LEARNERS' AND TEACHERS' PERCEPTIONS OF LEARNING ANALYTICS (LA): A CASE STUDY OF SOUTHAMPTON SOLENT UNIVERSITY (SSU)

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ABSTRACT

This paper depicts a perceptual picture of learning analytics based on the understanding of learners and teachers at the SSU as a case study. The existing literature covers technical challenges of learning analytics (LA) and how it creates better social construct for enhanced learning support, however, there has not been adequate research on whether learners and teachers understand the significance of LA and how they can utilise it for enhancement of learning and teaching. This qualitative study helps to shape understanding of an LA initiative based on one university, but with implications for other universities. Shared stakeholders' understanding of LA with an institutional strategic priority supported by a collaborative delivery would ensure a successful implementation of LA.

KEYWORDS

Learning Analytics, Case Study, Perception

1. INTRODUCTION

The purpose of this study is to find out how LA is perceived by the learners, teachers and other staff members of the Southampton Solent University (SSU) as a case study. Daniel (2015) mentions there are institutional challenges of collecting big data in a warehouse and subsequently analysing and visualising such data for the betterment of learning and teaching. In this paper the stakeholders are the learners, teachers and support staff members for LA as identified by Reyes (2015). The research paper presents a case study of SSU, a relatively new university gaining university charter in July 2005 (Southampton Solent University 2016). The university has a history of education dating back to 1856 and transformed itself into a higher education institution in 1989. It has always been a teaching intense university transforming local and national workforce. There is large body of highly technical literatures in LA and big data as well as non-technical literatures exploring the challenges and ethical dilemmas (Picciano 2014, Slavakis, Giannakis & Mateos 2014, Anonymous2015, Daniel 2015, Kash, Thappa & Kavitha 2015, Reyes 2015, Madhavan, Richey 2016) This research contributes into the social aspects of using LA. The research findings are highly relevant for any teaching intense university with social inclusivity as a major agenda and learning and teaching being a core academic activity.

2. THE FIELD OF LEARNING ANALYTICS

Enter the text here. Although LA is a relatively new concept, the literature is significantly large, varying from highly technical research papers to studies concentrating on the educational value of such technological intervention. Based on the research context, this paper identifies the proximate topics: definition, issues, and outcomes of learning analytics (Daniel 2015).

As Daniel (2015) highlights, LA is "an interdisciplinary area focusing on methodologies for identifying and extracting useful and meaningful patterns from large data sets" (p 906). The methodology "draws upon research in statistics, databases, pattern recognition, machine learning, data visualisation, optimisation and high performance computing" (p 906). LA is defined as a technological intervention based on large amounts of data on learners and teachers to enhance learning experiences and aid progression (Slade, Prinsloo 2013) Oblinger (2012) indicates that LA is set of data about individual learners that helps the institution and the teachers to support the student in learning. Oblinger (2012) and Sclater, Peasgood and Mullan (2016) differentiate between academic analytics and learning analytics, where academic analytics refers to macro data that helps the management of a higher education institution. On the other hand, there has to be an appreciation of how this supports educational decision making to ensure effective resource allocation, educational guidance, and enhanced retention through student success (Conde, Hernández-García 2015). The empirical literatures in development of LA as presented in Ali *et al.* (2012) , Ali *et al.* (2013) and Fidalgo-Blanco *et al.* (2015) also broadly agree with the above definitions. Siemens (2013) showcases how LA and related research has given rise to an emerging area of study in educational research.

The ultimate power of LA lies with its predictability (Dietz-Uhler, Hurn 2013, Agudo-Peregrina et al. 2014, Strang 2016b, Strang 2016a). A substantial data warehouse containing big data on learners can be analysed using statistical modeling to produce predictive analytics (Strang 2016b). However there should be proper reflection on the ethical issues surrounding learning and predictive analytics (Slade, Prinsloo 2013) The predictability should not be used in isolation and without the social context for a learner or group of learners (Hernández-García et al. 2015). On the other hand, Gašević *et al.* (2016) argue that learning conditions are an important factor to consider while using LA. There is a need for an appreciation of the value LA adds to the process of learning and teaching. For example, Persico (2015) explains how LA can inform the learning design. van Leeuwen *et al.* (2015) showed how teachers can benefit in their educational rationale by using LA. Whereas, Strang (2016a) and Strang (2016b) present how student learning outcomes and achievements can be predicted by LA.

3. RESEARCH DESIGN

This is a post-positivist research that applies a subjectivist paradigm (Cohen 2011, Lincoln, Guba 2003). This exploratory research applies case study methodology through a series of key stakeholder semi-structured interviews (Vanwynsberghe, Khan 2007, Yin 2003, Creswell 2014). SSU is the case in this study that constructs a holistic single-case design (Yin 2003), where the researcher builds an institutional perception as readiness for using LA within the SSU. Because the author is part of the LA initiative at the SSU, the axiological aspect demands the research to apply constructivist approaches to learning. The research tries to identify the perceptions of the stakeholders around LA in the SSU, where the context, existing belief systems, and institutional values stipulated by the mission statement create a local understanding of the topic. Cronje (2006) and Chen (2007) argue that objectivist and constructivist paradigms of learning can co-exist while designing learning environments. Therefore, in this research, there are multiple paradigms being applied i.e. post-positivist, subjectivist, and constructivist. The research addresses the following three questions:

RQ1: What is the perception of LA among the major stakeholders?
RQ2: Who are the wider stakeholders of LA?
RQ3: What are the challenges around LA as perceived by the stakeholders?

4. PERCEPTUAL FINDINGS

4.1 Student Perceptions

The students had no idea about LA and the author had to define LA. They thought presenting non-attendance with potential impact on academic performance would be useful for those who tend to miss learning opportunities. In a nutshell, they wanted to find out the correlation between missing learning opportunities and someone's grades, indicating the predictive analysis of learning opportunities. This demonstrates that students perceived LA as a support for learning (Oblinger 2012, Slade, Prinsloo 2013) while appreciating the predictive capability of such tool (Dietz-Uhler, Hurn 2013, Agudo-Peregrina et al. 2014, Tempelaar, Rienties & Giesbers 2015, Strang 2016a, Strang 2016b). They highlighted other engagement data to be correlated with academic performance e.g. library attendance and VLE attendance. These SSU students perceived comprehensive data collection on learners' activities useful (Sclater, Peasgood & Mullan 2016). When asked who else could have access to this sort of data, they replied negatively, as there could be personal reasons for non-attendance bringing the social dimension of LA (Hernández-García et al. 2015). However, they thought this sorts of data could be anonymous and be used in academic analytics as management information (Oblinger 2012, Sclater, Peasgood & Mullan 2016). The author asked about teachers as being potential stakeholders for such data and they replied that might be useful as long as students could opt out of such data disclosure (Slade, Prinsloo 2013). The students also felt comparative analytics could be useful as long as it was compared with a relevant cohort. This indicates that the university may want to include carefully chosen peer comparison within the analytical engine (Sclater, Peasgood & Mullan 2016).

4.2 Academic Staff Perceptions

The academic staff, unlike the students, knew about LA and defined it as a process of measuring some data about learners (Oblinger 2012, Slade, Prinsloo 2013, Sclater, Peasgood & Mullan 2016). They said the measurement involves collecting, analysing, reporting and making decisions about learners in order to achieve some strategic aims as defined by Daniel (2015) and Sclater, Peasgood & Mullan (2016) They emphasised the need for the accuracy of data collection and thorough data cleansing (Strang 2016b, Daniel 2015) before analysing the data to support institutional performance (Oblinger 2012, Sclater, Peasgood & Mullan 2016). They highlighted that it was more important to collect big data and analysed them for performance enhancement (Ali et al. 2013, Ali et al. 2012, Conde, Hernández-García 2015, Fidalgo-Blanco et al. 2015) irrespective of its usage at micro level or macro level. When asked what LA would be useful to enhance their teaching, the academics replied any data about the learners could be useful to custom tailor their teaching materials (van Leeuwen et al. 2014) for the learners for better engagement (Oblinger 2012, Slade, Prinsloo 2013). The academics wanted all sorts of factual data about their learners to be included in LA, e.g. demographic data, past educational attainments (Strang 2016a, Strang 2016b), professional experiences, engagement with learning activities (Slade, Prinsloo 2013, van Leeuwen et al. 2014), accessibility requirements, specific health requirements (Hernández-García et al. 2015).

The academics mentioned that having access to all data about learners was not useful for an academic rather it would be useful to have some insights about learners drawn from LA (actionable data mentioned by Slade and Prinsloo (2013), which can be readily utilised for enhanced pedagogy (Ali et al. 2012, Ali et al. 2013, van Leeuwen et al. 2014, Conde, Hernández-García 2015, Fidalgo-Blanco et al. 2015). The academics also thought all student support systems should have access to LA and their actions must be driven by data (Slade, Prinsloo 2013). Academics believed that the biggest technological challenge (Daniel 2015, Strang 2016b) of LA is the data collections that were not from application forms but through human interactions. This statement confirms with (Hernández-García et al. 2015) who spoke about the social context of LA. The academics mentioned about challenges around spotting patterns across big data and trying to predict situations in timely fashion to support systems that could make a difference (Dietz-Uhler, Hurn 2013, Agudo-Peregrina et al. 2014, Tempelaar, Rienties & Giesbers 2015, Strang 2016a, Strang 2016b).

4.3 Student Support Staff Perceptions

One of the student support manager, currently working on the SSU LA project, defined LA as big data appropriately presented to learners, teachers, support staff and management (Oblinger 2012, Slade, Prinsloo 2013) to facilitate their decision-making from their contexts (Gašević et al. 2016). She thought the purpose of LA for all of these stakeholders was to improve respective performances (Ali et al. 2012, Ali et al. 2013, Conde, Hernández-García 2015, Fidalgo-Blanco et al. 2015, Strang 2016a, Strang 2016b). She said it would also help the SSU to formulate relevant strategies, e.g. around retention and progression and would allow the organisation to measure progress against such strategies (Slade, Prinsloo 2013, Sclater, Peasgood & Mullan 2016) . She also described how LA could support course management and organisation (Persico, Pozzi 2015) and could support learners to achieve their personal goals (Strang 2016a, Strang 2016b). She clearly articulated a phased roll-out of LA but ultimately reaching every stakeholder, to make decisions based on data. While addressing potential benefits of LA for her student support team, she clearly mentioned predictive analytics (Hernández-García et al. 2015), which would predict current and future students at risk based on past patterns and trends in data (Daniel 2015, Sclater, Peasgood & Mullan 2016). This would particularly support her team to address retention issues with the SSU (Ali et al. 2012, Ali et al. 2013, Conde, Hernández-García 2015, Fidalgo-Blanco et al. 2015). She highlighted there needed to be a significant cultural shift at the SSU for successful LA to drive decision-making with accountability (Slade, Prinsloo 2013). The interviewee did not perceive any ethical dilemma and felt ethical issues can be managed with appropriate policy and procedures in place around usage of big data.

4.4 System Support Staff Perceptions

The system support staff member, currently working on the LA project, thought the learner in this digital age would understand what data could do to enhance their learning experiences but might just be struggling with the specific term LA. She initially thought learners' engagements understood by different touch points (VLE login, library attendance, classroom attendance etc.) would mean LA, but after the Jisc engagement, she realised that LA broadly dealt with macro and micro level data on learners (Sclater, Peasgood & Mullan 2016). She thought there might be academic staff that kept themselves informed about contemporary development in pedagogy (Persico, Pozzi 2015) and in the process learnt about LA. In response to the stakeholder question, she answered that the academic staff members, support staff members, and the management would be the key stakeholders of LA for daily operations (Oblinger 2012, Slade, Prinsloo 2013), whereas the information technology support staff would be fundamental in delivering the project around LA. Interestingly she did not think that the learners were stakeholders for LA. She thought of involving the student union or a recent SSU graduate employee to join the implementation project. She identified that there are very little offerings in the market place to amalgamate big data on learners encapsulating all the touch points. She understands that LA have predictive capability for which statistical analysis are needed. When asked about ethical dilemmas, she highlighted the implication of the Data Protection Act (1998) on LA (Slade, Prinsloo 2013).

5. CONCLUSION

The students at SSU do not understand the concept of LA. In contrast, there is a broad understanding among the academic and support staff members that aligns with existing literatures. The system staff member, though aware of the technological complexity, does not possess a fully evolved understanding of LA. The SSU staff members are more open in sharing relevant LA as long as the ethical issues are dealt with proper adherence of the Data Protection Act (1998). The SSU students questioned wider sharing of their data and comparative analysis that may disengage learners with poorer achievement records. In general they do not understand the technological complexity of LA. The support staff and academic staff members advocate a strong cultural shift for any LA related project to be successful, invoked by an institutional strategy based on a shared understanding of LA. The SSU staff members also appreciate the outcome driven and purposeful usage of LA for enhanced pedagogy, learners' achievement, and efficient resource allocation highlighted by existing literature. Interestingly no one at the SSU thought that LA should be a multidisciplinary and multi-stakeholder initiative (Reyes 2015, Daniel 2015). Neither anyone at the SSU understands that data could be learners generated as learning is a temporal dynamic construct, which can largely mitigate ethical issues (Slade, Prinsloo 2013). The research also discovered that there is little understanding around statistical modelling within an analytical engine to deliver LA (Daniel 2015, Tempelaar, Rienties & Giesbers 2015, Strang 2016a, Sclater, Peasgood & Mullan 2016). Completing similar case studies across several other universities would further strengthen these research outcomes to be more meaningful for teaching-intense universities.

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