Accepted manuscript version of: Howell, J. and Roberts, L. and Seaman, K. and Gibson, D. 2017. Are We on Our Way to Becoming a “Helicopter University”? Academics’ Views on Learning Analytics. Technology, Knowledge and Learning. DOI: 10.1007/s10758-017-9329-9.

Abstract

Higher education institutions are developing the capacity for learning analytics. However, the technical development of learning analytics has far exceeded the consideration of ethical issues around learning analytics. We examined higher education academics’ knowledge, attitudes, and concerns about the use of learning analytics though four focus groups (N = 35). Thematic analysis of the focus group transcripts identified five key themes. The first theme, ‘Facilitating learning’, represents academics’ perceptions that, while currently unrealized, there could be several benefits to learning analytics that would help their students. Three themes; ‘Where are the ethics?’, ‘What about the students!’, and ‘What about me!’ represented academics’ perceptions of how learning analytics could pose some considerable difficulties within a higher education context. A final theme ‘Let’s move forward together’ reflected that despite some challenges and concerns about learning analytics, academics perceived scope for learning analytics to be beneficial if there is collaboration between academics, students, and the university. The findings highlight the need to include academics in the development of learning analytics policies and procedures to promote the suitability and widespread adoption of learning analytics in the higher education sector.

Keywords: learning analytics; higher education; academic attitudes; big data

1.0 Introduction

Learning analytics is a fast growing area in technology enhanced learning research in higher education (Dyckhoff, Zielke, Bultmann, Chatti, & Schroeder, 2012). Learning analytics has stemmed from business intelligence, educational data mining, and recommender systems and can be described as the collection, analysis, and reporting of big data on students (Siemens, 2013). Many higher education institutions are developing, or are already using, learning analytics with a focus on predicting student retention (Arnold & Pistilli, 2012; Corrin & de Barba, 2014), yet learning analytics is also designed to understand student learner behaviors, and improve learning by providing personalized feedback and support (Siemens, 2013). Despite the capabilities for learning analytics to improve student learning experiences, there has been limited application of learning analytics to improve learning instruction (Dede, Ho, & Mitris, 2016), with higher education institutions preferring to focus on strategic priorities around finances, research, and marketing (West et al., 2015). The greater focus on prediction over learning emphasizes the gap in the application of big data and learning analytics towards enhancing learning and teaching, with further research required into how students and academics can use learning analytics to enhance learning (Dede et al., 2016).

The exponential development of learning analytics has mirrored that of other technological advancements, yet there has been limited consideration of the underlying ethical issues surrounding the use of learning analytics (Slade & Prinsloo, 2013; Swenson, 2014; Willis, Slade & Prinsloo, 2016). Colvin et al. (2015) identified the absence of consumer voices, such as students and academics, the intended users of many of the artefacts developed by learning analytics, as one of the key ethical issues. It is of considerable concern that students and staff are seldom consulted in the decision making process, as this may be detrimental to the systemic adoption of learning analytics in higher education settings (Beattie, Woodley, & Souter, 2014). Of the limited research available, the majority focus on students' attitudes (e.g., Arnold & Pistilli, 2012; Atif, Bilgin & Richards, 2015; Corin & de Barba, 2014; Kerly, Ellis, & Bull, 2008; Kosba, Dimitrova, & Boyle, 2005; Reimers & Noevsky, 2015; Roberts, Howell, Seaman, & Gibson, 2016; Santos, Verbert, Govaerts, & Duval, 2013; Slade & Prinsloo, 2015) rather than academics' attitudes.

The successful implementation and maintenance of learner-centered analytics is dependent upon the involvement of the intended end users. Whilst there are a range of potential end users; including students, student support staff, staff engaged in curriculum development and implementation, and managers; academics with teaching responsibilities comprise a core constituency whose views have seldom been the focus of learning analytics research. The Technology Acceptance Model (Adams, Nelson, & Todd, 1992; Davis, Bagozzi & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008) provides a useful theoretical model for understanding the impact of academics' perceptions on future use of learning analytics. At the core of the Technology Acceptance Model, the perceived usefulness and perceived ease of use of new technologies drives intention to use and actual use. The range of factors predictive of perceived usefulness and perceived ease of use broadly encompass individual differences, system characteristics, social influences, and facilitation conditions. In this article we first summarize the extant literature on academics' perceptions of learning analytics. We then report on the findings from four focus groups with academics, prior to situating the findings within the Technology Acceptance Model and making recommendations that higher education institutions use information on the perceptions of key stakeholders to develop clear policies, messages, and procedures that are acceptable to all involved.

1.1 Academics and learning analytics

Limited research to date has examined academics' perceptions of learning analytics. When academics have not used learning analytics, research indicates they express confusion about what learning analytics is and how it would be of benefit to their teaching practices (Corrin, Kennedy, & Mulder, 2013). However, research also indicates academics see the potential value of learning analytics in enhancing teaching practices and student learning. In a survey of 250 academics at a university in Australia, 70% agreed or strongly agreed that use of online resources would benefit students (Kregor, Breslin, & Fountain, 2012). Whilst surveys suggest learning analytics are viewed as potentially beneficial to teaching practices academics also express skepticism over the utility of learning analytics (Corrin et al., 2013; Kregor et al., 2012; Miles, 2015). Some academics hold reservations concerning students' ability to interpret such feedback (Corrin et al., 2013; Miles, 2015), could the possible impact on students' self-esteem and capacity to learn and grow (Corrin et al., 2013; West, Huijser, & Heath, 2016) and the additional workload learning analytics would impose (Miles, 2015). As identified in the Technology Acceptance Model (Davis et al., 1989), if staff retain concerns about the usefulness of learning analytics then they are likely to have a reduced intention to use learning analytics, which may impede acceptance and integration of learning analytics in their teaching practices. Given there are numerous benefits to organizations that use learning analytics, such as improved retention rates for universities (e.g., de Freitas et al., 2016), it would be informative to specifically identify how academics view learning analytics so that academic concerns can be addressed in the implementation of learning analytics systems. Such an approach may then facilitate the adaptation of technological advancements within academic settings.

As academics gain experience with learning analytics, there may be a change in their views of the utility of learning analytics (West et al., 2015). Experienced academics note advantages of learning analytics such as the ability to promptly address the needs of students identified ‘at risk’ (Arnold & Pistilli, 2012) and providing students with the means to track their own progress (Arnold & Pistilli, 2012; West et al., 2015). Students can use learning analytics to identify actions that improve their performance, resulting in improved understanding of the importance of completing quizzes and assignments (West et al., 2015) and increased activity in online forums, posting more questions related to assignment requirements well in advance of due dates (Arnold & Pistilli, 2012).

Academics have also noted disadvantages of learning analytics based on their experiences. Some have stated current data representations were not useful for students (Corrin et al., 2013; Drachsler & Greller, 2012), engaging adequately with the system was too time consuming (Kregor et al., 2012), and could result in excess emails from worried students (Arnold & Pistilli, 2012). As a result, although there are academics who are enthusiastic about learning analytics (Kregor et al., 2012), this enthusiasm lags compared to administrators/senior leaders and students (Kregor et al., 2012; Miles, 2015). One source of discontent for academics is the level of support and communication received about learning analytics. For example, West et al. (2015) reported training for learning analytics had only been attended by, at most, 15% of Australian academics surveyed; however 86% of their participants indicated they wanted to attend training. Similar results have been reported in other countries included the United Kingdom (Reed, 2012). The key message throughout these quantitative studies is the current lack of support and communication academics receive when faced with learning analytics (Kregor et al., 2012; Reed, 2014; West et al., 2015).

The perceived lack of support may explain, in part, academics’ lack of enthusiasm compared to administrators and students (Kregor et al., 2012; Miles, 2015). Lack of enthusiasm may also stem from reported concerns about students’ ability to effectively use the feedback (Drachsler & Greller, 2012), concerns over the secure and ethical use of the analytics (West et al., 2015), perceived incompatibility of learning analytics with academics’ current workload (Arnold & Pistilli, 2012; Reed, 2014), and concerns that the learning analytics system would not be easy to use (Corrin et al., 2013). The lack of readiness from one of the intended main users of learning analytics, academics with teaching responsibilities, poses a threat to the uptake within higher education settings, whilst the speculative nature of these studies highlight the need to further explore higher education academics’ knowledge, attitudes and concerns towards learning analytics.

Academics have also raised ethical concerns about learning analytics. In a review of several universities’ practices, Willis et al (2016) raised concerns about who should be using and acting upon the messages from learning analytics systems provide a range of data about learners’ activities and interests, yet there is uncertainty around who is in control of the data, and who needs to respond to the data: students, teachers, or the institution? (Willis et al. 2016). The obligation to act centers on questions of if, when, how, and who engages with the student (Prinsloo & Slade, 2017; West et al., 2016; Willis et al., 2016). An important consideration is the inherent power imbalance between academics and students and the associated concept of fiduciary duty (Willis et al., 2016). With this imbalance in mind, concern has been expressed that learning analytics may be used punitively or to profile/label students (Corrin et al., 2013; Lawson, Beer, Rossi, Moore, & Fleming, 2016; Scholes, 2016; West et al., 2016). The use of data in such ways conflicts with ethical principles such as non-maleficence, justice and beneficence; principles cited by academics as key to guiding the implementation and use of learning analytics (West et al., 2016).

Academics have identified transparency to students and staff as a key consideration for the implementation of learning analytics. Without this there is concern data may be used for purposes such as performance management (West et al., 2016). In a survey of academics, data openness and transparency were considered to be the second and third most impacted 'soft barriers' to the implementation of learning analytics (Drachsler & Greller, 2016).

Although the research suggests that there are concerns held by academics, the studies to date have focused on how learning analytics may be integrated into teaching practices (e.g., West et al., 2015) or academics views regarding the ethics of learning analytics (e.g., West et al., 2016). The majority of studies have utilized surveys (e.g., Drachsler & Greller, 2012; Kregor et al., 2012; West et al., 2016) that required the evaluation of constrained statements, which does not allow for a thorough exploration of academics' attitudes towards learning analytics. In an exception to this Corrin et al. (2013) conducted focus groups with 29 academics, seeking to examine academics' views on their current teaching practices and how learning analytics could be integrated into their teaching (Corrin et al., 2013). Corrin et al. (2013) reported themes about how learning analytics could be used to help identify 'at risk' students and improve curriculum design by understanding better how students learn (Corrin et al., 2013). There were other potential uses for learning analytics identified such as tracking student compliance with mandatory safety modules, enrolment within tutorial groups and guidance for future subject selection (Corrin et al., 2013). The academics from Corrin et al.'s (2013) focus groups further noted practical obstacles in the implementation of learning analytics such as, accurately tracking student's online engagement and prior knowledge were considered to be difficult tasks. These are all important concepts that require consideration from institutions implementing learning analytics. Further research is required to extend Corrin et al.'s (2013) study to explore the broader range of academics attitudes, perceptions, and concerns regarding learning analytics beyond Corrin's focus on integrating learning analytics into current teaching practices. Such a project would sufficiently allow researchers, and higher education institutions, to identify how they communicate to academics about learning analytics to improve academics engagement with technology systems, whilst simultaneously reducing any perceived concerns or barriers to such systems. The current study builds on the limited previous research to further explore academics' perceptions of learning analytics. By systematically exploring academics' attitudes towards learning analytics across a variety of teaching roles and expertise, we hope to provide new insights that can inform the development and implementation of learning analytics programs in higher education, ensuring learning analytics are developed and delivered in a manner that is acceptable to academics and provide a focus on student learning.

2.0 Method

2.1 Research Setting

This research was undertaken in a university that is in the early stages of developing learning analytics capability. The university currently collects, collates, and analyses student data from across the university to develop models of student retention. Future aims are to provide richly interactive and personalized learning experiences. At the time this research was conducted (2016) academics did not routinely have access to learning analytics.

2. 2 Participants

To explore staff perceptions of learning analytics four focus group with current staff in varying teaching and professional roles were conducted at a large university in Australia. Previous research has typically employed self-selected samples (e.g., Corrin et al., 2013; Draschler & Greller, 2012; West et al., 2015), likely resulting in over-representation of academic staff who are already interested in, or engaging with, learning analytics. To overcome biases associated with self-selection we purposively sampled and invited groups to participate, and where possible scheduled the focus groups at their regular meeting times to maximize participation. These groups were selected to provide a range of types of teaching experience and expertise. The groups comprised a) 12 academics teaching undergraduate psychology, b) nine academics teaching into a smaller disciplinary cohort (undergraduate and postgraduate disciplinary courses) in speech pathology, c) eight Directors of Teaching and Learning from across a Health Sciences faculty who provide leadership in teaching and learning across their respective schools, and d) six Academy Fellows who are university-recognized exceptional leaders in teaching and learning from across the university The first two focus groups comprised teaching teams within disciplines, with academics ranging from new entry-level academics through to experienced senior academics.

2.3 Materials and Procedure

The research was approved by the Curtin University Human Research Ethics Committee (RDHS-37-16/AR01) and forms part of a larger project exploring both student (Roberts, Howell & Seaman, 2017; Roberts et al., 2016) and academic attitudes towards learning analytics. Rather than requiring academics to complete surveys or submit text responses, which can limit the exploration of a phenomena, focus groups were used to provide the academics space to consider their own opinions and perceptions in addition to their peers.

Four focus groups were conducted by the first two authors. After providing informed consent participants were asked to discuss their current knowledge about learning analytics. Participants were then shown a brief video on learning analytics in higher education (Sclater, 2015). Additionally, participants were provided with information on the current state of learning analytics within their own university. The participants were then provided an opportunity to discuss their reactions towards learning analytics in response to the video and information. Following this discussion participants were presented a brief summary of the themes from focus groups with students (Roberts et al., 2016). Throughout the focus groups non-directional prompts were used to elicit further information (e.g., 'can you tell me more about [concept]?'). Focus groups ran for approximately one hour. After each focus group, JH, LR, and KS discussed the emerging findings from the focus groups.

Data were collected through audio-recordings of each focus group and were transcribed verbatim. The transcriptions were imported into NVivo (Version 10; Castleberry, 2014), and checked with the recordings to ensure transcription accuracy. The transcriptions were subject to a thematic analysis, as outlined by Braun and Clarke (2006). Following data familiarization, data were sorted into starting codes (represented as nodes in NVivo) of attitudes, preferences, misconceptions and concerns, with additional child nodes generated through an inductive process during coding. These initial codes were grouped into overarching themes. KS conducted the initial coding and theme development. Themes were refined through revision of transcripts and team discussions (JH, LR, & KS). During these discussions, relationships between themes were identified and iterations of thematic maps, which depicted the relationships between themes, were created to aid the discussion and finalization of themes. Saturation was assumed after four focus groups, as no new themes were emerging. This is consistent with reports that 80% of all themes can be identified within two to three focus groups (Guest, Namey & McKenna, 2016). Key findings from the analysis were summarized and sent to all focus group participants as a form of member checking, a technique for establishing the credibility of the findings (Lincoln & Guba, 1985). No changes were made to the findings as a result of the member checking.

3.0 Findings

Five key themes; ‘facilitating learning’, ‘where are the safeguards?’, ‘what about the students!’, ‘what about us!, and ‘let’s move forward together’; were developed from the thematic analysis of staff focus group transcripts. The theme ‘facilitating learning’, comprised sub-themes relating to early intervention and identifying patterns, risk and protective factors. The theme ‘where are the safeguards?’ comprised sub-themes related to inappropriate use, data integrity and redundancy. The theme ‘what about the students! reflected concerns the academics held for students regarding informed consent, and the impact on student learning and wellbeing, whilst ‘what about us!’ detailed the potential influence on academic wellbeing and workload. The final theme ‘let’s move forward together’ highlights the potential for university, staff and student engagement in developing learning analytics within a higher education system.

3.1 Theme: Facilitating learning

The theme ‘facilitating learning’ reflected academics’ perceptions that learning analytics could have the potential to benefit both academics and students. The majority of academics had some awareness of learning analytics and its use to develop predictive models of student retention. Most were aware of some of the types of data that were collected, but lamented the lack of immediate application of this data to improving student learning: *“We're collecting vast amounts of data and it doesn't seem to connect through to linking with practice or changes in practice”*. Related to this was concern about how the data collected was analyzed and presented in a way that would be useful to staff and students:

> *All these bits of information, and the key part there is, actually how do you make it meaningful for the intended recipient? Staff, student. … at what point does abstraction from that data actually create meaning? Or actually lose meaning.*

Despite questioning how data could be meaningfully presented for the intended recipients, many academics discussed the potential for learning analytics to be used to assist their teaching.

<u>3.1.1 Early Intervention</u>

Academics viewed learning analytics as having potential to provide information to drive early intervention when students were not coping. The difficulty in identifying students needing additional assistance without learning analytics was recognized; *“We don't know they're struggling until they're really really really struggling, until it becomes critical”*; along with the reduced likelihood of successful intervention at late stages: *“quite often they’re already discouraged. Their sense of self-efficacy is out the window and they are gonna pull out anyway”*. The identification of at-risk students was viewed as an opportunity to provide additional support to those students who needed it; *“I'd want to be able to identify those ones that are down at the lower level so that I could actually ask them personally to come to me if they would like some* *help";* while another discussed the possibility for an early referral to support services: *"there's a fundamental disconnect between the student knowing what services are available and connecting them to those services. If a system like that could potentially enhance that, then you see the positives of it".* Also welcomed was the potential to identify students whose results differed from their usual performance: *"Something that would maybe be more useful is that this student has got something that's abnormal to the other units or in this unit".*

3.1.2 Identifying Patterns, Risks and Protective Factors

While identification of at-risk students was deemed important, academics expressed a desire for learning analytics systems to extend beyond a focus on at-risk students to identify factors associated with student learning: *"Look at what can make a successful student",* and *"the protective factors" rather than risk factors".* As commented by one academic:

> *"It'd be good to look at both things, you know, what helps keep students retained as well as not always focusing on the negative stuff about, you know, dropouts and so on, but about focusing on retention and assistance and so on".*

Academics were interested in using learning analytics to identify patterns within cohorts to inform teaching: *"If we know that in a psychology cohort, there are particular types of students that enroll into this unit and there are particular needs, I think that's really helpful for us to know as a way of us as a school being able to address particular risks".* Based on patterns identified, changes could be made to teaching: *"If you look at it and you notice that there's a particular pattern of – I don't know – engaging with the online stuff. Okay. Well, what can I do to change it? It's clearly not working, what I'm doing at the moment. What can I do differently?"* Identified patterns could be used to predict the support services required for current and subsequent cohorts. Overall, academics identified that learning analytics would signal an opportunity for the academic to engage in a more reflective process. In this way, academics discussed how learning analytics could signal a change in the way academics teach. Namely, academics would no longer be reacting to student issues after the student has already started to disengage, but proactive in their approach to assisting students at some of the first signals that there could be an issue.

3.2 Theme: Where are the safeguards?

The theme 'where are the safeguards?' captured academics' reflection about the potential for the misuse of learning analytics. Academics identified several key concerns around the ethical use of learning analytics, specifically whether learning analytics would be used appropriately, whether the data captured, and therefore the conclusions made, are accurate, and then whether learning analytics is a redundant system.

3.2.1 Inappropriate Use

The greatest concern expressed by academics was the potential for learning analytics to be used inappropriately, for purposes other than student learning: *"There's so much risk of this data being used inappropriately, you've only gotta look at the NAPLAN system[1] to see what happens when data that could have been really valuable is used inappropriately"*. Academics also noted the potential for analytics to be used as staff performance indicators, rather than for student learning; *"I can see it being incredibly useful as long as it is not hijacked and added into [university omitted] expectations for academic performance";* and *"There is the scariness that that could definitely link to KPIs".* The potential for learning analytics to be used for other corporate purposes was also feared; *"We start off with something that's aimed at better teaching … It gets hijacked into meeting requirements from government, or requirements from the senior executive team, or whoever. It ends up as an admin task that we have to do"*. This discussion centered on the potentially conflicting interests of the university as a business versus the university as a place of education, with one academic noting that "*there's such contrasting priorities as far as university is concerned"*. The unknown potential range of application of learning analytics was a particular concern:

> *I guess I'm a bit concerned about this big umbrella, learning analytics, when there's clearly different components of abuse and function within the organization …Feedback to students versus the business end of the university versus amenity use. They are all so disparate. To me, it's just a bit too all-encompassing.*

Additional concerns were related to encouraging students to continue within a course when it may not be in their best interests. Academics acknowledged that *"some students just aren't cut out to come to university"*, and that "*At this particular point in time, they're not ready to be here and that's okay"*. Concern was expressed that learning analytics may 'push' students to continue with courses, *"helping people who are going to limp through several years of their degree and dislike all of it, but have been provided with so many resources that they feel they should be doing well"*, which was viewed as detrimental to students' well-being and self-efficacy: *"and that's unethical because if it's not for them, it's not for them"*.

Concern was also raised that learning analytics could be used to mold the 'perfect' student:

> *We're trying to kind of create the perfect student. So we're kind of poking and prodding and manipulating to prompt them to engage in activities at times that we think are gonna be the best fit for success in terms of their engagement and in terms of retention and all that.*

[1] NAPLAN (National Assessment Program – Literacy and Numeracy) is an annual assessment for Australian primary and secondary school students, with school results posted online.

Here the point is made that a 'one system fits all' approach based on analytics of effective student learning may not be applicable or appropriate to all members of the heterogeneous student population. Molding could go beyond directing activities to setting expected standards for students that may not be supported: "*who are we to say to a student that credit isn't a brilliant mark... I think we're imposing these ridiculous expectations"* and *"prediction set expectations. They don't necessary set opportunity for intervention"*.

Concern was also expressed that learning analytics based on student demographics had the potential to negatively label students even prior to their admission to university:

> *I think there's a potential tension between the economic imperative and the moral imperative, like what if it's – came out that kids from* [low socioeconomic areas] *drop out too much or whatever, so let's not bother advertising* [to] *them or going to their schools and ... and I see that as a massive, massive problem.*

Although many academics explored and agreed with the concerns about the inappropriate use of learning analytics, several academics explained how universities could mitigate these concerns. To counteract the potential for inappropriate use of learning analytics academics emphasized the importance of conceptual clarity in the proposed intent and use of learning analytics: "*intent has to be clear... The benefits have to be clearly laid out, because we can be overwhelmed with so many data that just ... they become very murky"*. To avoid 'murkiness', the importance of learning analytics being driven by a question rather than the available data was highlighted:

> *We need a question to start with. Then we go and collect that information. Then we make sure the interpretations we make from that data is warranted from the information. If we're looking at learning, then our question would be around learning and the inferences made from that. I think, in any kind of project, we would need that conceptual clarity about what are we actually wanting to know. How do we frame our question? Then, where would we best collect that information?*

This was contrasted with the perception of what was currently occurring:

> *It almost feels like this is coming the wrong way round. If we're going, "We're really concerned about student retention and the student experience. Then let's design an experiment to answer our questions." Instead, what we're doing is going, "Well there's all this data, how can we use it?" It just feels the wrong way round.*

3.2.2 Data Integrity

Academics were also concerned about the potential for learning analytics to collect data that did not accurately reflect student activities. Online lecture recordings were used as an example of this: *"The lecture recording, if you allow students to download* [rather than stream] *then you don't know whether they viewed it or not anyway and so those data are meaningless"*. A major limitation of data currently collected was the focus on online activities at the expense of offline activities, with the potential for students who do not leave electronic breadcrumbs to be identified as at risk. An example was provided:

> *A student who always attends lectures, let's say they live on campus or they walk to university or ride a bike so they don't log in to the parking system. They don't go onto Blackboard to download the lecture because they've watched it in person. They don't go to the library, or if they do they don't borrow. They're electronically silent. They don't exist and yet they're racing through.*

Many academics expressed concerns that relevant learning-related data would not be captured, especially if it is not digitized:

> *Just because you don't post on discussion board, you might have come to class and asked all your questions in class, had a healthy discussion, talked later, you might have e-mailed the unit coordinator and had a meeting with them. But that's not reflected anywhere, that's not captured.*

There was a strong consensus throughout the focus groups that learning analytics will potentially fail to collect relevant data for students who prefer face-to-face engagement.

> *Maybe it's the things prior to the disengagement from the online learning that might be more important. Like interaction with staff and things like that. I think it would be important to clarify that line of evidence and investigate at appropriate points.*

The idea that learning analytics was limited through not capturing face to face interactions continually resurfaced, *"It's missing those personalized elements and how we meet with students individually and as a team, too. It doesn't capture that and that's going to have a huge impact on student retention as well"*. Staff noted the importance of face-to-face interactions with students, *"There was some people who were feeling really valued when the lecturer knew at the end of the course their names. That was really important for them to find their mentor. That is absolutely not captured in this,"* and:

> *Our students will say that they really value it when staff know their names. They say it to me at the end of the course. You know when you go up to them at graduation and call them by their name, they'll say, "That's amazing that you know my name." You see it all over their faces. It's really important. That's not captured there.*

Conversely the assumption that physical presence equates to engagement was also raised as a concern, *"You could have students who attend and are present there, physically present, but not actually engaged. They're doing their shopping or Facebook"*.

Whether data collected was electronic or physical there was concern it could be inaccurate. To enhance the potential for accurate information staff discussed the lengths analytics may have to go to*, "But then do we start tracking how many students inquire and ask a question at the end of the lecture and which students they are and how long is their conversations? Where does it stop?"* The importance of face-to-face interactions to the student experience and the concern learning analytics would not capture the *"whole picture"* echoed strongly throughout the focus groups.

> *It's the same with any model, it's a model, it's uncaring and dispassionate. If you put good stuff into it, you'll get good stuff out. If you put garbage into it, you will get garbage out. My fear is we'll end up making decisions of the basis of flawed data.*

Furthermore, staff discussed the potential damage to self-esteem arising from inaccurate data: "*early days where everyone's getting messages inappropriately or something like that – this program is getting rolled out, you can see immense damage"*. An example was provided of the possible impact of a high achieving student incorrectly being sent an alert suggesting their performance was poor: *"So what could that have done to that kid's self-esteem if they'd suddenly got that and thought – oh my God, all this stuff I thought about myself, I had this confidence. That's just gone. If you have a low resilience person"*.

<u>3.2.3 Redundancy of Services</u>

Academics discussed the potential redundancy of some features of learning analytics. For example when discussing the potential for predicting at-risk students, one academic noted:

> *That's what* [first year unit] *is for.* [unit] *have formative assessments very early on to – and they contact students who are struggling. They have the* [program to support students] *in there. They have all sorts of staff in there to catch students before they start failing…*

Academics also noted other systems in place to provide support for struggling students: "*we write to all the conditional students and invite them to come to meetings,"* and "*make an appointment with the student with you, we already do that"*. The potential doubling up of services was seen as an inappropriate use of resources: *"But it also means someone is getting paid to do this and make pretty graphs when maybe that funding – those resources could be used elsewhere more appropriately in the university"*.

3.3 Theme: What about the Students!

The theme 'what about the students!' captured the concerns that academics had for their students. In considering the students, academics identified three key concerns: the nature of informed consent, whether learning analytics would actually help or support students to learn, and the potential detrimental effect on student wellbeing.

3.3.1 Informed Consent

During early discussions the importance of students providing informed consent for the use of their data in learning analytics was raised. Concern was expressed that students may not be fully aware of the data collected about them and how it was being used for learning analytics :*"They don't really know everything and I find that to be quite problematic"*, and

> *When students enroll and they fill in all the forms … are they under the impression that that information is purely for their enrolment or … are they aware that that information is then put with a whole lot of other information … I would never have, as a student, thought that if I'm filling in my name and address and giving contact details that that would be used for anything other than contact details"*

Academics explained that there is a lack of clarity around how the university would use student data and what it would be used for. In this way, academics identified concerns that went beyond student awareness, and moved to student approval: *"And do they agree with how it's gonna be used?"* With this concern in mind, the difficulties associated with opt-out consent procedures were discussed: *"It's not informed. It's opt-out. It's implying that if a student has issues, they can contact them and ask to have this data not collected, but without letting people know upfront that they can opt out".*

3.3.2 Impeding Personal Responsibility

Academics were also concerned that learning analytics may impede the personal responsibility of the student for their own learning. There was concern learning analytics would delay the development of work-readiness:

> *… at some point, they have to learn to be grownups. We can't keep parenting and there's a lot of discussion about the fact that students are growing up much later and developing – and don't – aren't as resilient, etcetera, because they are being so well-looked after from the time they come in to university and they actually struggle when they get out into the workforce because they've actually have to do stuff by themselves without people reminding them all the time.*

Concern was expressed that independent skill development could slow due to the highly supported university environment:

> *It almost prolongs the development of those skills, doesn't it? Yet, within our course, to being a speech pathologist, you do need to be an independent learner, you do need to develop all those skills … If we're going to start following up and going, "You haven't been to class, you haven't engaged in online learning. What's going on?" I don't know, when does it become their responsibility?*

The idea that learning analytics could foster a ‘parenting’ style of teaching was raised: *“I think we have to be really wary of moving away from the active learning principles and making them almost back to children”* and “*We don't want a helicopter university”*.

3.3.3 Impact on Student Well-being

Academics acknowledged the potentially damaging effects of the provision of learning analytics information on student wellbeing. Of key concern was the impact on students who were not performing well:

> *... as soon as you identify someone as struggling, you have just slashed their self-esteem. If all of a sudden, this kid who thought they were going okay gets a message saying, “You’re not going okay,” there’s so much risk of damage.*

The potential for poorly performing students to continuously receive negative feedback highlighted the need for additional support services to be provided. Without adequate existing systems, the key question was “*Who bears the responsibility for the follow up?”* As one academic asked, *“Where is that immediate ... Someone on the other end to support them?”* In response academics began discussing the possibility that responsibility for aftercare may lie with them, *“Surely we have a responsibility if we're going to highlight to students that they're not doing well, that we can provide a service to them”*.

Concern was also expressed about the potential negative impact of learning analytics information on the anxiety levels of high achieving students: *“they're going to want all of it* [information from learning analytics] *and we know it's not healthy for them. But they will go for it and they will opt in and that anxiety cycle will spiral out of control,”* and *“You give them more data about how they’re performing in relation with everybody else, the stress levels, the anxiety, the appeals…”*. This was seen as also having workload implications for academics: *“They'll be at our doors,”* and students may ask *“Can I come and meet with you, I'm so disappointed I only got 85% on my test”*. Concern was expressed that the university did not have adequate systems in place to deal with the anticipated increased levels of anxiety in students: “*We know that counselling services are already so stretched out”*.

3.4 Theme: What about us!

The theme ‘what about us!’ represents a concern expressed by academics in relation to the level of involvement and work that might be expected of them. In particular, academics were concerned about the impact learning analytics would have on workloads. Uncertainty was expressed over who would bear responsibility for acting upon learning analytics; *“Who bears the responsibility for the follow up?”* and *“Is the expectation that the course, or the unit coordinator would be the person that does this for all lecturers?”*; and how other staff would be kept informed: *“There's got to be some kind of line of communication. Also, at the other end of it, not* *doubling up so that your unit and course coordinators are doing exactly the same thing"*. The extent of the obligation to act upon learning analytics was unclear: "*What responsibility do the staff have to pursue ... Given this information, to do something about it?*. This concern about responsibility extended beyond providing feedback to students to the provision for pastoral care: *"Care for the student if they're constantly getting information that's very negative? Where is that immediate ... Someone on the other end to support them?"* It was noted that support services would need to be *"available all the time, day or night, if the students are going to get that information"*, when the current reality was that *"We know that counseling services are already so stretched out … Surely we have a responsibility if we're going to highlight to students that they're not doing well, that we can provide a service to them."*

Academics recognized that there needed to be clear instructions made available to ensure that learning analytics is an active process used within the higher education sector rather than a passive approach to facilitating student learning. Although several academics identified that they would want to ensure that there are clear boundaries regarding who should act on learning analytics and when this action should take place, many reflected that at some point everyone involved with a course should be made aware of how their students are performing so that their teaching can become more adaptive throughout a semester, which may ultimately help support students, rather than a reactive approach to learning support.

Despite the views that academics wanted to ensure services were not redundant, academics were primarily concerned that the additional load would not be supported; *"And how much is this in our workload?"* and "*I would hate to see this become an expectation of people's workloads, without having the support that they need to use it effectively";* and that this would become a source of tension: *"Workload – is it gonna be a source of anxiety"*.

Related to the concern over workload was the potential to lose control over time management through automated appointments driven by a learning analytics system:

> *… it's actually quite scary because if they're thinking that they've identified the student who has problems and they're going to put that student's appointment in your Outlook calendar, I can certainly see my Outlook calendar. I can't actually do any work because it's full up with students who have appointments and that some arbitrary system has decided.*

The underlying concept of learning analytics providing personalized learning was rejected by some academics: *"I'm sorry, but with 250 students in a unit, I cannot personalize their learning. I think this notion that we can personalize learning is a foofy [lie]"*. Throughout these discussions academics wanted further clarity on what the university would expect of them with regards to their interaction with learning analytics.

3.5 Theme: Let's move forward together

The theme 'let's move forward together' represented the academics' belief that there is a place for all academics and students to come together and discuss learning analytics with university decision makers. Throughout the focus groups was the call for academics and students to be involved in the development and implementation of a learning analytics system. Academics noted the tendency for systems to be led by those not involved in teaching: *"Sometimes I think this project is driven by the IT people …. Not by the people who actually work on the ground,"* and "*There isn't often on these committees people who are at the ground level. People who are actually teaching and who are interacting with students and who have a much better picture of what's actually happening at the ground level"*. The need for student involvement was also acknowledged: "*I'd also involve the students too"*.

4.0 Discussion

The objective of the present research was to identify and better understand academics' perceptions of learning analytics and the use of 'big data'. Within the context of this objective, academics saw the potential for learning analytics to improve learning practices (theme 'facilitating learning'), particularly where early intervention may benefit students at risk of failing. However, academics were concerned about the potential for the misuse of learning analytics (theme 'where are the safeguards?') and what learning analytics would mean for students, especially if students have not provided consent and do not know what data is collected and how it is used (theme 'what about the students!'). As such, academics reflected on the importance of developing ethical protocols that the university should follow, which would ultimately address concerns about informed consent and dealing with student distress. In turn academics noted the importance of transparency and communication between what is collected and analyzed within learning analytics and what academics are expected to enact as a result of these analyses (theme 'what about us!'). Despite these concerns, academics favored the development of learning analytics with student and academic input (theme 'let's move forward together') to ensure that learning analytics empowered student learning rather than facilitated 'helicopter teaching'. Of particular interest is that these themes emerged across all focus groups, which involved academics from different levels of the University. The key difference that emerged between these focus groups was how quickly the academics explored different issues. For example, academics with teaching responsibilities were quick to identify the potential impacts learning analytics may have on student wellbeing. While the psychology academics largely focused on the impact of learning analytics on students who were not performing well, speech pathology academics had a stronger focus on the impact of learning analytics on high performing students. The Academy fellows were quicker than other groups to identify, and discussed in more depth, the broader role learning analytics may have at an institution level and beyond, such as how learning analytics could be incorporated to follow graduates outside of the immediate institution.

The finding that academics saw the potential for learning analytics within higher education (theme: 'facilitating learning') expands on previous research about providing meaningful data to students (e.g., Corrin et al., 2013; Drachsler & Greller, 2012). In particular, it identifies that academics want to be able to feedback to students' key progress indicators (i.e., online engagement) based on the assumption that this information is both meaningful for the student and can be impacted by either instructor or student future behaviors. Underlying the theme of 'facilitating learning' was an emphasis that the key progress indicators should be based on present and potential future activity rather than just on past performance. This is consistent with the finding that academics would appreciate the opportunity to determine how students are progressing before it could be considered 'too late', as also noted in previous research (Arnold & Pistilli, 2012; West et al., 2015). The findings further indicate that learning analytics could form the basis for an important reflective tool for improving teaching practices and allow for an adaptive rather than reactive teaching practice.

Despite these potential benefits, the academics from the present study were skeptical that learning analytics would only be used for the benefit of the student or teaching practices (theme 'where are the safeguards?'). Extending upon previous findings, academics in our focus groups expressed concern over the potential for the inappropriate use of learning analytics as a performance management tool (West et al., 2015). Whilst academics across all teaching levels were concerned about the potential misuse of learning analytics data for labelling or stereotyping of students (Corrin et al., 2013; West et al., 2016), staff members were also concerned about whether learning analytics truly captures the information required. Although there is promising research on how learning analytics improves retention and student grades (de Freitas et al., 2015), academics were concerned about whether the data obtained represents the best predictors of student success. Academics in the present study were concerned that if there are a range of behaviors that are not captured, then the data collected, and subsequent analytics, are fundamentally flawed and misrepresent the student behaviors that may lead to success. The relevance and completeness of data collected for learning analytics purposes is a key concern for not only the academics in this research, but for the field of learning analytics generally (Siemens, 2013). Even if the analytics presented by higher education sectors is appropriately represented, it is vital for the institutions to communicate the reliability and practicality of the data to the staff members to allay fears about misrepresentation, and possibly improve enthusiasm for learning analytics.

In addition, academics were also concerned about whether the information derived from learning analytics would be acted upon appropriately by students (theme 'what about the students!'). Consistent with this finding, previous research has also questioned whether students have the capability to interpret the feedback that they receive (Corrin & de Barba, 2014; Miles, 2015). The present study additionally found that academics were concerned that alert systems used with learning analytics systems might impede personal responsibility for learning (Roberts et al., 2016), and as a consequence facilitate a 'helicopter university' that ultimately restricts the students' ability to learn independently. Further research is needed to determine how students interpret and use learning analytics feedback and to assist higher education institutions to develop clear guidelines and materials to assist academics and students in interpreting the feedback received from learning analytics. In addition to how students might (mis)interpret learning analytics feedback, academics expressed concern about the possible negative impact on student well-being. Concerns over the potential negative impact of learning analytics on students have been raised by other researchers (e.g., Gasevic, Dawson & Siemens, 2015), yet the extension of this view in academics' perceptions highlights the need for higher education institutions to develop mechanisms for dealing with the potential for student distress.

Academics raised another concern as to the extent to which students were aware of, and consented to, the use of their data for learning analytics. Learning analytics in some operational contexts of the business of higher education is arguably not research, and hence the protocols for obtaining informed consent in research are not mandated. However, the issue of whether and how to obtain consent from students for the use of their data in learning analytics is frequently raised (e.g., Greller & Draschler, 2012; Pardoo & Siemens, 2014; Roberts, Chang & Gibson et al., 2016; Slade & Prinsloo, 2013). In the absence of an agreed protocol we suggest that it is the responsibility of each university to develop transparent policy and procedures for obtaining informed consent from students.

Building upon previous reports (Corrin et al., 2013; Miles, 2015) the present findings also highlight the concerns some academic staff have about the additional workload learning analytics might impose. The present study identified that staff were concerned that they would ostensibly be expected to use learning analytics to improve student learning, yet there may be insufficient training provided, or that learning analytics could be used to inappropriately judge the academics teaching quality (theme 'what about us!'). These concerns expressed by academics further highlight the need for institutions to be transparent and clear with the purposes for learning analytics and to provide training, workload allocation and support for academics interested in using learning analytics. As clearly identified by the Technology Acceptance Model (Davis et al., 1989), if academics retain reservations about how learning analytics is going to be used, they may not readily adopt or integrate learning analytics in their own teaching practices. Encouragingly, despite these reservations, the majority of academics indicated their interest in the further development of learning analytics and supported academic and student engagement in this process (theme ‘Let’s move forward together’), which is promising for the implementation of learning analytics.

4.1 Limitations

The findings from our research should be interpreted within the context of the study. First, this research was conducted with academics who are not primarily involved in learning analytics, but do have a lot of experience with blended learning. As observed by West et al. (2015), academics views could be shaped by the level of contact that they have with learning analytics. It is possible that the views reported by the academics would differ from those reported by other academics that have no experience with learning analytics or blended learning. It is also important to note that the academics involved in the focus groups were primarily from a health sciences faculty, although the focus group with Academy Fellows included academics from across the university. It is possible that the differences in teaching approaches and assessment materials in other faculties could further influence perceptions regarding learning analytics. Future research across disciplines is required to understand disciplinary differences in academic attitudes towards learning analytics.

It may also be informative for future research to explore academic perceptions of various learning analytics systems, such as how the data is presented and what an academic would then be required to do. Doing so would provide scope for various quantitative paradigms that could help determine the best way a higher education institution displays learning analytics for academic staff.

4.2 Summary and Application of Findings

Viewing the introduction of learning analytics through a Technology Acceptance Model, the findings from this research indicate the importance of understanding the drivers of intention to use, such as perceived usefulness or perceived ease of use, may influence the adaptation and implementation of technology systems such as learning analytics. Academics appreciated the potential benefits of learning analytics to student learning and their own teaching practices, these positive beliefs or attitudes could indicate that academics would be more likely to adopt learning analytics. However, these positive beliefs were tempered by reservations about how learning analytics might impact on student learning, result in ‘helicopter’ teaching, and could ultimately be misused, highlighting the importance of addressing system characteristics. The current research findings also highlight the need for the university to focus on ‘facilitating conditions’ when implementing learning analytics, with the need for transparency and clear communication between the project and technical staff implementing learning analytics and academics as priorities.

The findings highlight the need to engage academics, as one of the key user groups of learning analytics, in the decision-making process when developing and implementing learning analytics initiatives. Whilst there are no quick solutions to the development of policies and procedures that address the concerns held by academics, one of the first points that should be addressed is the involvement of academics in the decision making process. This is consistent with previous requests that students, as another key stakeholder in learning analytics, should be involved in the decision making process (Beattie et al., 2014; Prinsloo & Slade, 2014; Roberts et al., 2016; Slade & Prinsloo, 2013). The involvement of academics as key stakeholders is important to develop institutional procedures and policies that are actionable within the higher education context. One way that universities can accomplish this is by including academics in learning analytics working parties, with responsibility to both provide input into decisions and distribute information to the wider academic community. By communicating clearly to other academics what decisions are being made and the rationale behind these decisions, and also providing an opportunity to raise concerns back to the working party would likely improve the acceptability of learning analytics within higher education. We hope that our findings stimulate further research and encourage higher education institutions to explore the perceptions of key stakeholders and use that information to develop clear policies and procedures that are acceptable to all involved.

References

Adams, D. A., Nelson, R. R., & Todd, P. A. (1992). Perceived usefulness, ease of use, and usage of information technology: A replication. *MIS Quarterly, 16*, 227–247.

Arnold, K. E., & Pistilli, M. D. (2012). *Course signals at Purdue: Using learning analytics to increase student success.* Paper presented at the Proceedings of the 2nd international conference on learning analytics and knowledge. Retrieved from http://s3.amazonaws.com/

Atif, A., Bilgin, A., & Richards, D. (2015). *Student preferences and attitudes to the use of early alerts*. Paper presented at Twenty-first Americas Conference on Information Systems, Puerto Rico. Retrieved from http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1297&context=amcis2015

Beattie, S., Woodley, C., & Souter, K. (2014). Creepy analytics and learner data rights. In B. Hegarty, J. McDonld, & S. K. Loke (Eds.), *Rhetoric and reality: Critical perspectives on educational technology. Proceedings ascilite* (pp. 421-425). Retrieved from http://www.ascilite.org/conferences/dunedin2014/files/concisepapers/69-Beattie.pdf

Castleberry, A. (2014). NVivo 10 [software program]. Version 10. QSR International; 2012. American journal of pharmaceutical education, 78(1), 25. doi: 10.5688/ajpe78125

Colvin, C., Rogers, T., Wade, A., Dawson, S., Gašević, D., Buckingham Shum, S., & Fisher, J. (2015). Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement. *Sydney: Australian Office for Learning and Teaching.* Retrieved from http://www.research.ed.ac.uk/portal/files/21121591/Final_Report_190615.pdf

Corrin, L., & de Barba, P. (2014). Exploring students' interpretation of feedback delivered through learning analytics dashboards. In B. Hegarty, J. McDonld, & S. K. Loke (Eds.), *Rhetoric and reality: Critical perspectives on educational technology. Proceedings ascilite* (pp. 629-433). Retrieved from http://ascilite.org/conferences/dunedin2014/files/concisepapers/223-Corrin.pdf

Corrin, L., Kennedy, G., & Mulder, R. (2013). Enhancing learning analytics by understanding the needs of teachers. *Electric Dreams. 30th Ascilite Conference Proceedings 2013* (p. 201-205). Retrieved from http://ascilite.org/conferences/sydney13/program/papers/Corrin.pdf.

Davis, F. D., Bagozzi, R. P., &Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*, 982–1002.

Dede, C., Ho, A., & Mitros, P. (2016). Big data analysis in higher education: Promises and pitfalls. *EDUCAUSE Review, 51*(5), 22-34.

Drachsler, H., & Greller, W. (2012, April). The pulse of learning analytics understandings and expectations from the stakeholders. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 120-129). ACM. Retrieved from http://dspace.learningnetworks.org/

Draschler, H., & Greller, W. (2016, April). Privacy and analytics: It's a delicate issue a checklist for trusted learning analytics. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 89-98). ACM. doi:10.1145/2883851.2883893

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and implementation of a learning analytics toolkit for teachers. *Educational Technology & Society, 15*(3), 58–76.

de Freitas, S., Gibson, D., Du Plessis, C., Halloran, P., Williams, E., Ambrose, M., . . . Arnab, S. (2015). Foundations of dynamic learning analytics: Using university student data to increase retention. *British Journal of Educational Technology, 46*, 1175-1188. doi:10.1111/bjet.12212

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64-71. doi:10.1007/s11528-014-0822-x

Guest, G., Namey, E., & McKenna, K. (2016). How many focus groups are enough? Building an evidence base for nonprobability sample sizes. *Field Methods.* 28, 1-20. doi:10.1177/1525822x16639015

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Educational Technology & Society, 15*(3), 42-57.Retrieved from http://www.jstor.org/stable/jeductechsoci.15.3.42

Kerly, A., Ellis, R., & Bull, S. (2008). CALMsystem: A conversational agent for learner modelling. *Knowledge-Based Systems, 21*(3), 238-246. doi:10.1016/j.knosys.2007.11.015

Kosba, E., Dimitrova, V., & Boyle, R. (2005, July). Using student and group models to support teachers in web-based distance education. In *International Conference on User Modeling* (pp. 124-133). Springer Berlin Heidelberg.

Kregor, G., Breslin, M., & Fountain, W. (2012). Experience and beliefs of technology users at an Australian university: Keys to maximising e-learning potential. *Australasian Journal of Educational Technology, 28*, 1382-1404. doi:10.14742/ajet.777

Lawson, C., Beer, C., Rossi, D., Moore, T., & Fleming, J. (2016). Identification of "at risk" students using learning analytics: The ethical dilemmas of intervention strategies in a higher education institution. *Educational Technology Research and Development, 64*(5), 957–968. doi:10.1007/s11423-016-9459-0

Lincoln, Y. S. & Guba, E. (1985). *Naturalistic enquiry.* Beverly Hills, CA: Sage.

Miles, C. (2015, June). Australian university teachers' engagement with learning analytics: Still early days. In EdMedia: World Conference on Educational Media and Technology (Vol. 2015, No. 1, pp. 108-108).

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology, 45*, 438-450. doi:10.1111/bjet.12

Prinsloo, P., & Slade, S. (2014). Educational triage in open distance learning: Walking a moral tightrope. *The International Review of Research in Open and Distributed Learning, 15*(4), 306-331. doi:10.19173/irrodl.v15i4.1881

Prinsloo, P., & Slade, S. (2017). An elephant in the learning analytics room – the obligation to act. In *LAK'17 Proceedings of the Seventh International Learning Analytics and Knowledge Conference* (pp. 46-65). ACM. doi:10.1145/3027385.3027406

Reed, P. (2014). Staff experience and attitudes towards technology enhanced learning initiatives in one Faculty of Health & Life Sciences. *Research in Learning Technology, 22*. doi:10.3402/rlt.v22.22770

Reed, P. (2012). Awareness, attitudes and participation of teaching staff towards the open content movement in one university. *Research in Learning Technology, 20*, . doi:10.3402/rlt.v20i0.18520

Reimers, G., Neovesky, A., & der Wissenschaften, A. (2015). *Student Focused Dashboards.* Paper presented at the 7th International Conference on Computer Supported Education. Retrieved from http://s3.amazonaws.com

Roberts, L. D., Howell, J. A., & Seaman, K. (2017, online first) Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. *Technology, Knowledge and Learning.* doi: doi:10.1007/s10758-017-9316-1

Roberts, L. D., Howell, J. A., Seaman, K., & Gibson, D. C. (2016). Student Attitudes toward Learning Analytics in Higher Education:"the fitbit version of the learning world". *Frontiers in Psychology*, 7:1959. doi:10.3389/fpsyg.2016.01959 .

Roberts, L., Chang, V., & Gibson, D. (2016). Ethical considerations in adopting a university- and system-wide approach to data and learning analytics. In B. Kei Daniel (Ed.). *Big data and learning analytics in higher education* (pp. 89-108). Switzerland: Springer.

Santos, J. L., Verbert, K., Govaerts, S., & Duval, E. (2013). Addressing learner issues with StepUp!: An evaluation. *Paper presented at the Proceedings of the Third International Conference on Learning Analytics and Knowledge.*Retrieved from https://lirias.kuleuven.be/bitstream/123456789/396691/1/lak-santos-final.pdf

Scholes, V. (2016). The ethics of using learning analytics to categorize students on risk. *Educational Technology Research and Development, 64,* 939-955. doi:10.1007/s11423-016-9458-1

Sclater, N. (Producer). (2015). Jisc learning analytics architecture. Retrieved from https://www.youtube.com/watch?v=PoH0NXUbrjw

Sclater, N. (2015). What do students want from a learning analytics app. Retrieved from http://analytics.jiscinvolve.org

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, 57, 1380-1400. doi:10.1177/0002764213498851 .

Slade, S., & Prinsloo, P. (2013). Learning analytics ethical issues and dilemmas. *American Behavioral Scientist, 57,* 1510-1529. doi:10.1177/0002764213479366

Slade, S., & Prinsloo, P. (2015). Student perspectives on the use of their data: Between intrusion, surveillance and care. *European Journal of Open, Distance and E-learning, 18*(1), 291-300.

Swenson, J. (2014). Establishing an ethical literacy for learning analytics. *LAK'14. Proceedings of the Fourth International Conference on Learning Analytics and Knowledge* (pp. 246-250). Retireved from http://dl.acm.org/citation.cfm?id=2567613

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273-315.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*, 186–204.

West, D., Huijser., Heath, D., Lizzio, A., Toohey, D., & Miles, C. (2015). Higher Education Teachers' Experiences with Learning Analytics in Relation to Student Retention. In T. Reiners, B. R. von Konsky, D. Gibson, V. Chang, L. Irving & K. Clarke (Eds.). *Globally connected, digitally enabled: Proceedings of the ascilite 2015 conference* (pp. 296–307). Perth, 29 November–2 December.

West, D., Huijser, H., & Heath, D. (2016). Putting an ethical lens on learning analytics. *Educational Technology Research and Development, 64,* 903-922. doi:10.1007/s11423-016-9464-3

Willis, J. E., Slade, S., & Prinsloo, P. (2016). Ethical oversight of student data in learning analytics: A typology derived from a cross continental, cross-instititutational perspective. *Educational Technology Research and Development, 64*, 881-901. doi: 10.1007/s11423-016-9463-4