Action-oriented, Accountable, and inter(Active) Learning Analytics for Learners

Simon Knight, Theresa D. Anderson

Connected Intelligence Centre
University of Technology Sydney
Broadway, Ultimo, NSW 2007, AUS
Simon.Knight@uts.edu.au,
Theresa.Anderson@uts.edu.au

ABSTRACT
This short paper describes our developing theorizing around the nature of learning analytics, and specifically 'learning analytics for learners'. We describe a value sensitive, participatory, design process for the development of a learning platform and learning analytics. Preliminary design sessions with students illustrate the approach we have taken to developing analytics in one masters level course at the University of Technology Sydney. We highlight 'three As' in our approach. We argue that: (A1) learning analytics for learners should be action oriented, with a focus on process-based analytics that lead to actionable insight; (A2) accountable, supporting sensemaking around learning data across stakeholders; and (A3) (inter)active, involving students in understanding their own learning through analysis of processes (per A1), made visible and accessible to them (per A2), and in which they have a say. We thus argue that engaging students in participatory design of learning analytics and their platforms is a key potential of LAL.

Categories and Subject Descriptors
K.3.1 [**Computers and Education**]: Computer Uses in Education

General Terms
Measurement, Design, Human Factors, Theory

Keywords
Learning Analytics, Participatory Design, Algorithmic Accountability, Social Learning Analytics, Value Sensitive Design, Human Data Interaction, Collaborative Sensemaking, Learning Analytics for Learners

1 INTRODUCTION
Learning analytics is the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs," [1]. However, there has been concern that learning analytic technologies focus on passive interventions for 'predictions' around 'underperforming' and 'at risk' students, rather than empowering students to create and use their own learning analytic tools [14]. Many learning technologies are pedagogically neutral, with little user-centered or participatory design involved in their conception or implementation [15]. In parallel, there is a desire to move 'beyond the LMS' in understanding student learning data [10], with calls for development of an open and modularised approach – making use of a variety of open source tools which might be linked in ad hoc ways across different, social, learning contexts [23], with openness entailing [23]:

1. Openness of process (algorithms and tech)
2. Modularized integration
3. Openness of data and platforms across stakeholders such that the needs and values of respective stakeholders are met – a key focus of our own work

In our work we have drawn association between this desire for open learning analytics (OLA) and the value sensitive design (VSD) approach [4], in particular regarding the third point above. In VSD, there is a focus on the role of values and how they are undermined or promoted in the design of computer systems. For example, Friedman notes that the design decision not to include an 'off' switch on systems that monitor behavior (for whatever legitimate work or leisure reasons), removes a freedom from users to maintain their own privacy. Of high relevance to learning analytics, Friedman [4] also notes that user autonomy can be maintained in cases where some design decisions encode particular ways of working (for example, technical implementations of search functions) into a system, while maintaining user freedom over other elements (for example, the formatting of their texts); what is key, is that "autonomy is protected when users are given control over the right things at the right time." [4 p.18].

A number of key foci emerge from the VSD approach [5] that are of relevance to learning analytics for learners; thus value sensitive design:

1. Is 'proactive' – it should run through a whole design process
2. Has a broad focus, including the role of technology in educational contexts
3. Encompasses a broad set of values, (e.g. beyond 'cooperation' in computer supported cooperative work (CSCW) research)
4. Makes use of an integrated methodology involving analysis of conceptual, empirical, and technical concerns.
5. Takes an interactional approach, in which it is understood that values emerge in the interaction between technologies and social systems, but are not determined by either in isolation.
6. Holds that some moral values are independent of the particular group or individual (e.g. values relating to human welfare and justice).
7. Holds that some values are universally held, but vary in instantiation across cultures and contexts (e.g. how privacy is understood and implemented).

For learning analytics, the implications are – at least – that we should:

1. Consider values in the design and implementation of learning analytics, throughout the process, considering how technologies can reify values, and their interpretive flexibility. In earlier work we have considered this concern in light of underlying theoretical positionings [12], with more recent explication [13] pointing to the potential of 'Claims Analysis' – analysis of the ways values are implemented in systems – to clarify and critique implicit models of user-tool interactions [see, 17]
2. Consider the ways that analytic devices might capture, operationalize, and represent, constructs of significance in the learning sciences across contexts and cultures, and the role of learners and educators in that.

With regard to the iterative process taken in VSD, three kinds of analysis are conducted: conceptual, empirical, and technical. In conceptual investigations the nature of values from different stakeholders, and the ways that technologies support or diminish them are analysed. Conceptual investigations are thus analyses of the key constructs of interest in the design process, and their weight and balance. Empirical investigations, then, investigate specific social contexts for the designed technology, and – iteratively – the impact of the technology on those contexts. Third, technical investigations provide analysis of the suitability of particular technological designs for the values and context targeted.

This approach to design meets some of the ethical concerns raised around learning analytics [20, 25], with calls for students as collaborators at varying intervals through a design and analytic process in a student-centric approach to learning analytics. As such, VSD may be targeted at maintaining student autonomy, and ensuring students are included in analytic devices (including through provision of educational resources regarding those analytic devices). Through involvement in the design of analytics, stakeholder needs (and acceptable constraints) can be conceptualized and operationalized into technologies in ways that support, rather than diminish, their values.

2 THE MDSI CONTEXT

At the University of Technology Sydney, the authors' centre (the Connected Intelligence Centre) runs a new transdisciplinary Masters in Data Science and Innovation (MDSI). In support of that course, the authors and other UTS colleagues have begun a participatory design process with a subset of students from the MDSI (for which UTS ethics approval has been granted).

Using a participatory design and action research [3] process UTS staff and MDSI students are co-developing a space for creatively exploring transdisciplinary and professional connections across their course supported by a 'community steward'. The intention is that this open environment will enable students to actively participate with professionals and shape an online community to supplement their more traditional online offerings (e.g. Blackboard). Learning analytics will provide students with data about their learning to interrogate and respond to for formative purposes and academics with data about the value of this model of engagement for postgraduates. The research thus aims to engage a participatory co-design methodology through which researchers and students develop deeper understandings of learning 'beyond the LMS'.

Framed as participatory action research, the project pursues the iterative design of an online environment for learning. Interested students will volunteer to attend challenge days to develop the online environment, with all students invited to use and feedback on the developed technologies on an ongoing basis informally and using established course feedback mechanisms. We aim to establish a co-design method for development of an online learning environment (the process), with a learning environment as an end product, for use by students in their own learning. Design artefacts will be collated through the iterative process, with participants and academic co-designers encouraged to reflect on the process and the needs a developing online environment might meet.

In both the initial specification, and ongoing implementation process, a community steward will support the iterative design. The steward will act in line with Wenger et al.'s [8] description of technology stewards:

> *Stewarding technology involves knowing a lot but it also involves a lot of intuition, guesswork, and the patience to tolerate uncertainty and not knowing. Tech stewards face fundamental questions that can't be answered in advance or from a distance. This uncertainty requires insight and inventiveness on the part of tech stewards and the community, whether through making do with what's available, inventing technical workarounds, or forging ahead with new design efforts…Determining what communities will tolerate or demand, including their needs, interests and motivations, makes stewarding interesting work. This kind of work cannot be reduced to one formula* [8 p.146]

The steward's role is one of advocacy and responsiveness, supporting student activity within the community (and its technologies) to foster a *participatory* value sensitive design process. They will thus use their knowledge and intuition in the fluid design of the online space, supporting effective community use of the space, developing workarounds, and co-developing new designs. Critically, this role requires understandings about the human **and** the technological contexts of the learning space we are developing for the MDSI program. The steward will work to understand the community's needs and values through interaction online, supporting platform and learning analytic design and community concerns for UTS-staff, professional-partners, and students.

At the time of writing, the first 'design day' has been conducted, with 8 physically co-located students and 7 contributions from online survey responses. An ideation process has been used which asked participants to consider the following questions individually and in groups:

1. Why do you participate in online environments?
2. Thinking about specific activities involving tools or online spaces, do you have any examples of great practice?
3. In your MDSI experience thus far, what obstacles have you encountered in online learning? What has prevented you from participating as you would have liked?
4. If you could design anything to support your learning, what would it be?

These questions were designed to elicit responses that: considered the range of tools and platforms available; would focus on examples of ‘getting it right’, of design spaces that have successfully met challenges; and that this consideration would be targeted at specific challenges (3) to be met through actionable design changes (4). A final question was asked: “Now to sum this up – how do we reconcile all this? All the support is now in place – what has to happen next?” This last question was designed to encourage the students to ‘get concrete’, and particularly to consider actions we could make to support them in their design process.

Through the process of the design day, a number of themes (expressed as questions) have been identified; these are now being discussed further in an ongoing online design process:

- How do we ensure our site is responsive, and well designed?
- How do we tackle the need for a sustainable, searchable, tagged knowledge base & Q&A space?
- How do we integrate external tools and platforms effectively?
- How do we guide learners through resources? (E.g. sticky posts and collaborative filtering)
- How do we manage identities internally and externally, integrating existing profiles, and crediting engagement & participation (reputation management)?
- How do we create a constructive feedback and discussion area (possibly with multimedia tools)?
- How to we engage with industry through the site, and understand what they’re looking for?
- How do we build a space for constructive-community-based feedback and formative iteration, with possible ‘employer-ready’ output?
- How do we gamify and show participation to support learning and effective community?

In addressing these design questions we have taken an (inter)active participatory approach focusing on action orientation, and understanding the various lenses and levels through which the design will be seen. For example, rather than imposing a perspective of gamification which foregrounds data only to lecturers, and focuses on content learning over interaction, we are engaging in a value sensitive approach to understanding what ‘gamification’ and ‘participation’ might mean in this learning context and community and whether or not learners see it as adding value to their experience.

3 AAA APPROACH TO LAL

Through our work with students, and the VSD approach we have taken, we have begun to think of learning analytics for learners (LAL) in terms of three ‘A’s, in brief:

1. Action oriented, integrating (social) processes – LAL should focus on what we do, not just what we know, and how we change, not just where we are. We see learning as fundamentally interactional, and tool-mediated in nature; learning analytics brings new potential for process oriented feedback and support.
2. Accountable, Accessible, and Multi-layered – LAL should be accountable, and accessible, at various levels of the learning analytic system, from the micro (individual teachers and students) to the macro (institutions and collections of institutions). New challenges around collaborative sensemaking are foregrounded by learning analytics, but this multi-layered feature should be embraced and remain visible rather than shied away from.
3. (Inter)active, Participatory, and Engaging – LAL should involve learners in understanding their own learning, through analysis of processes (A1), made visible and accessible to them (A2), and in which they have a say (A3). Engaging students in participatory design of learning analytics and their platforms is a key potential of LAL.

The potential of such a shift is to bring students into active discussion about their own learning, and the diversity of experiences of that learning (as is explicit in VSD). For example, our approach might explore the means through which diversity of experience can be valued in the application of models of social learning analytics, which have a focus on learners as producers (for example, through blogs where learners are encouraged to share and discuss learning as it is unfolding and not just showcase outcomes) [2]. One aim, then, is for systems of learning process analytics to understand “what is going on in a learning scenario” [21 p.1632] rather than predictive models of future outcomes (or, to shift to process rather than ‘checkpoint’ analytics [16]).

While these processes level analyses afford new and important potential to support student learning – and their own understanding of that learning – they also introduce complexities. In earlier work (by the first author, [11]) it was noted that conveying learning information to multiple audiences – from students, teachers and parents, to vice-chancellors, heads of professional associations, and government ministers – is complex. This complexity is compounded by the various skill levels and needs of the audiences, with users which to gain different insights from any data (from personal learning improvement, to systems-level change), and having differing skills to interpret and make use of that data towards their needs. There we noted that “LA may in part be about personalization of learning through analytics, but it is also about engaging learners and educators in a sensemaking process around the data” [11 p.3]. Understanding of learners’ and educators’ interpretations of learning, and of the value of the data, may be explored through analysis of this sensemaking process.

An emerging field of 'Human Data Interaction' (HDI) builds on work in human computer interaction (HCI) to explore the specific interactions of agents with data to "support end-users in the day-to-day management of their personal digital data..." with an understanding of data as of an "inherently social and relational character" [3 p.1]. Thus, "HDI is a distinctively socio-technical problematic, driven as much by a range of social concerns with the emerging personal data ‘ecosystem’ as it is by technological concerns, to develop digital technologies that support future practices of personal data interaction within it" [3 p.3].

HDI, then, highlights the tensions between ‘our’ data and ‘my’ data, and the corresponding issues of data ownership and control. These issues are of course key in learning analytics, where data is ‘produced’ by individuals through their learning processes, and analysed (and contextualized) through comparison with other groups and individuals within the specific learning activity, often through the use of institutionally owned technologies.

HDI, then, is concerned not only with how people use and create data, but with how they both visualise and understand the data, and how that data is made use of within social relational systems (by data creators and processors); the problems of connecting learning analytics across levels from the macro, meso, and micro, can thus be seen in terms of HDI.

In learning analytics contexts one of the things we're interested in is how stakeholders - managers, educators, students, parents, etc. - interact with 'their' data at the various levels of granularity. Of course part of that is about how that data is represented and visualised, and the kinds of collaborative sensemaking processes that stakeholders engage in.

The challenges – flagged in [3 p.3] – of relevance to learning analytics, then are:

- *Personal data* ***discovery****, including meta-data publication, consumer analytics, discoverability policies, identity mechanisms, and app store models supporting discovery of data processers*
- *Personal data* ***ownership and control****, including group management of data sources, negotiation, delegation and transparency/awareness mechanisms, and rights management.*
- *Personal data* ***legibility****, including visualisation of what processors would take from data sources and visualisations that help users make sense of data usage, and recipient design to support data editing and data presentation.*
- *Personal data* ***tracking****, including real time articulation of data sharing processes (e.g., current status reports and aggregated outputs), and data tracking (e.g., subsequent consumer processing or data transfer).*

[3 p.18] (emphasis added).

In the learning analytics context, the particularly interesting challenge is to make these concerns *legible* in such a way as to make it clear to learners not only what behaviour or change is expected/observed in them, but how their data has been collated and used, how their data-feedback is both an end-product and fundamental component of the analytic process, and how changes to the data (for whatever reason) might relate to them and the fuller analytic set. Of course part of HDI must be how we facilitate data subjects to understand their data-relations; some of this will be difficult, understanding the balance of clarity and accessibility alongside conceptual (and methodological) complexity is an important challenge. Some ideas are hard, and working with their coarseness is exactly what makes them productive.

Learning analytics for learners, then, must include accountability and accessibility considerations. Yet, while algorithms are key to learning analytics, their design and implementation are restricted to a small group of individuals, often excluding students and even academic educators. Thus, a concern has been raised regarding the pedagogic and ethical imperative for “algorithmic accountability” (Diakopoulos, 2014). This concern implies the need to ensure appropriately accountable and accessible (or, legible) HDI across the range of stakeholders. In considering a broader discourse around the nature of programming and code as ‘actors’ in education Williamson [24 citing , 6] notes the construct of calculated publics:

> *as algorithms are increasingly being designed to anticipate users and make predictions about their future behaviours, users are now reshaping their practices to suit the algorithms they depend on. This constructs ‘calculated publics,’ the algorithmic presentation of a public that shapes its sense of itself.* [24 p.30]

That is, learning analytics have the potential to impact on how learners and educators (and administrators) act, and interact (as HDI foregrounds). Consideration of these changes, and of the actors’ understanding of them, is important to building learning analytics. Other communities have tackled such issues, for example the end-user customization community has explored the ways in which end-users modify software applications through their embedded eco-systems, and the ways in which interfaces enable such adaptation (MacLean, Young, Bellotti, & Moran, 1991).

In other work reviewing ‘collaborative visualisation’ [8] the relationships between visualization and computer supported cooperative work (CSCW) are highlighted, with CSCW holding key potential in understanding:

- The relationships between users and their roles (for example, student, administrator) and how their tasks and needs (and, per VSD, their values) are defined
- The kinds of learning gain, insight, consensus, etc. gained in the process of collaborative visualization (as compared, say, to a focus on creation of fixed ‘products’).
- The *processes* of data interaction (or, as discussed above, HDI), and visualization development
- The insights groups gain through collaborative visualisations, and how this is understood in the context of group success, and the qualities of the visualisations themselves.

In learning analytics, understanding these concerns offers an additional site for analytics in itself. Understanding the ways in which stakeholders at various levels make sense of, and draw value from, data affords opportunity to investigate that sensemaking as a learning process. The potential is to understand both how stakeholders extract meaning from data, and action this, and in understanding how best to support these processes across and within stakeholder levels.

In our perspective, one means through which to engage in the process of developing effective means for collaborative sensemaking is through engaging in participatory design processes. By co-designing, learners are engaged in understanding the kinds of values technologies can instantiate, and their connection to the social and technological context of their learning. The potential outcome is for learners to be involved in open sensemaking around their own learning processes, as they are made visible and accessible to them in ways that they have been involved in designing.

While earlier research has analysed participatory processes in understanding the learning context [7], it has not, to our knowledge, involved development of the platforms and analytic approaches for that learning. In that earlier work [7], processes of peer interaction and public development of learning artefacts alongside ‘badges’ (credits given for particular kinds of in-course behaviours) were central. As the Open University’s Innovating Pedagogy 2013 report highlighted, there is untapped potential in mobilising badges and learning analytics for the support of learning [22]. Their potential is in the recognition of learning across sites and diverse sets of knowledge and skills, in support of novel assessments [9]. Moreover, there is potential for peer-badging in participatory collaborative contexts [19], bringing together social learning, participatory learning design, and learning analytics.

In forthcoming work of this kind, McPherson et al., [18] use focus group analysis, asking participants “what data related to their learning they would like to have and why they would like to have it” [18 p.2], suggesting that through analysis of disciplinary differences, student data needs (in their specific contexts) can be assessed and met. Designing in partnership with learners what 'meaningful' participation is (and how it should be credited) helps with elusive measurement in blended learning where 'activity' is often limited to what actions are visible to the tool and the teacher. We thus see great potential in the kind of participatory, value sensitive, design process we describe here, which builds on open learning analytics, to take an ethical approach to human data interaction and collaborative sensemaking.

4 DISCUSSION

Participatory design approaches support human values by embedding a practice of transparency and openness into the design process. By foregrounding values and helping teachers as well as learners navigate the value-laden terrain of systems designed for learning, VSD adds another critical dimension to the design of learning analytics that are meaningful for learners. What is particularly significant about VSD is the focus on supporting enduring human values. Unlike many other design techniques that will focus on the workplace or the classroom context, VSD enlarges the arena in which one considers ethical issues and the values that centre on human well-being, dignity, justice, welcomes, and rights. It is not just about designing technology, it is about recognising the (often invisible) impact and implication of protocols and policies that surround and inform the use of any technology. Applying a VSD mindset helps us – as researchers and teachers – and our student co-designers articulate the human values we seek to account for in the 'design' of the MDSI learning experience and in the process the LAL that will make that experience visible to all stakeholders. Thinking about our design intentions can inform not only the design of the blended learning environment we are aspiring to co-create, but also the institutional practices and protocols that will shape its use. It invites us to have conversations and discuss the relative overlaps and potential contradictions of our value systems in the design of learning analytics for learners.

5 REFERENCES

[1] 1st International Conference on Learning Analytics and Knowledge 2011 | Connecting the technical, pedagogical, and social dimensions of learning analytics: 2011. *https://tekri.athabascau.ca/analytics/about*. Accessed: 2013-05-21.

/[2] Buckingham Shum, S. and Ferguson, R. 2012. Social Learning Analytics. *Educational Technology & Society*. 15, 3 (2012), 3–26.

[3] Crabtree, A. and Mortier, R. 2015. Human data interaction: Historical lessons from social studies and CSCW. *ECSCW 2015: Proceedings of the 14th European Conference on Computer Supported Cooperative Work, 19-23 September 2015, Oslo, Norway* (2015), 3–21.

[4] Friedman, B. 1996. Value-sensitive design. *interactions*. 3, 6 (1996), 16–23.

[5] Friedman, B. et al. 2002. Value sensitive design: Theory and methods. *University of Washington technical report*. (2002), 02–12.

[6] Gillespie, T. 2014. The relevance of algorithms. *Media Technologies: Essays on communication, materiality and society*. T. Gillespie et al., eds. MIT Press. 167–194.

[7] Hickey, D.T. et al. 2014. Small to Big Before Massive: Scaling Up Participatory Learning Analytics. *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge* (New York, NY, USA, 2014), 93–97.

[8] Isenberg, P. et al. 2011. Collaborative visualization: Definition, challenges, and research agenda. *Information Visualization*. 10, 4 (Oct. 2011), 310–326.

[9] Jovanovic, J. and Devedzic, V. 2014. Open Badges: Novel Means to Motivate, Scaffold and Recognize Learning. *Technology, Knowledge and Learning*. 20, 1 (Aug. 2014), 115–122.

[10] Kitto, K. et al. 2015. Learning analytics beyond the LMS: the connected learning analytics toolkit. (2015), 11–15.

[11] Knight, S. et al. 2013. Collaborative Sensemaking in Learning Analytics. *CSCW and Education Workshop* (San Antonio, Texas, USA, 2013).

[12] Knight, S. et al. 2014. Epistemology, assessment, pedagogy: where learning meets analytics in the middle space. *Journal of Learning Analytics*. 1, 2 (2014).

[13] Knight, S. and Buckingham Shum, S. in submission. Theory and Learning Analytics.

[14] Kruse, A. and Pongsajapan, R. 2012. Student-centered learning analytics. *CNDLS Thought Papers*. (2012), 1–9.

[15] Laanpere, M. et al. 2012. Pedagogy-Driven Design of Digital Learning Ecosystems: The Case Study of Dippler. *Advances in Web-Based Learning - ICWL 2012*. E. Popescu et al., eds. Springer Berlin Heidelberg. 307–317.

[16] Lockyer, L. et al. 2013. Informing Pedagogical Action: Aligning Learning Analytics With Learning Design. *American Behavioral Scientist*. (Mar. 2013), 0002764213479367.

[17] McCrickard, D.S. 2012. *Making Claims: The Claim as a Knowledge Design, Capture, and Sharing Tool in HCI*. Morgan & Claypool Publishers.

[18] McPherson, J. et al. Forthcoming. Learning analytics and disciplinarity: Building a typology of disciplinary differences from student voices. *Proceedings of the 6th International ACM Conference on Learning Analytics and Knowledge* (Edinburgh, UK, Forthcoming).

[19] Pedro, L. et al. 2015. Peer-supported badge attribution in a collaborative learning platform: The SAPO Campus case. *Computers in Human Behavior*. 51, Part B, (Oct. 2015), 562–567.

[20] Prinsloo, P. and Slade, S. 2015. Student privacy self-management: implications for learning analytics. *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge* (Poughkeepsie, New York: A. C. M., 2015), 83–92.

[21] Schneider, D. et al. 2012. Requirements for learning scenario and learning process analytics. (2012), 1632–1641.

[22] Sharples, M. et al. 2013. *Innovating Pedagogy 2013*. Technical Report #2. The Open University.

[23] Siemens, G. et al. 2011. Open Learning Analytics: an integrated & modularized platform. Society for Learning Analytics Research (SoLAR).

[24] Williamson, B. 2015. Digital education governance: data visualization, predictive analytics, and "real-time" policy instruments. *Journal of Education Policy*. 0, 0 (Apr. 2015), 1–19.

[25] Willis, J.. et al. forthcoming. Ethical oversight of student data in learning analytics: a typology derived from a cross-continental, cross-institutional perspective. *Educational Technology Research and Development*. (forthcoming).