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Learning Analytics for Inclusive Higher Education

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Abstract: Learning analytics is gaining attention and increasingly being adopted in higher educational institutions. Research have shown that learning analytics is promising in addressing high priority issues in education such as prediction of student retention, enrolments, and learning gains. However, learning analytics also presents barriers and challenges for students with disabilities which could prevent them from fully benefiting from learning analytics, hence create inequality in education. This position paper discusses the opportunities and challenges in learning analytics for inclusive higher education, focusing on students with disabilities.

Keywords: Learning analytics, students with disabilities, higher education, inclusion

1. Introduction

Digital technology brings increased opportunities for inclusive education with digital educational resources and delivery methods such as MOOCs and E-learning platforms. More students have access to education that they would not be able to access without digital technology. However, digital technology also create barriers for students with disabilities. According to the World Health Organization, disability is an umbrella term, covering impairments, activity limitations, and participation restrictions (WHO, 2011). Impairments may be physical, mental, intellectual, sensory impairments, or a combination of multiple factors. These impairments may hinder full and effective participation in society on an equal basis with others.

In the time of Covid-19, when universities and colleges were closed down with very short notice, faculties were under time pressure to migrate to digital education. Many barriers and challenges for students with disabilities are created following the rush to digitalization. Inaccessible digital learning platforms and tools such as learning management systems, MOOC platforms, digital exam applications, and inaccessible digital learning materials such as e-textbooks, lecture notes, documents and presentations could prevent students with disabilities from gaining equal information as non-disabled students and from fully engaging in learning activities. For example, if videos are published to students without captions or transcripts, students who are deaf or hard of hearing will not be able to get the information provided by the videos. If images or graphs are used to convey information but without text descriptions, blind students will miss the information. Text with low colour contrast will create barriers for students with low contrast sensitivity or colour blindness. Learning platforms that only support interaction with mouse will create barriers for students who can only use keyboard for interaction. Serif font types such as Times New Roman and Georgia will make the text difficult to read for students with dyslexia. The accessibility barriers and challenges may further cause failure and dropout for students with disabilities. According to (Verdinelli & Kutner, 2016) students with disabilities are enrolling in online graduate programs at increasing numbers, yet they tend to graduate at lower rates than students without disabilities. The lack of consideration of accessibility in digital education can be one of the reasons. Starcic & Bagon (Starcic & Bagon, 2014) argued that "*ICT-supported learning should be investigated and designed on the basis of universal design, providing accessibility and facilitating inclusion for all*".

Although barriers are continually being dismantled in digital contents and delivery platforms, learning analytics, a relatively new field of research and practice, has not paid much attention to inclusion and accessibility. The lack of accessibility of tools and information can potentially prevent students with disabilities from enjoying the full benefits of learning analytics.

The goal of this position paper is to put inclusive education on the agenda in the learning analytics community. Neil Selwyn (Selwyn, 2018) in his keynote speech at the 2018 Learning Analytics and Knowledge (LAK) conference pointed out that learning analytics researchers should take an expert friend position on the health warnings that come with learning analytics. We argue that the lack of consideration of accessibility and inclusion is one of the health warnings and learning analytics can potentially contribute to exclusion of students with disabilities from higher education. It is time that our community becomes aware of the possible barriers learning analytics systems create for students with disabilities and take measures to ensure that they are accessible and inclusive.

2. Background

The number of students with disabilities in higher education is increasing. According to Snyder, de Brey, & Dillow (Snyder, de Brey, & Dillow, 2019), it is estimated that individuals with disabilities constitute 11% of the college population in the US in 2011/2012, compared to 10% in 2007/2008. In the latest European Student Survey (Hauschildt, Vögtle, & Gwosć, 2018), an average of 18% student in higher education reported to have a disability (including chronic diseases).

(Collins, Azmat, & Rentschler, 2019) defines inclusive education as occurring when all individuals regardless of exceptionality, are entitled to the opportunity to be included in a regular classroom environment while receiving the supports necessary to facilitate accessibility to both environment and information. In the context of higher education, a large body of research have been carried out to identify barriers by looking into the experiences of students with disabilities, understanding their challenges, and making suggestions on activities, methods and approaches to address the challenges (Moriña, 2017). In addition, research focusing on accessibility of learning management systems (Chen, Sanderson, Kessel, & Królak, 2015), on faculty' attitudes towards students with disabilities and their knowledge and competence in making digital learning accessible (Chen, Sanderson, & Kessel, 2018), as well as on providing training to faculty on inclusive education (Hsiao, Burgstahler, Johnson, Nuss, & Doherty, 2019) have been conducted and published. Despite of the attempts and efforts to address the challenges and implement inclusive education in practices, including establishing inclusive education policies, strategies, and action plans in higher education institutions, providing training to faculty and staff to increase awareness and competence, making curricula, classrooms, labs and campus accessible, and promoting inclusive practice in pedagogy and assessment (Gibson, 2015; SELI, 2019), there is still a considerable gap between the current state of the art research and practice and a fully inclusive higher education.

Learning analytics as a promising emerging field has demonstrated its benefits in higher education, including targeted course offerings, curriculum development, student learning outcomes, behaviour and process, personalized learning, improved instructor performance, post-educational employment opportunities, and enhanced research in the field of education (Avella, Kebritchi, Nunn, & Kanai, 2016). Learning analytics has the potential to contribute to quality assurance and quality improvement, boost retention rate, assess and act upon differential outcomes among the student population, and enable the development and introduction of adaptive learning (Sclater, Peasgood, & Mullan, 2016).

A quick literature search has revealed that little attention in learning analytics research has been paid to inclusion and accessibility for students with disabilities. A few research have been focusing on integrating learning analytics into serious games in order to provide engaging learning experience for people with intellectual disabilities (Cano, Fernández-Manjón, & García-Tejedor, 2018; Nguyen, Gardner, & Sheridan, 2018). The Journal of Learning Analytics has no publications on students with disabilities in higher education. The only record found was (Kaczorowski & Raimondi, 2014) which focuses on using video data analysis to facilitate flexible learning optimized for diverse elementary-aged students learning mathematics, including students with learning disabilities. In the conference proceedings of Learning Analytics and Knowledge (2011-2020), there is only one paper on students with disabilities in higher Education. (Cooper, Ferguson, & Wolff, 2016) in their seminal paper at LAK'16 presented a comparative analysis of completion rates between disabled and non-disabled students based on a dataset collected in a 5-year period in an e-learning system and identified a large discrepancy between the two groups. Disabled students were found less likely to complete a module than non-disabled students. Although the authors stated that through their work they hope to *stimulate others involved in the research, development and roll-out of learning analytics to work towards realising their potential to meet the needs of disabled students*, this unfortunately has not been followed up in the learning analytics community.

3. Critical perspectives on Learning Analytics in the Context of Inclusion

Critical perspectives can be viewed through the lens of key activities in learning analytics (Figure 1). A learning analytics cycle generally covers four main interrelated stages: data collection and pre-processing, data modelling, presentation of results, and interventions (Gašević, 2018).

In the data collection and pre-processing stage, what types of data are collected has direct consequence for the other activities followed. (Cooper et al., 2016) used student self-declared disability data. However, research have shown that the majority of student choose not to disclose their disability (Roberts, Crittenden, & Crittenden, 2011). In many countries collecting information about students' disability, family income, and minority status is governed by privacy laws and needs to be approved by a national ethics committee in addition to consent from students.

At the data modelling stage statistics modelling, machine learning and predictive algorithms using different data including demographic and interaction data for classification, ranking, rating have potential risks of digital redlining(Gilliard & Culik, 2016) and discrimination, which can exert potentially harmful effects for some students and student groups. The number of students who declare disability is often low and there are fewer data points for them. They may also use longer time on activities than average. These factors may result in poor representation and poor performance of the algorithms when dealing with data of this student group. Their data risks of being excluded as outliers or edge data even at the pre-processing stage in order to emphasize the dominant patterns at the modelling stage. (Cooper et al., 2016) stated that their approach was not valid when the number of disabled students was low and suggested that a minimum of 25 disabled students in a module was appropriate for the comparative analysis of completion rate between disabled and non-disabled students.

When presenting the results from learning analytics algorithms, the interface design can create potential barriers for students with disabilities. Poorly designed information visualization and dashboard with, for example, low colour contrast, lack of keyboard navigation support, lack of text explanation for graphics and chart, could prevent students with disabilities from accessing information presented and making sense of the data. One of the causes of the barriers could be that the design process of student interfaces for learning analytics did not involve students with disabilities. Another reason could be that the designers of the learning analytics interface do not have awareness of the potential barriers and knowledge on how to create accessible visualizations and dashboards. A literature review showed that when evaluating student-facing dashboards the major focus has been on acceptance, usefulness and ease of use as perceived by users (Jivet, Scheffel, Specht, & Drachsler, 2018). However, dashboards are often not evaluated from the perspective of students with disabilities. Accessibility principles and guidelines such as Web Content Accessibility Guidelines (W3C, 2018) have not been taken into consideration when designing visualization and dashboards for learning analytics.

Intervention actions can be automatic or carried out by faculties or students themselves. Faculties and students may take actions based on the results from learning analytics algorithms. Because of the challenges in the previous stages, the interventions have not considered the disability of students. This can prevent faculties from providing effective support to students with disabilities and students from benefiting from learning analytics. In addition, in this stage learning analytics systems often do not provide explanations of their decision-making. Therefore, users often do not have opportunity to understand how the feedback or recommendations are made in the algorithms, and they are not able to influence the process or correct the decisions by the systems so that the systems learn from the feedback and improver the performances for analysing data from students with disabilities.

Figure 1. Critical Perspectives on Learning Analytics in the Context of Inclusion.

4. Discussion and Conclusion

In this paper, we have discussed learning analytics in the context of inclusive higher education. Learning analytics has potential to contribute to inclusive education and enhancing learning experiences for students with disabilities. In addition to the general benefits of learning analytics identified in studies as shown in several literature reviews (Avella et al., 2016; Sclater et al., 2016), learning analytics can also contribute to identifying and addressing barriers and challenges students with disabilities face, identifying courses, modules or programs with high dropout rate of students with disabilities, and providing personalized learning path for students with disabilities. (Cooper et al., 2016) suggested that by carrying out critical learning path analysis of those modules with high dropout rate of students with disabilities and comparing the critical learning paths of students with and without disabilities could potentially pinpoint where significant accessibility challenges lie that are really impacting on learning.

Inclusion is not only an ethical issue, but also a technological issue and a pedagogical issue. For learning analytics, collecting and using student disability data as well as using student interaction data to predict disabilities (David & Balakrishnan, 2014) pose ethical challenges. From a technical point of view, how to design statistics modelling, machine learning and predictive algorithms in order to handle data from students with disabilities that are often considered outliers or edge data? How to implement algorithmic accountability (Ivarsson, 2017) and increase transparency of learning analytics technologies? How to design and evaluate learning analytics to ensure accessibility and usability for diverse students? It is promising to notice that in recent years user-centred, participatory and co-design approaches have been adopted to learning analytics design (Dollinger & Lodge, 2018). Furthermore, learning analytics design, in particular visualization and dashboard design should follow accessibility principles and guidelines. On the pedagogical level, how can learning analytics identify critical aspects of the learning experience for students with disabilities and support faculties to customise their pedagogical design to adapt to students' needs? In order for learning analytics to contribute to inclusive education, such questions should be discussed and addressed. This calls for an inclusion by design strategy to ensure that inclusion is integrated into all the stages in the life cycle of learning analytics systems.

Inclusion does not only refer to disabilities, but also covers gender, social, economic and cultural background and status. In (Lim & Tinio, 2018) considering 'how the collection, analysis, and use of data about learners and their contexts have the potential to broaden access to quality education and improve the efficiency of educational processes and systems in developing countries around the world', (Gašević, 2018) viewed the adoption of learning analytics through the lens of three key challenges facing education systems in the Global South: quality, equity, and efficiency. Equity in this context, does not only refer to education access and general participation in the traditional sense, but also refers to *education completion rates, to the transition from one educational level to another, and to* *overall educational achievement across different groups, based on factors such as gender, income, geographic location, minority status, and disabilities*.

Learning analytics can help to address the gap between an increasingly diverse student population and a "one-size-fits-all" approach in education. Student diversity calls for personalized and adaptive solutions to which learning analytics has the potential to contribute. Through this paper we hope to put inclusion on the agenda in the learning analytics community, increase awareness of inclusion among educators, students, designers, developers, data scientists, researchers and other stakeholders, and make learning analytics an essential contributor to success of all students.

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