

Moreover, our work is supported by observations from a recently launched ongoing case study (see Chapter 5), which relates to digital transformation in education and applies the EXOD (expert-oriented digitalization) model [3]. In its first phase, the EXOD model emphasizes the exploration of development opportunities and communicating these to the experts (such as teachers) involved and defining the desired target level with them. In its second phase, the EXOD model emphasizes reengineering, where the major high-level changes and main requirements are defined, and these are communicated by the experts involved.

4 EDUCATION ANALYTICS MODEL

The education analytics model is presented in Fig. 1. It is a taxonomy of different analytics areas in the education domain, namely study, learning, teaching, and process analytics, as well as several supporting areas, namely environmental, biometrics, and behavioral analytics, among others. Fig. 1 emphasizes areas of education analytics, since at least from the viewpoint of the minimum viable principle, these are the ones that should be considered first in the education domain. Later, it is possible to assist these areas of analytics with their supporting ones.

In the model, study analytics refers to the progress of the student, such as time spent studying and tasks completed, as well as related interventions or needs from the teacher. Learning analytics refers to the learning outcomes and gaps in learning related to the learning goals. Teaching analytics can be seen as having a similar idea for the teacher as study analytics has for the student, since, for example, it refers to how much time the teacher has spent on teaching, interventions, and developing teaching materials. Finally, the process analysis refers to the institutional aspects in education such as resource management, organizational (business) practices, and processes as discussed in Chapter 2.

Of the supporting areas, environmental analytics refers to the physical environment such as temperature of the classroom or movement of the student. Biometrics analytics refers to sensor-gathered data from the individual, for example, the pulse or alertness of the student or teacher, while behavioral analytics refers to the observed behavior of the student or teacher. There may also be other applicable supporting areas of analytics.

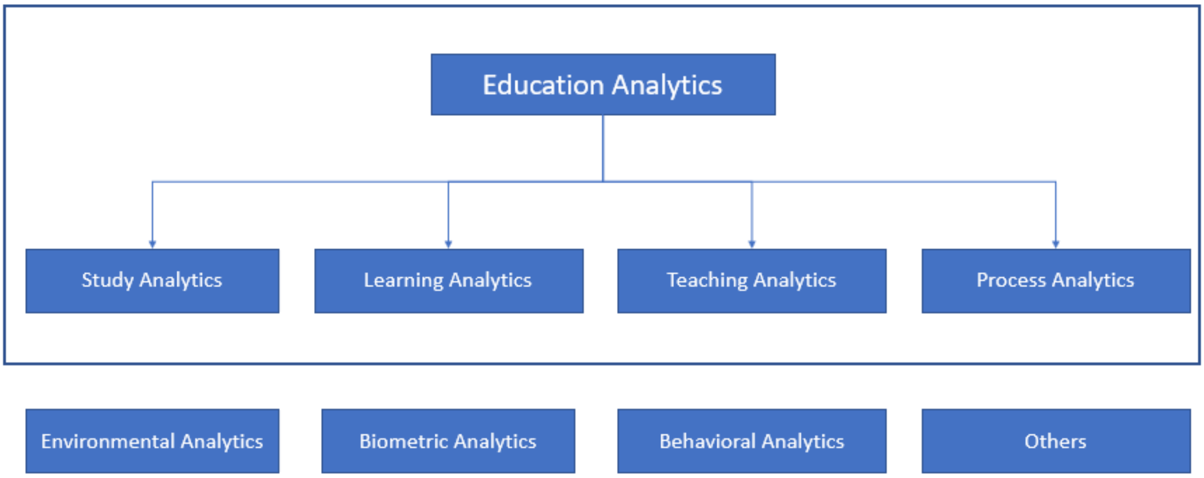

Figure 1. Education analytics model.

However, considering education analytics in isolation from the environment does not correspond to reality. As pointed out in Chapter 2, it is important to see the big-picture scope of education analytics (see Fig. 2), not just concentrate on different areas of analytics and pedagogical choices that teachers make. Pedagogy is one way for teachers to adapt to different situations, but there are factors outside their power that affect, limit, and dictate what kinds of pedagogical alternatives teachers really have. For example, if the size of the teaching group doubles for budgetary reasons, the pedagogical approach must be adjusted, no matter how well it was working before. There are other examples as well: in some countries, the education authorities have strongly encouraged open-space learning (no classrooms in schools, big open spaces), phenomenon-based learning, student centric learning etc. If municipal authorities decide to build a school without any inner walls, teachers' pedagogical choices are not the only determinant. Similarly, other school-, regional-, and national-level decisions do affect learning outcomes, and these effects must be measured and analyzed as well.

In addition, there are other cultural actors to be considered. Students are not "tabula rasa," but their environment strongly affects how they are motivated and dedicated to studying. Parents and relatives are important as role models and supporters (or not supportive) of students' studies. In Finland, where education is free and strongly financially supported by the government so that every student has the same opportunities, at least in theory, it has been found that working-class students do not select university-level studies as often as students from the middle class, and if they do, the transition to university-level studies is slower than their middle-class peers [21].

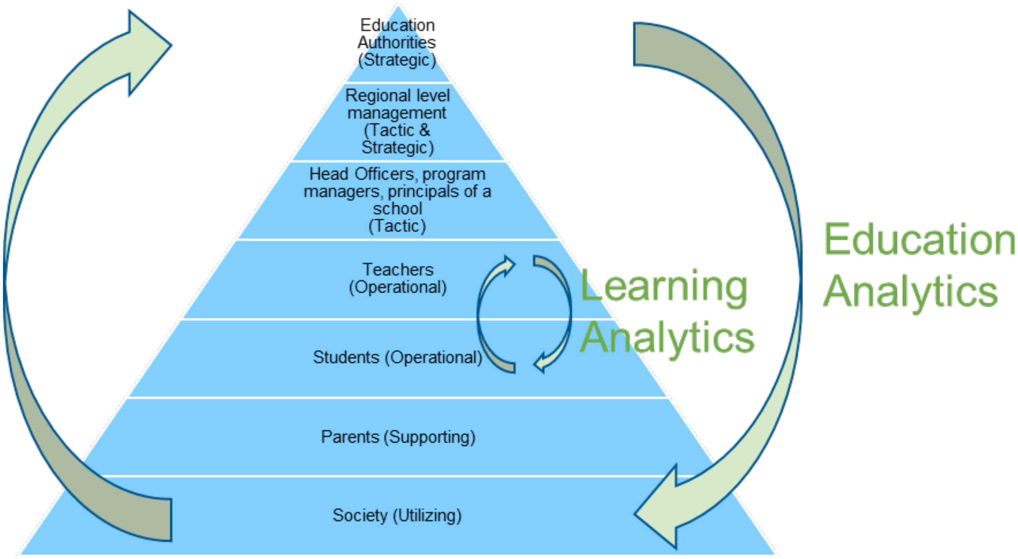

Figure 2. Education analytics model scope.

By creating laws, norms, and expectations, society plays an important role as well. Some norms may be that girls do not normally enter into technical studies, nor boys into well-being studies. In the worst case, some student groups are excluded because of gender, ethnicity, or social status, and even if the law prescribes equality, attitudes change slowly. All these can be measured, and the impact of corrective actions can be analyzed.

Society has an important role by creating expectations about the skills and knowledge needed in working life. Sometimes, developing economies have very specific requirements for the school system, and fulfilling these needs may change not only the school but the whole society remarkably. To make the right changes, there must be a formal system to collect and evaluate the needs coming from society, and the impact of changes must be analyzed on the societal level as well.

5 DISCUSSION AND CONCLUSIONS

When the education analytics model is applied, there are several aspects to be considered. Firstly, it has to be understood that all the layers presented in Fig. 2 are interrelated and affect each other. In practice, this means that, for example, society affects not only parents but also students, teachers, and the whole education system. So, it is not enough if only single two-way interaction is studied. However, the analysis is easiest when we begin with the two-way interactions between different levels, and in Fig. 2, we have grouped the most interesting levels side by side. Secondly, even the adjacent levels have several different relationships and interaction mechanisms, and it is important to select which are really essential and important to measure and which can be left out.

Thirdly, analysis of some of the levels is easier and gives results faster than analysis in other levels. For example, analysis on the effectiveness of parents' support and attitudes or of the used pedagogy is rather easy to measure and follow when changes happen, but strategic educational changes are implemented slowly, and the effects can be measured only after some time. Fourthly, at different levels of education, the relationships and their importance differ: for example, the parents' role can be significant at the K12 level, but it may be less important in higher education. Also, measuring the learning is more complex in higher education than in K12, and in general, national-level tests or exams are used at the K12 level but not in higher education.

Based on our work so far, we see two important key aspects when minimum viable education analysis is considered during education digital transformation (RQ1): 1) In the beginning, it is important to concentrate on the levels (Fig. 2) with the most impact and quickest results, and 2) a clear roadmap for building education analytics should be planned well before the education digitalization project is started. The first aspect, in practice, means starting with levels closest to the students: parents, teachers, schools (head officers, principals, program managers, etc.). Also, this means that it is good to focus first on the study and learning areas of education analytics (Fig. 1). However, the second aspect emphasizes the importance of planning ahead to also account for other areas as soon as possible. A roadmap is a good tool for this.

When building the roadmap, it is also important to discuss the overall target of education analysis. If we think about current learning analytics objectives, we can see two main goal dimensions at the school level: 1) To enable personalized learning by measuring the student's starting level and defining the target level based on that, and 2) to optimize the use of teaching resources so that they can be allocated as efficiently as possible. There should also be a third dimension: education quality assurance. This is because it is not enough to focus on students' progress on a personal level, nor on teachers teaching the maximum number of students, if the learning results are not sufficient for the next education level, for employers, or for society in general. For this, there must be elements inside the education analytics coming from outside the education system, such as from parents and society as a whole (employers, citizens, government). To have these kinds of elements in education analytics, real-world feedback loops are an essential but challenging part of education analysis, and they should be included in future research.

In our ongoing case (the Eduditra project, Education Digital Transformation), we study education digital transformation in developing economies. In the project, we are looking for meaningful ways to make digital change happen from scratch also, first in K12 schools and then in higher education institutions. The Eduditra project was started at the beginning of 2020 in co-operation with a Namibian company (Glowdom) operating in the education sector; so far, we have 11 pilot schools where small groups of teachers are changing their teaching processes with new kinds of education software solutions. Because of the local challenges with infrastructure and technical knowledge of the teachers, it has been seen as vital to proceed with minimum viable steps in education digitalization, and this is applied in education analytics as well. Due to the current COVID-19 situation, the need for digitalized solutions has grown remarkably, but it is still important to find a meaningful roadmap to proceed and follow. As a matter of fact, because societies and education are being forced to change rapidly right now, there is no room for big mistakes, and the importance of a good roadmap cannot be overemphasized. It is essential that this kind of roadmap will be studied and developed in the future; this paper gives a good basis for them.

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