Citizen Science: The Ring to Rule Them All?

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Abstract: There are many uncertainties about the future of e-Learning, but one thing is certain: e-Learning will be more data-driven in the future. The automation of data capturing, analysis and presentation, together with economic constraints that require evidence-based proof of impact, compels this data focus. On the other hand, the importance of community involvement in learning analytics and educational data mining is an accepted fact. Citizen science, at the nexus of community engagement, and data science can bridge the divide between data-driven and community-driven approaches to policy and content development. The rationale for this paper is the investigation of citizen science as an approach to collecting data for learning analytics in the field of e-Learning. Capturing data for policy and content development for learning analytics through citizen science projects is novel in the e-Learning field. Like any other new area, citizen science needs to be mapped in terms of the existing parent fields of data science and education so that differences and potential overlaps can be made explicit. This is important when considering conceptual or functional definitions, research tools and methodologies. A preliminary review of the literature has not provided any conceptual positioning of citizen science in relation to the research topics of learning analytics, data science, big data and visualisation in the e-Learning environment. The intent of this paper is firstly to present an overview of citizen science and the related research topics in the academic and practitioner literature based on a systematic literature review. Secondly, we propose a model that represents the relationship between citizen science and other salient concepts and shows how citizen science projects can be positioned in the e-Learning environment. Finally, we suggest research opportunities involving citizen science projects in the field of e-Learning.

Keywords: E-learning, learning analytics, data science, citizen science

1. Introduction

The data revolution is under way and it is reshaping knowledge production through new ways of data capturing, analysis and reporting in all spheres of life (Kitchin, 2014). Data science and learning analytics provide the educator with methods to obtain evidence-based information towards improving the experience of the learner in higher education (Baker *et al.*, 2006; Clarke and Nelson, 2013; Scheffel *et al.*, 2014; Prinsloo *et al.*, 2015; Willis, Slade and Prinsloo, 2016; De Freitas and Bernard, 2017), both in an out of the classroom. A later and dynamically growing approach to capturing data is the citizen science approach. However, big data and, more specifically, citizen science as platforms both to capture data and to report data for learning analytics are not widely used or reported in literature (Chen *et al.*, 2016; Chaurasia and Frieda Rosin, 2017).

Given the various, sometimes contradicting definitions of the terms related to the data revolution, we present our interpretation of the terms *data science*, *learning analytics* and *citizen science*, and some contextualisation in the field of higher education, as follows:

Data science has been defined as the study of the generalisable extraction of knowledge from data (Dhar, 2013). Modern society produces vast amounts of data, but most data is unstructured and requires processes and methods to extract useful information and present it in an understandable and useful format (Provost and Fawcett, 2013). ***Citizen science*** can be described as the engagement of ordinary citizens in gathering large quantities of data through various projects over an extended period of time that have a direct impact on either the society or the environment (Ali *et al.*, 2013; Allan and Redden, 2017). Traditionally, citizen science, is used in the fields of natural sciences and environmental sciences to gather data across a wide spectrum of research fields. Often, projects engaging citizens in gathering data, aim at obtaining vast quantities of data across a spectrum of participants that is unattainable by the individual researchers. In recent years this field has grown, and professional citizen science societies have been established throughout the world. Within e-Learning, ***learning analytics*** can be described as the measurement, collection, analysis and reporting of electronic data gathered in a virtual learning environment about learners in their contexts, with the purpose of understanding and optimising the learning environment in which it occurs (Agudo-Peregrina *et al.*, 2014; Baer and Norris, 2016; Muslim *et al.*, 2016). Earlier definitions of learning analytics focused on the use of data in predicting and advising future learning (Hiller, Kyrillidou and Self, 2008; Palmer, Holt and Bray, 2008; Zhang *et al.*, 2016). For the purpose of this paper, we use the definitions of *analytics* and *learning analytics* proposed by Barneveld,

Arnold and Campbell (2012) as "*an overarching concept that is defined as data-driven decision making*" and "*the use of analytic techniques to help target instructional, curricular, and support resources to support the achievement of specific learning goals"* respectively. The use of data in various formats to obtain a certain goal is eminent in these two definitions. However, in the e-Learning environment the adoption of tools and mechanisms that can be used by the educator to gather data required for data mining, data analysis and visualisation in integrated environments is lacking. Frameworks and tools may be designed for specific learning management systems (LMSs), such as seen in the proposed solution developed for the Moodle LMS (De Freitas and Bernard, 2017) and the proposed Workbench by Rodrigo *et al.* (2012).

As mentioned, data science and learning analytics provide the educator with methods to obtain evidence-based information towards improving the experience of the learner in higher education, but educators and policy makers often require additional training and software to gather data or apply data mining and visualisation techniques both in and out of the classroom (Baker *et al.*, 2006; Clarke and Nelson, 2013; Scheffel *et al.*, 2014; De Freitas and Bernard, 2017). The use of citizen science in higher education and e-Learning is a relatively new area of practice and research. In this field, the community can contribute to learning analytics through well-designed citizen science projects. Learners, parents, educators, facilitators, policy makers and the public, among others, can contribute to learning analytics through citizen science. Bochichhio (2015) identifies mobile crowd sensing as a viable way to introduce students as the community to new learning environments, but in doing so, it also allows for the collection of big data and provides a platform for reporting back to the community.

The purpose of this paper is to determine, through a systematic literature review process, studies that address the use of citizen science as a scientific research tool in gathering data to be used in relation to the e-Learning environment and present a conceptual model positioning citizen science in the field of e-Learning and relating it to other critical concepts such as data science, big data, learning analytics and visualisation. To conclude this paper research opportunities in e-Learning are identified that can contribute to future research areas. The outcomes of these studies will be used in future studies to determine the instructional, architectural and theoretical angels as trend in this research field.

2. Methodology

The systematic literature review process followed here is described in section 2.1. Based on the findings of this process, we have identified research trends and areas positioning citizen science in relation to the e-Learning environment. These results are presented in sections 3.1 and 3.2, and we propose a model that positions citizen science in relation to the salient related concepts in the e-Learning environment. In section 3.3, a synthesised set of concepts are proposed that can be considered for placing citizen science in the field of e-Learning. In section 3.4, research opportunities related to citizen science are highlighted.

2.1 Systematic literature review

The purpose of the systematic literature review is to gather current published research on learning analytics in the domains of citizen science and data science. A literature review is a rigorous and systematic process undertaken to identify, select and critically appraise relevant research and summarise applicable literature. Based on the typology published by Grant and Booth (2009), the systematic review method was selected. The purpose of this review process is to systematically search for, appraise and synthesise research evidence using specific search criteria. The knowledge obtained through a systematic literature review is explicit, reproducible and without prior assumptions about the relevance of the literature (Pickering *et al.*, 2015). The data gathered is captured in a system that includes not only bibliographic information, but also the methods applied, responses, results and the location of the search (Pickering *et al.*, 2015). These allow the researcher to identify research trends, illuminate research opportunities and provide a way of synthesising the concepts emerging from the literature review process. The databases used in this study included ACM, Emerald, IEEE Xplore, Science Direct Elsevier, JSTOR, Sabinet, Scopus, Web of Science, EBSCO and Proquest. A search was done for publications from 2010 to January 2018. The document types included journal papers and conference papers (excluding keynotes). The following keywords were used: *citizen science, learning analytics, data science, big data, visualisation/visualization* and *business intelligence.* Table 1 depicts the number of items found per database on each of the key. This broad search was done to extract and identify as many possible publications addressing any or all the keywords. Throughout this paper the terms *citizen science* and *crowdsourcing* are used interchangeably as the literature often refers to one or the other without making a clear distinction.

Table 1: Summary of items found per database

Keywords / *Database*	*Data science*	*Visualisation*	*Big data*	*Citizen science*	*Business intelligence*	*Learning analytics*
ACM	22 275	16 496	3 870	1 229	1 347	1 996
Emerald	40 035	6 134	24 061	8 695	8 974	1 437
IEEE Xplore	67 4846	44 970	20 422	13 306	6 029	16 773
Science Direct Elsevier	4 361 522	140 022	273 983	27 964	18 024	6 140
JSTOR	126 175	8 861	29 107	11 047	8 761	683
Sabinet	51 339	24 110	11 451	5 221	9 071	3 608
Scopus	13 209	406 545	89 435	4 686	13 698	3 560
Web Of Science	58 358	79 773	42 381	3 519	3 844	2 783
Proquest	1 707 786	184 518	3 451 310	115 919	1 633 182	9 972
EBSCO	680	967		25	388	12
SUBTOTAL	7 056 225	912 396	351 443	191 611	70 136	46 964

To make the search more comparable, we used the above literature on the same group of databases and narrowed the search by combining the keyword *learning analytics* with each of the other keywords, for example: [*learning analytics* AND (*citizen science* OR crowdsourcing)]; [*learning analytics* AND (*data science*)], etc. Table 2 depicts the number of items found per database using the above search strings. The search was ordered according to relevance. The results in Table 2 show that *crowdsourcing* is the more commonly used term. Although used interchangeably in literature, *crowdsourcing* focuses on data capturing whereas *citizen science* seems to be associated with interaction with communities**.**

Table 2: Summary of the items found per database with the narrowed search

learning analytics AND	***citizen science/ crowd-sourcing***		***data science***		***big data***		***visualisation/ visualization***		***business intelligence***	
	*SC**	*C**	*SC*	*C*	*SC*	*C*	*SC*	*C*	*SC*	*C*
ACM	5	0	4	0	17	0	2	0	4	0
Emerald	1	4	2	11	11	77	9	72	13	179
IEEE Xplore	7	36	19	238	122	1 411	200	1 483	14	25
Science Direct Elsevier	4	5	36	81	154	547	83	128	6	99
JSTOR	1	4	12	8	33	45	6	11	0	5
Sabinet ePublications	0	1	0	1	1	8	7	23	0	2
Scopus	1	9	6	12	62	326	53	234	0	18
Web Of Science Core Collection	1	2	4	6	51	141	40	104	0	6
Proquest	288	2 082	1 817	3 062	191	599	59	120	9	88

*[*citizen science* (SC) OR *crowdsourcing* (C)]

Although the count of articles (n = 8 315) is much smaller, it is still a very large repository of articles. We have narrowed down the selection to the first 20 items, or all items in cases where there were less than 20 items, from each of the databases and these papers added to a Mendeley group. Owing to connection problems with the institutional library database and EBSCO, this source was omitted during this search. Duplicates were removed, and the 365 abstracts of these articles were read by the authors to select the publications that focused on the research. The identified key words were selected. The complete list of these articles can be download from https://goo.gl/6Yz4jg. Some of these articles did not contribute any insights to the topics under investigation; others included the identified keywords in the reference list or heading of the paper, but not in the article itself. Many the articles focused on learning analytics and data gathered using traditional methods but did not use citizen science or crowdsourcing to gather data. Some of the articles cited did not address learning analytics but made valuable contributions to data through digital community projects. The following details of each paper were extracted and tabulated: title, key words, purpose, abstract, implementation methodologies and suggestions for future research. The individual sections were discussed to find consensus and 125 papers were selected for thematic analysis. The analysis was done independently by the authors, and the results discussed to identify the topics and opportunities mentioned in Section 3.4. Finally, 101 papers and articles were identified, approved and cited.

The process of searching the databases and selecting the combining results are depicted in Figure 1 with the keywords: "learning analytics" AND ["citizen science " OR "crowdsourcing"], "data science", "big data", ["visualisation" OR "visualization"] , "business intelligence"

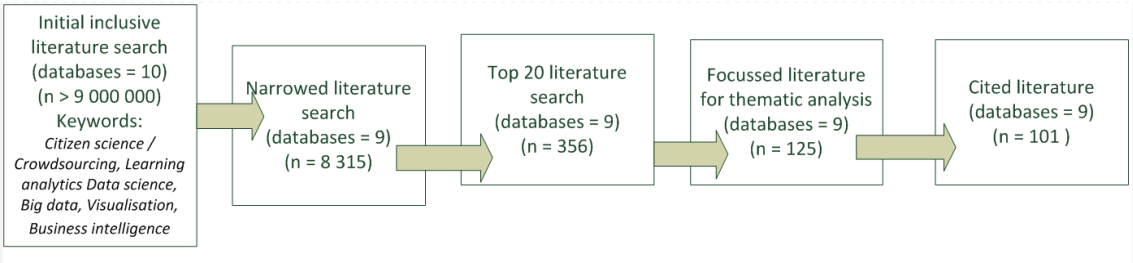

Figure 1: Process of database searches

3. Results

3.1 Literature review results

Considering research topics, the following main domains emerged from the thematic analysis: citizen science, big data, data science, analytics, business intelligence and analytics, reporting, policies, privacy and other ethical issues, as well as various implementation methodologies. The domains are depicted in Table 3, followed by references to articles. Owing to space limitations, only domains are listed. The table with a complete list of references can be downloaded from https://goo.gl/6Yz4jg.

Table 3: Domains of the adoption and use of citizen science in learning analytics

Domains
Citizen science or crowdsourcing (Participants may include any citizen, educator, learner, researcher or policy maker.)
Data science and big data collection in general
Big data collection for learning analytics
Business intelligence and analytics (The development of technologies and applications to gain insights into the business and use thereof to improve e-Learning.)
Reporting and data visualisation (Referring to various reporting mechanisms applied and used in learning analytics.)
Policies (Referring to the development of policies that learning analytics impacted directly.)
Implementation methodologies (Referring to various applications and methodologies applied in literature on the research topics.)
Predictive analysis (Referring to the use of machine learning in predictive analysis.)
Privacy, ethical issues and reliability of measurements and observations

These papers were added to a Mendeley group and read by the authors who abstracted the papers and highlighted the knowledge elements in each paper. Domains were identified based on the frequency of the underlying knowledge element or the potential of adding new insights to the study.

3.2 Model of domains for the adoption and use of citizen science in learning analytics

Refer to the domains identified in Table 3. The model in Figure 2 below depicts the domains and their relationship to one another. The model depicts the relationship between the concepts investigated, showing that learning analytics in data science can use citizen science as a source of big open data. Furthermore, through reporting and data visualisation, business intelligence can be used to enhance policies and curricula (among other things), but it can also be given back to the community through various reporting mechanisms such as dashboards and social media. This is a matter of ethics and privacy that should always be kept in mind, because sometimes participants are unaware that they are donating data. The triangle represents three legs of learning analytics, namely the collection, analysis and reporting of electronic data. In this model, learning analytics falls within the data science field, and uses citizen science as a platform to capture big data and to report back to the community.

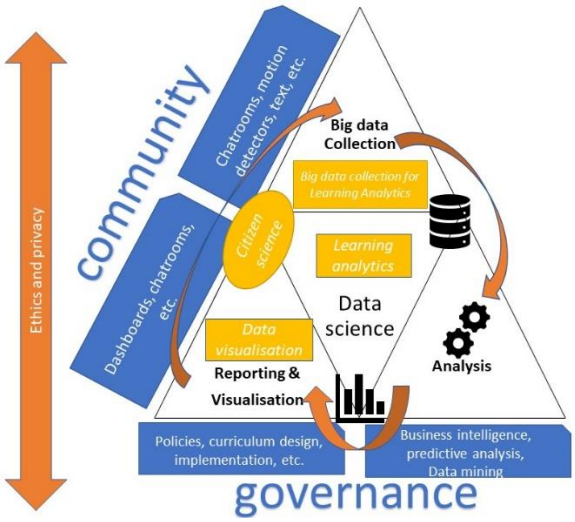

Figure 2: Model of domains for the adoption and use of citizen science in learning analytics

3.3 Synthesised set of concepts

Applying the model to initiate and guide the use of citizen science in the learning analytics environment, the following applications can be considered: *"Project in learning analytics using data captured in citizen projects towards the evaluation of existing practices and …"*

Table 4: Examples of citizen science projects to be used in learning analytics

What?	Who can contribute?	Examples of citizen science projects	Examples of reporting (to be used in learning analytics and to give feedback to the community)
Curriculum and policy development	Peer reviews Articles Educators	Peer reviews using social media Meta data from articles	Summary of contributions
Assignment development	Peer reviews Learners	Using log data from programming courses, Cloud experimentations	Meta data, HCI studies
Learner experience	Learners Educators	Online discussions, Social media chatrooms, Digital gaming Rubrics with commentary Projects designed specifically for use in citizen science projects	Narratives, Online Questionnaires, Chat logs Motion tracking, Click streams Summary of hashtags (e.g. Twitter), Meta data
		Use of online library portals Use of online learning portals (LMS and MOOCs)	Predictive analysis and summaries of databases and online learning tools accessed

3.4 Opportunities for research into citizen science in education

Citizen science: a new domain for learning analytics: In addition to data and meta data gathered through traditional LMSs, citizen science provides a new domain for applying learning analytics. Future research into learning analytics can lead to the finding of effective applications of data analytics with the potential to transform policy; and the use of citizen science to predict and integrate specific incidents and events to influence and improve learning analytics. Amongst others, the following opportunities and future research areas are identified in the literature: (1) using citizen science as an instrument to collect data, (2) implementing ethics, integrity and privacy mechanisms, (3) developing applications and tools for data gathering that requires minimal effort from the participant (meta data, real-life data, textual detection, temporal analytics), (4) developing algorithms for the validation of the gathered data, (5) creating mechanisms for the aggregation of data from different sources, (6) developing tools to report findings, such as dashboards, point maps, clusters and rating maps and (7) research into the social media tools that can be used as data collection instruments.

Gathering data and reporting back to the community: One of the main characteristics of learning analytics is its ability to measure and report on data captured in a virtual environment. For this, the use of citizen science

as an instrument in business intelligence can play a vital role (Sayedi, Ghafari and Hojati, 2017)**.** From literature it is evident that well-designed graphical user interfaces (GUIs) for the capturing of the data are of high importance, and not enough research into human computer interaction (HCI) has been done in this regard. Furthermore, developing tools to report on results is important not only to the researcher and policy makers, but also to the citizen who has initially made the contribution (Bae *et al.*, 2017). Although there are mechanisms for reporting the results of data analyses to the researcher and policy maker, not enough research and tools are readily available to make the information available to the original contributor, namely the citizen.

The community as an open laboratory: Through citizen science, the community can become an open laboratory for learning analytics. Allowing the data gathered to be open data which is accessible for other research opportunities is vital in facilitating cross-scale information sharing. This requires that the data gathered, stored and presented be consistent and standardised. Machine learning techniques can be applied to learning analytics in order to create best practices and reduce risks (Baer and Norris, 2016; Baig and Jabeen, 2016). **Training and opportunities in higher education:** The adoption and implementation of the above research opportunities will require partnership between the fields of data science and e-Learning. The field of data science requires information technology developers to create the required software and computer scientists who can apply machine learning techniques to build predictive analysis tools. In the field of e-Learning, research is required to understand business needs, interpret analyses of big data and provide leadership for the development of data-informed decision and policy making (Chiang, Goes and Stohr, 2012).

4. Discussion

We are living through a data revolution – data science and the components of big data, advanced analytics, enhanced reporting and visualisation are increasingly impacting on e-Learning. Research into learning analytics and how it can benefit education is undertaken and implemented at various levels and reported on in scholarly articles. This paper provides an overview of the literature on citizen science from 2010 to early 2018, based on a systematic selection of 125 publications in the learning analytics domain. Articles were sourced from ACM, Emerald, IEEE Xplore, Science Direct Elsevier, JSTOR, Sabinet, Scopus, Web of Science and Proquest. Our systematic literature review gives an overview of existing research on citizen science and how it relates to the concepts of data science, big data, learning analytics and reporting in the e-Learning environment. Those insights have been synthesised and are presented as a conceptual model. We have identified citizen science as a platform that can be used in learning analytics, both to gather data but also as a platform to report on and present the data to the community. When citizen science is used, it becomes possible to gather data from the community. Such data can contribute to data-driven decision making, using analytic techniques to identify current trends and to assist in predictive analysis. We have also identified areas for future research and identified possible research projects in the field of e-Learning, which include the development of more refined GUIs, automated data collection strategies and policies. Attention should also be paid to matters of ethics, integrity and privacy. The paper proposes that a synthesised set of concepts be considered for placing citizen science projects in the field of e-Learning.

5. Conclusion

In this paper we investigated the role and positioning of citizen science in the field of e-Learning using a systematic literature review. The novel contribution of the paper was to present a conceptual model positioning citizen science in the field of e-Learning and relating it to other critical concepts such as data science, big data, learning analytics and visualisation. We conclude this paper by acknowledging that learning analytics in the field of data science can use citizen science as a platform to the benefit of both the researcher and the citizen in the community. Citizens then have a platform that allows them to participate in data gathering and to receive feedback on identified problems and solutions. Researchers get the opportunity to gather data through citizen science projects, and to contribute to learning analytics in an open, big data environment and in real time using statistical techniques. Future research opportunities include research into the development of tools for using citizen science in learning analytics; and research into interaction with the community as an open laboratory. Finally, there is a need for research into curriculum development for learning analytics in higher education.

References

Agudo-Peregrina, Á. F. et al. (2014) 'Can we predict success from log data in VLEs? Classification of interactions for learning analytics and their relation with performance in VLE-supported F2F and online learning', Computers in Human Behavior, 31(1), pp. 542–550. doi: 10.1016/j.chb.2013.05.031.

Ali, L. et al. (2013) 'Factors influencing beliefs for adoption of a learning analytics tool: An empirical study', Computers and Education, 62, pp. 130–148. doi: 10.1016/j.compedu.2012.10.023.

Allan, S. and Redden, J. (2017) 'Making citizen science newsworthy in the era of big data', Journal of Science Communication, 16(2), p. C05. Available at: https://jcom.sissa.it/archive/16/02/JCOM_1602_2017_C01/JCOM_1602_2017_C05%5Cnhttps://jcom.sissa.it/archive/16/02/JCOM_1602_2017_C01/JCOM_1602_2017_C05.pdf.

Bae, S.-H. et al. (2017) 'Scalable and Efficient Flow-Based Community Detection for Large-Scale Graph Analysis', ACM Transactions on Knowledge Discovery from Data, 11(3), pp. 1–30. doi: 10.1145/2992785.

Baer, L. L. and Norris, D. M. (2016) 'A Call to Action for Student Success Analytics', Planning for Higher Education, 44(4), p. 1. Available at: http://search.ebscohost.com.lib.kaplan.edu/login.aspx?direct=true&db=edb&AN=119398939&site=eds-live.

Baig, A. R. and Jabeen, H. (2016) 'Big Data Analytics for Behavior Monitoring of Students', Procedia Computer Science. Elsevier Masson SAS, 82(March), pp. 43–48. doi: 10.1016/j.procs.2016.04.007.

Baker, R. D. et al. (2006) 'Adapting to when students game an intelligent tutoring system', Proceedings of the 8th International Conference on Intelligent Tutoring Systems, pp. 392–401. doi: 10.1007/11774303_39.

Barneveld, A. Van, Arnold, K. and Campbell, J. (2012) 'Analytics in higher education: Establishing a common language', Educause: Learning Initiative, (January), pp. 1–11. doi: 10.1111/j.1468-2273.2009.00438.x.

Bochicchio, M. A., Zappatore, M. and Longo, A. (2015) 'Using Mobile Crowd Sensing to teach technology and entrepreneurship in high schools: An experience from Southern Italy', in 2015 IEEE Global Engineering Education Conference (EDUCON). IEEE, pp. 948–953. doi: 10.1109/EDUCON.2015.7096087.

Chaurasia, S. S. and Frieda Rosin, A. (2017) 'From Big Data to Big Impact: analytics for teaching and learning in higher education', Industrial and Commercial Training, 49(7/8), pp. 321–328. doi: 10.1108/ICT-10-2016-0069.

Chen, B. et al. (2016) 'Putting temporal analytics into practice', in Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16. New York, New York, USA: ACM Press, pp. 488–489. doi: 10.1145/2883851.2883865.

Chiang, R. H. L., Goes, P. and Stohr, E. A. (2012) 'Business Intelligence and Analytics Education, and Program Development', ACM Transactions on Management Information Systems, 3(3), pp. 1–13. doi: 10.1145/2361256.2361257.

Clarke, J. and Nelson, K. (2013) 'Feature Perspectives on Learning Analytics: Issues and challenges. Observations from Shane Dawson and Phil Long', The International Journal of the First Year in Higher Education ISSN The International Journal of the First Year in Higher Education, 4(1), pp. 1838–29591. doi: 10.5204/intjfyhe.v4i1.166.

Dhar, V. (2013) 'Data science and prediction', Communications of the ACM, 56(12), pp. 64–73. doi: 10.1145/2500499.

De Freitas, K. and Bernard, M. (2017) 'Enabling Integrated Data Mining Analysis in Moodle With FlexEDM', Academic Conferences International Limited, Kidmore End, 6, pp. 66–74.

Grant, M. J. and Booth, A. (2009) 'A typology of reviews: an analysis of 14 review types and associated methodologies', Health Information & Libraries Journal. Blackwell Publishing Ltd, 26(2), pp. 91–108. doi: 10.1111/j.1471-1842.2009.00848.x.

Hiller, S., Kyrillidou, M. and Self, J. (2008) 'When the evidence is not enough', Performance Measurement and Metrics, 9(3), pp. 223–230. doi: 10.1108/14678040810928444.

Kitchin, R. (2014) The data revolution: Big data, open data, data infrastructures and their consequences. Sage.

Muslim, A. et al. (2016) 'A rule-based indicator definition tool for personalized learning analytics', in Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16. New York, New York, USA: ACM Press, pp. 264–273. doi: 10.1145/2883851.2883921.

Palmer, S., Holt, D. and Bray, S. (2008) 'Does the discussion help? The impact of a formally assessed online discussion on final student results', British Journal of Educational Technology, 39(5), pp. 847–858. doi: 10.1111/j.1467-8535.2007.00780.x.

Pickering, C. et al. (2015) 'Publishing not perishing: how research students transition from novice to knowledgeable using systematic quantitative literature reviews', Studies in Higher Education. Routledge, 40(10), pp. 1756–1769. doi: 10.1080/03075079.2014.914907.

Prinsloo, P. et al. (2015) 'Big(ger) data as better data in open distance learning', The International Review of Research in Open and Distributed Learning, 16(1), pp. 284–307. doi: 10.19173/irrodl.v16i1.1948.

Provost, F. and Fawcett, T. (2013) 'Data Science and its Relationship to Big Data and Data-Driven Decision Making', Big Data, 1(1), pp. 51–59. doi: 10.1089/big.2013.1508.

Rodrigo, M. et al. (2012) 'Development of a workbench to address the educational data mining bottleneck', Proceedings of the 5th International Conference on Educational Data Mining, pp. 152–155.

Sayedi, M., Ghafari, P. and Hojati, E. (2017) 'Analysis of the Effects and Factors of Implementing Cloud Business Intelligence in Banking Systems', in Proceedings of the10th International Conference on Utility and Cloud Computing - UCC '17. New York, New York, USA: ACM Press, pp. 197–198. doi: 10.1145/3147213.3149213.

Scheffel, M. et al. (2014) 'Quality Indicators for Learning Analytics', Journal of Educational Technology & Society, 17(4), pp. 124–140. doi: 10.1145/2567574.2567593\r10.1145/2567574.2567591\r10.1145/2567574.2567588.

Willis, J. E., Slade, S. and Prinsloo, P. (2016) 'Ethical oversight of student data in learning analytics: a typology derived from a cross-continental, cross-institutional perspective', Educational Technology Research and Development. Springer US, 64(5), pp. 881–901. doi: 10.1007/s11423-016-9463-4.

Zhang, C. et al. (2016) 'Multi-source Hierarchical Prediction Consolidation', pp. 2251–2256. doi: 10.1145/2983323.2983676.