Hayashi, Y., et al. (Eds.) (2017). Workshop Proceedings of the 25th International Conference on Computers in Education. New Zealand: Asia-Pacific Society for Computers in Education

Teacher-actionable insights in student engagement: A learning analytics taxonomy

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Abstract: In the emerging field of learning analytics (LA), actionable insight from LA designs tends to be a buzzword without clear understandings. Student engagement is commonly measured in LA designs and used to inform actionable insight. Moreover, in K-12 education, where the teacher is a key stakeholder, what teacher-actionable insights can be derived from LA designs? Towards providing greater clarity on this issue, we concretize a taxonomy of LA decision support for teacher-actionable insights in student engagement. Four types of decision support are conceived in this taxonomy with relevant teacher implications. Through this taxonomy, we hope to offer possible pathways for actionable insight in LA designs and make clearer the role of the teacher.

Keywords: Learning analytics, teacher, design, taxonomy, actionable insight

1. Introduction

In the field of data analytics, the term "actionable insight" often represents buzzwords without clear definitions. Recognizing this, Tan and Chan (2015) provide a three-tiered definition for actionable insights in general data analytics systems – analytic insight (understanding and inferring individual information), synergistic insight (contextualizing, combining and linking information), and prognostic insight (deriving information of future results). Similarly, in the field of education, there have been several conceptions and understandings of actionable insight. For instance, Cooper (2012, p. 4) defines actionable insight as analytics that are "concerned with the potential for practical action rather than either theoretical description or mere reporting". The report highlights that insight from learning analytics (LA) needs to provide a "level of clarity" such that a "rational person" can choose a path of action (Cooper, 2012, p. 4).

Additionally, Clow (2012, 2013) elaborated that in any LA design, there is a cyclical process of learners generating data, which is processed into metrics. This then informs interventions, and these actions affect learners. In particular, these actions can be performed by the learner, teacher, manager or policy maker (Clow, 2012).

Evident from extant literature is that the specificity of "actionable insight" in LA can be understood in several ways and from different stakeholders. Many LA designs have focused on providing interventions such as tasks and recommendations for the learner. However, comparably less attention is paid to a closely intertwined stakeholder, the teacher (Sergis & Sampson, 2017). While learner-actionable insights are important, in this paper, we examine teacher-actionable insights, especially within the K-12 education context, where the teacher more often than not plays a crucial 'make-or-break' role in the learning and teaching process (Hattie, Masters, & Birch, 2015).

In K-12 education, the role of the teacher is paramount in the learning equation. With younger learners, teachers are the learners' coach, lifeguard, instructor, technology decider, and more. This context is markedly different from Higher Education, where learners are relatively more independent of their teachers throughout the learning process, and where teachers play a more academic role. Higher education students tend to decide on their own technology and systems, as well as have access to a wide range of technologies and/or engage in online learning. On the other hand, in K-12, technology access is still an issue (Monroy, Rangel, & Whitaker, 2013; Rodríguez-Triana, Martínez-

Monés, & Villagrá-Sobrino, 2016), and blended learning is the dominant mode of learning with technology .

In a recent systematic literature review on teaching and LA (Sergis & Sampson, 2017), the research identified only 50 papers that examined the role of the teacher in the field of LA. Of these papers, only four papers (7.4% of the papers) provided concrete actionable insights for teachers. The bulk of LA designs (92.6% of the papers), provided unstructured and/or ad-hoc actionable insights for teachers. Also, many papers are exploring what types of LA are useful for teachers, and ways to provide better feedback for them. For instance, Van Leeuwen et al. (2017) details a high school teacher making sense of and responding to LA tools to offer the possibility of how LA can be used pedagogically for student learning.

What teacher-actionable insights can be derived from LA systems? Towards scoping this question, we premise the design of many LA systems in the area of engagement in learning. In the pedagogical core of learning there is an interaction between learners and the content, as well as between peer learners (Tan & Koh, 2017). Hence, student engagement is commonly measured in LA designs and used to inform actionable insight (Lu, Huang, Huang, & Yang, 2017). We posit that LA can provide teacher-actionable insights for understanding this engagement in learning. As such, we conceptualize a taxonomy of LA decision support for teacher-actionable insights in student engagement.

This taxonomy will be illustrated with examples from two prototype LA systems, My Groupwork Buddy (MGB) and the Collaborative Video Annotation and LA (CoVAA) Learning Environment. Briefly, MGB is a formative assessment tool for teamwork while CoVAA is a time-point based video annotation system.

2. Related work

2.1. Student engagement and LA

Student engagement is associated with learning performance as well as student motivation and the reduction in school dropouts (Fredricks, Blumenfeld, & Paris, 2004; Wang & Eccles, 2012). While there are many definitions, student engagement is generally defined as a multi-dimensional construct consisting of behavior, emotion and cognition (Fredricks et al., 2004). Student engagement is commonly measured in LA through the engagement of students with the content, and with other peers in the system (Lu et al., 2017; Monroy et al., 2013; Tan & Koh, 2017; Tan, Yang, Koh, & Jonathan, 2016). Moreover, many of these sub-types of engagement are currently in LA designs.
A typical learning analytic design focuses on behavioral engagement which relies on the concept of participation (e.g., Monroy et al., 2013; Tan et al., 2016). Metrics for behavioral engagement include logins, page views, mouse clicks, time on page, task submissions, and other forms of trace data. There are also different levels of granularity for behavioral engagement metrics. A related behavioral engagement technique is social network analysis; it shows a description of connections between learners, i.e., who is talking to who.

Another level of engagement is the affective or emotional engagement. Although less common, this is also another emerging area that can be collected and detected by LA designs (e.g., Grawemeyer et al., 2016). These include emotions such as boredom and off-task behaviors, as well as positive emotions like happiness and curiosity. Past research has derived algorithms to measure off-task behavior. Sentiment analysis is also another technique that uses text and online discourse.

The third category of engagement is cognitive engagement. This deals with what the students' have learned, mastered, and understood. Many LA measure and assess students' knowledge, skills, and other learning. This can be in terms of the right answers to a quiz, the correct moves in a game, the number of attempts, a coded set of words and/or keywords in a dialogue etc. This is common in intelligent tutoring systems.

With engagement as a common backdrop in LA designs, we next describe the types of teacher-actionable insights in LA.

2.2. Teacher-actionable insights in LA

In the general field of analytics, drawing from many best practices of data science and system development, extant literature has conceived a continuum of analytics ranging from descriptive, diagnostic analytics, to predictive and prescriptive analytics (Gartner.com). Actionable insight can be derived from these various types of analytics. Many business solution providers advise developing predictive and prescriptive analytics, which emphasize system recommendations, in order to derive greater business value, although this is the most technologically challenging. Predictive analytics, similarly, is advocated in LA in order to provide likely future states of learners, and to design appropriate interventions to enhance learning outcomes (Clow, 2013). For instance, Lonn et al. (2012) developed a predictive model to classify students into three categories based on students' assessment grades and login activity on the Learning Management System. This provided an early warning system to allow teachers (academic advisors) to encourage students who were doing well, explore with students who could need more help, or engage with those who were possibly at-risk.

Nevertheless, descriptive analytics are still an important area for LA. To understand learning engagement, we first have to measure such descriptions of engagement. Descriptive analytics generally provide aggregations of metrics of engagement indicators, as described earlier.

As for diagnostic analytics, these are learning analytic designs that pinpoint relationships between two variables e.g., visualizations that plot effort and academic achievement (Nagy, 2016). Diagnostic analytics can also be derived from statistics and machine learning.

The primary challenge is turning data into actionable insights for teachers (Melero, Hernández-Leo, Sun, Santos, & Blat, 2015; Monroy et al., 2013; Rodríguez-Triana et al., 2016). Sergis & Sampson (Sergis & Sampson, 2017) identify and review 50 papers on teacher inquiry in LA and found that a majority of teacher actions do not provide an additional layer of decision support. For instance, they found that some designs identify different clusters of students, or a visualization of interactions of learners with teachers, without providing scripts or further structured support for teacher action. Teachers are left to their own resources and capabilities to take action.

On the other hand, the review also identified two types of teacher-actionable insights. First, Yen et al. (2015) provided explicit suggested instructions to the teacher using rule-based, pre-defined feedback templates that were informed based on data analyses. A second type of study used a script-aware monitoring process to provide actionable insight for teachers (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015). Teachers would first define key learning outcomes for students, and the LA design monitored students' progress, and provided feedback on students' progress to teachers. This feedback of the process allowed the teachers to better manage the learning process of students. These examples of actionable insights for teachers are specific recommendations to help teachers improve their teaching and learning practice.

As can be seen, there are different ways of implementing LA designs for teacher-actionable insights. The next section illustrates our proposed taxonomy.

3. Conceptualizing a LA taxonomy for teacher-actionable insights

Informed by extant literature, we conceptualize four types of LA decision support for teacher-actionable insights in student engagement: *descriptive*, *diagnostic*, *predictive* and *prescriptive*. The proposed taxonomy is depicted in Table 1. The second column in Table 1 describes the areas of teacher-actionable insight which is a more macro view of system feedback to the teacher. The third column highlights certain data science methodologies and techniques required while the last column provides implications of this decision support for teachers.

3.1. Descriptive

Descriptive analytics describes what students' activities on the system are, depicting indicators of student engagement for the teacher. It represents the foundational data structures in LA and asks, what are my students' engaged in? It describes what students' activities on the system are. For instance, in MGB, submission data (whether students have completed their teamwork reflection or not), is summarized for the teacher to easily find out who has not participated, and take appropriate action. In CoVAA, teachers are able to download a set of participation data including annotation type, critical lens tag, and comment description, which makes it convenient for them to examine and provide feedback on students' answers.

Many LA designs provide such engagement data in real-time so teachers are able to see and monitor the activities of students instantaneously. Descriptive analytics typically summarize these different engagement types (behavioral, emotional, and cognitive) for teachers using descriptive statistics in words, tables, graphs, charts and/or other visualizations and are the essentials of teacher dashboards. Still there are challenges in terms of what metrics to measure as learning designs become more sophisticated, and how best to represent them.

Teacher-actionable insight at this layer tends to directly relate to the metric or indicator measured e.g., submission data. Besides giving the teacher an aggregated understanding of the students, and/or comparison of learners, the LA engine typically does not provide further decision support for the teacher. Teacher actionable insight depends on the capacity and agency of the teacher to take action. Teachers have to make sense of the data and decide for themselves appropriate interventions (Melero et al., 2015). In that sense, descriptive analytics offers broad ranging areas of teacher-actionable insights, but also relies on the capacity of teachers to decide and perform more targeted interventions.

Table 1: A taxonomy of LA decision support for teacher-actionable insights in student engagement

Type of LA decision support	Areas of teacher-actionable insights	Possible data science methodologies	Implications for teachers
Descriptive	What are students engaged in? What are they doing, feeling, and/or, learning?	Dashboard summaries, visualizations, descriptive statistics	Broad ranging areas of action, relies on the agency of teachers
Diagnostic	Why are students' engaged?	Visualizations, process mining, drill-down tools, correlations, data discovery, and data mining	More specific areas of action, but still requires teacher discernment for intervention
Predictive	What will students' be engaged in? Which groups of students' will be engaged?	Machine learning, regression analysis	Relieves load of teachers for certain areas of action, but could provide opportunities for teachers to look at other areas of engagement
Prescriptive	What can be done to engage students?	Machine learning, algorithms, predefined conditions	

3.2. Diagnostic

Diagnostic analytics tries to explain why students did what they did. Why did students engage in that manner? Why are students engaged? What patterns are there between pieces of data? This is analyzed after data is collected. Data science methodologies and techniques include visualizations, process mining, drill-down tools, correlations, data discovery, and data mining.

This LA design attempts to link relationships to explain student engagement (and all the different forms of engagement). This LA support helps teachers to pinpoint specific areas for possible interventions. Still, teachers should be discerning and decide pedagogically if they should intervene.

For both MGB and CoVAA, this layer of diagnosis is currently done in the back-end using existing statistical techniques by researchers, and shared with the teachers, as data-driven evidence for teachers to take action. In MGB, in attempting to explain why students were more cognitively engaged in teamwork, we performed a correlation and found a significant and higher association between peer-rated teamwork scores and students' goal-setting status check completion. In other words, there was a relationship between students who claimed they completed their target goals related to their teamwork behaviors, and their peer-rated teamwork dimensions. With this, one possible implication is that the teachers should ensure that students fulfil their targeted goals.

3.3. Predictive and prescriptive

Predictive and prescriptive analytics are closely related. While predictive analytics provide empirical evidence of what students will be engaged in, prescriptive analytics provide recommendations to the student, reducing the immediate intervention required by the teacher. Predictive analytics provide empirical evidence of what students will be engaged in, or the groups of students who will become engaged. This layer provides teachers with foresight, what will happen based on probability estimates. Techniques include machine learning, regression analysis etc.

On the other hand, prescriptive analytics asks the question of "what can be done to engage students" and prescribes actions that the system takes on behalf of the teacher. It computes activities and responses that the system can do now based on predefined conditions, that were determined by diagnostic and predictive analyses.

Predictive analytics provides very clear and specific teacher-actionable insight. Decision support for the teacher is precise and could include filtering and identifying different clusters of students such as those potentially at risk from academic failure and dropout. It can also identify students who are potentially on an accelerated trajectory. Teachers' usage of system tools can also predict student achievement.

Prescriptive analytics then seeks to identify specific sets of activities that students can take, without the immediate intervention from the teacher.

While on one hand these two types of support may seem to reduce the need for the teacher, we posit that at the same time, this provides opportunities for teachers to go beyond the common set of responses to probe deeper into student engagement or examine new trends among their students.

Seemingly, this could help to relieve the load of teachers' direct instruction to the student, and could help the teacher to focus on other areas of student engagement that is not provided for by the system.

As such solutions require more time and testing, these analytics are part of the future work planned in MGB and CoVAA.

4. Discussion and Conclusion

This paper conceptualizes a taxonomy of teacher-actionable insights based on student engagement in LA designs. As can be seen in these four types of decision support, teacher-actionable insights range from broad to specific. While these types may seem to have some sort hierarchical relationship, e.g., each type being a more complex type of the other, we realize that each type could uncover engagement ranging from the superficial, simple to complex and deep. We do not offer any type as better than the other, but highlight that these are possible pathways of providing feedback to teachers, and that each pathway is important to examine student engagement. There are important teacher-actionable insights that can be highlighted for each category in the taxonomy.

In fact, the broader socio-cultural issues of teacher ownership and agency are a concern for each type. Many of these teacher-actionable insights require the teacher's capability and impetus to take action. This is echoed in many of the K-12 LA designs reported (Sergis & Sampson, 2017).

Helping teachers to discern and decide on actions to take is a process that requires the partnership of research, design and pedagogical teams.

It is hoped that this taxonomy will help learning designers, developers and teachers to consider the engagement of their learners from behavioral, affective and cognitive outcomes and the multiple pathways of LA. Moreover, this taxonomy could provide greater clarity of where their respective LA designs are at and where it could be heading towards. For instance, an LA design which is of type descriptive might want to consider building capacity and development towards predictive analytics, to provide opportunities for teachers to help students in other behavioral, affective or cognitive aspects.

An underlying assumption in this typology, is that all these types of LA need to show some measure of validity or reliability (such as its confidence level, statistical significance), and/or an acknowledgement of limitations or bias (Cooper, 2012). Especially for the descriptive level, this helps to scope decision areas for teachers, rather than overwhelm teachers with a large pool of possible indicators. It also highlights the importance of intentional LA design that makes explicit its pedagogical value (Knight, Shum, & Littleton, 2014; Koh, Shibani, Tan, & Hong, 2016; Lockyer, Heathcote, & Dawson, 2013). While the typology provides a heuristic in understanding the complexity and potential of teacher-actionable insight, these insights are in recognition of the learning design of the LA. In other words, the actionable insight should be in line with the overall learning goal and LA design.

This taxonomy is a first step towards providing a clearer framework of teacher-actionable insights in LA designs. It is based on current and international literature and trends. It also recognizes the importance of the role of the teacher, especially with regard to the K-12 context, and provides a conceptualization to map different kinds of LA designs in student engagement. Teacher-actionable insights in student engagement is a crucial area for the emerging field of LA, and in clarifying possible pathways, LA designs can be made more useful for teaching and learning.

Acknowledgements

This paper refers to data and analysis from the project NRF2015-EDU001-IHL08 and NRF2015-EDU001-IHL09 funded by the Singapore National Research Foundation, eduLab Research Program. The views expressed in this paper are the authors' and do not necessarily represent the views of the National Institute of Education.

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