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ORIGINAL PAPER

Learning Analytics Research in Relation to Educational Technology: Capturing Learning Analytics Contributions with Bibliometric Analysis

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Abstract
In this study the authors conducted an empirical, bibliometric analysis of current literature in learning analytics. The authors performed a citation network analysis and found three dominant clusters of research. A qualitative thematic review of publications in these clusters revealed distinct context, goals, and topics. The largest cluster focused on predicting student success and failure, the second largest on using analytics to inform instructional design, and the third on concerns in implementing learning analytics systems. The authors suggest that further collaboration with educational technology researchers and practitioners may be necessary for learning analytics to reach its interdisciplinary goal. The authors also note that learning analytics currently does not often take place in K-12 settings, and that the burden of creating learning interventions still seemed to reside mainly with practitioners.

Keywords Bibliometrics · Citation network analysis · Educational technology · Learning analytics

Learning analytics is the use of student generated digital data to improve learning and teaching (Sclater et al. 2016). There has been massive growth in the field of learning analytics over the last decade due to the new availability of student generated digital data (Viberg et al. 2018). However, due to factors such as government regulation and lack of uniformity in systems of data collection, learning analytics systems have been slow to penetrate the formal educational landscape (Manyika 2011). Learning analytics research also originally grew out of collaborations between computer science and learning science researchers (Dawson et al. 2014), and recent reviews of the literature are designed with current learning analytics researchers in mind (Seimens 2013). These and other factors suggest that there is not an easy point-of-entry for researchers and practitioners in related fields who wish to explore the discipline of learning analytics.

This lack of easy entry is not unique to learning analytics. Fields that were contrived specifically to be interdisciplinary can be successful in creating a discovering new and novel theories that would otherwise have gone unnoticed. However, maintaining the cohesion of these fields is not as simple a task. Cognitive science shares many similarities with learning analytics as both were explicitly defined and organized as interdisciplinary fields (Miller 2003), and both combine social science and computer science to create rigorous, quantitative, scientific theories (Gardner 1987). While cognitive science produced an explosion of new theory in the 70's and 80's (Pinker 2003) it is debated whether cognitive science truly has accomplished the goals it set out to achieve. Núñez et al. (2019) argue that the cohesive field and accompanying rigorous theory have not succeeded, and Núñez et al.'s accompanying bibliometric analysis suggests that the majority of cognitive scientists have retreated back to their respective fields, leaving the field as a whole in a state of decay. There might be a reason to believe that learning analytics is susceptible to a similar phenomenon. A bibliometric analysis by Research by Dawson et al. (2014) suggests that the research being published in learning analytics before that time period was divided into two distinct groups that did not necessarily collaborate: a learning sciences group, and a computer science group.

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Problem Statement and Research Purpose

In its mission statement, the Society of Learning Analytics Research (SoLAR) casts a wide interdisciplinary net that includes "academic researchers, product developers, educators, students, institutional administrators, [and] government policy analysts" (SoLAR 2019, para. 3). The interdisciplinary nature of learning analytics research means that it can be difficult for individuals in these different areas to discover research that is useful for their specific context. SoLAR acts as a central location for the sharing and dissemination of learning analytics research in an attempt to remedy this issue. Unfortunately, SoLAR's yearly conference and single journal simply do not have the resources to keep up with the growth of learning analytics research.

In order to reach this wide audience, learning analytics research will need to permeate far beyond the specialty journals designed specifically for technical and theoretical learning analytics publications. While the field of learning analytics is relatively new, it is growing quickly. A search of the Web of Science database for the term *learning analytics* returns only 37 publications published in 2011, while the same search returns over 450 publications published in 2018, over a 1000% increase in publication. This growth over the last decade suggests it may be a good time to ask: is learning analytics achieving its interdisciplinary goals?

In order to address this overarching question, we proposed three specific research questions:

1. What publications (outside of those explicitly designed for learning analytics research) publish learning analytics research?
2. What authors are most actively publishing in non-learning-analytics publications?
3. Are there certain topics or themes that are common in interdisciplinary learning analytics publications?

Literature Review

Recent reviews of learning analytics research capture part of this landscape, but no popular reviews focus on the interdisciplinary nature of learning analytics. Due to the growth of learning analytics research, many quality reviews are already out of date only a few years after their publication (e.g. Papamitsiou and Economides 2014). While some reviews capture the methodologies or structural nature of learning analytics research, these do not analyze the current topics central to learning analytics (e.g. Dawson et al. 2014). Publications that do capture topics do not expose how these topics are related to the structure of the learning analytics community and tend to focus on more technical aspects of the discipline, not its interdisciplinary aspects (e.g. Viberg et al. 2018).

Viber et al.'s (2018) literature review is one of the more recent and well-cited reviews of learning analytics. Among other things, it finds that learning analytics is beginning to shift from a focus on increasing learner outcomes to using it as a tool for understanding student experiences. It limits itself, however, to learning analytics in the context of higher education. It also is concerned mainly with the methods of research in learning analytics (e.g. quantitative vs. qualitative, case studies, experimental designs etc.), and does not cover research topics in detail. A review by Papamitsiou and Economides (2014) does consider a broader range of learning analytics research, but due to the growth of the field, reviews from that time period are already out of date. One of the most popular alternatives to qualitative literature reviews is citation network analysis, such as was conducted by Dawson et al. (2014). Citation network analysis is a quantitative technique for revealing the structure of a scientific discipline through the construction of networks based on which publications and authors cite each other (Kirby et al. 2005). As mentioned earlier, Dawson et al. (2014) does capture the structure of learning analytics research, finding that there is a divide between the computer science and education research in learning analytics research. His paper focuses mainly on the relationships between authors, not necessarily the content of their research. It also considers only journal articles and conference proceedings published by SoLAR.

Method

The purpose of this study was to better understand the current structural and topical features of learning analytics research in interdisciplinary contexts to help researchers and practitioners in various fields better understand and incorporate learning analytics into their existing practices and research. This study used a bibliometric approach adapted from Gasevic et al. (2014). Bibliometrics is a broad term for different analysis techniques used in the field of scientometrics. The two bibliometric techniques used in this study are citation network analysis and optimal clustering. In addition to these two methods, descriptive statistics were collected on the frequency of different authors and sources (i.e. journals or conference proceedings) within the data. Finally, in order to answer RQ3, we performed a qualitative review of themes within clusters of publication.

Definitions

This section gives simple definitions helpful to understanding the results section.

- Nodes: The items of analysis within a network. For this research context, each publication acts as a node.
- Edges: Connections between nodes. For this research context, a citation of one publication by another publication acts as an edge.
- Density: The ratio of the number of edges over the number of possible edges in a network.
- Geodesic Distance: The shortest distance between two nodes, measured as the minimum number of nodes a path between two nodes must pass through.
- Centrality: Any measure of the importance of nodes within a graph. In this research the centrality of any given node was measured (roughly) by the number of geodesic distances that went through that node. For a full explanation of the mathematics used, see Freeman et al. (1979).
- Modularity: the fraction of edges of a network that fall within a cluster minus the expected fraction if edges were distributed at random (see Newman 2006). This measure is used in clustering algorithms employed in this analysis.

Data Collection

The data for the bibliometric analysis of learning analytics research were collected from the *Web of Science* database. While the use of one database is not ideal, it is common practice in bibliometric studies due to the difficulty of transposing data from multiple databases into a single format (e.g. Cheng et al. 2014; Dawson et al. 2014). While this also poses a limitation for this study, it is generally accepted that a subset of publications can be used to make tentative generalizations to the larger research community (Pavlo 2014).

The following criteria were used to select publications:

- Publications must be peer-reviewed.
- Publications must include at least one of the keywords *learning analytics, learning and knowledge analytics,* or *educational data mining*.
- Publications from SoLAR, as well as from the Educational Data Mining society were excluded from analysis in order to focus on interdisciplinary research.
- Must have been published between 2011 and 2018. 2011 was chosen as the beginning year because it was this year that SoLAR was formed and the field of learning analytics was more properly codified.
- Indexed under the Web of Science category *Education Educational Research*.
- Publications also had to have been cited 10 or more times to be included. This cutoff is admittedly arbitrary, because no rational could be found in the literature for a specific cutoff, and whether or not a paper is considered highly cited is relative to the field. Ten was chosen as an arbitrary cutoff because: (a) it allowed for inclusion of only influential research likely to be considered by outside researchers; and (b) the limited size allowed for an optimal clustering method not possible with larger data sets due to computational limits. Another limitation of this cutoff is that it favors older publications, as they have had more time to accrue citations. However, it was decided that it was imprudent to extrapolate citations for younger papers and potentially include papers that would ultimately not be highly cited.

Before the citation cut-off was applied, a total of 1344 total were select. Of these, 90 publications met the citation criteria.

Data Analysis

Publications were exported from the *Web of Science* database in a format that included: authors, title, keywords, source (Journal or Conference Proceeding), abstracts, citations, and times cited. This data was uploaded into R where the iGraph package was used to automatically compare references and create the necessary variables to generate a citation network.

Descriptive Statistics In order to answer RQ1 and RQ2, descriptive statistics about the 90 publications included in the data set were extracted including authors and publications.

Citation Network Analysis In order to answer RQ3, two bibliometric techniques were utilized. The first bibliometric technique was citation network analysis. Citation network analysis is built on the same theoretical framework as social network analysis and assumes researchers can measure the social fabric and relationships between individuals in a community (Borgatti et al. 2009). It is useful for discovering the *shape* of communities and is widely used across disciplines in the social sciences (e.g. Boyd et al. 2006; Gustafsson et al. 2014; Pieters and Baumgartner 2002; Tight 2008). In this case of this study, it was used to determine the structure of interdisciplinary publications about learning analytics. Simple citation network analysis was chosen over the often-used co-citation network analysis (Cho et al. 2013) because of the relatively small size of the data set.

Cluster Analysis The created network was clustered by maximizing the modularity score of the entire network. Modularity is the fraction of edges of a network that fall within a cluster minus the expected fraction if edges were distributed at random (see Newman 2006). The advantage of modularity versus other clustering algorithms it does not rely on the researcher to arbitrarily select the number of clusters and does not rely on random initiation. After clustering, text frequency tables were created for each of the three largest clusters. This number acted as a natural cut-off as there were three clusters that included five or more publications.

Qualitative Literature Review

With three distinct clusters of interdisciplinary learning analytics publications discovered, a qualitative review was performed (Cooper et al. 2009) to look for themes and similarities within the different clusters, as well as differentiating features between the clusters. After qualitative review by the researchers to ensure trustworthiness, an external reviewer was recruited to perform peer debriefing on the publications discovered. After the peer debriefing was done, themes were compared and discussed until a consensus was reached about major themes (Lincoln and Guba 1985).

Results

RQ1: What publications (outside of those explicitly designed for learning analytics research) publish learning analytics research?

A total of 90 publications met the inclusion criteria for analysis. Descriptive statistics were collected on the 90 publications in order to gain a preliminary understanding of learning analytics research. Four journals were found to have three or more publications included in the data (Table 1).

RQ2: What authors are most actively publishing in non-learning-analytics publications?

Eight authors had three or more publications that met the inclusion criteria (Table 2). While this should not be construed as a ranking of authors, the high number of authors with multiple publications inside a relatively small network (Gasevic was an author on 12% of publications within the network) does suggest a tight knit ingroup of researchers who are especially influential in publishing learning analytics research outside of learning analytics publications.

RQ3: Are there certain topics or themes that are common in interdisciplinary learning analytics publications?

Table 1 Influential journals and conference proceedings

Source	Number of Publications
Computers & Education	12
British Journal of Educational Technology	9
Internet and Higher Education	7
Journal of the Learning Sciences	4

Table 2 Influential authors

Author	Number of publications
Gasevic, D.	11
Dawson, S.	6
Hatala, M.	4
Williamson, B.	4
Joksimovic, S.	3
Jovanovic, J.	3
Kovanovic, V.	3
Pardo, A.	3

Network Structure Of the 90 publications that met the inclusion criteria, 55 were connected by citation to other publications (Table 3). In other words, 39 publications the met the inclusion criteria were not cited and did not cite any of the other publications in the data set. These publications, referred to as *isolates*, were removed from the network before cluster analysis was performed, as each isolate would be treated as its own cluster, and give no meaningful information about the structure of learning analytics research. It is notable that a 41% isolate rate is not outside of common rates seen among other networks of more established fields and journals (see Cho et al. 2013).

The 55 publications included in the network grouped into seven components. Each component is a group of interconnected nodes that are isolated from all other nodes. In other words, while they were pulled from the same data set, different components could each be considered their own network, and do not overlap or connect to any other components (see Fig. 1 for a visual representation of the network, clusters, and components). The largest component was made up of 40 publications (72% of all connected publications), suggesting that the majority of highly-cited learning analytics research is interconnected. The largest of the six smaller components contained only 4 publications, and five contained only 2 publications.

Cluster Formation As there is a high computational cost for clustering of large networks, many citation network analyses are forced to rely on non-optimal, randomly initiated algorithms for clustering nodes (Kruskal 1956). But in the current study, due to the relatively small size of this discovered network allowed for an optimal clustering method using modularity as a measure of clustering quality. This optimal network is one with clusters that maximize the sum of the modularity of all nodes within the network structure (Brandes et al. 2008). This optimizes both the number of clusters as well as the boundaries of those clusters. As mentioned in the Analysis section above, while each cluster in Fig. 1 above is mathematically valid, only the three largest clusters above were chosen

Table 3 Summary of citation network

Item	Learning analytics network
Number of nodes	94
Number of nodes connected	55 (59%)
Number of connections	54
Number of components	7
Number of nodes of the biggest component	40
Overall density of whole network	0.01235415
Overall density after removing unconnected nodes	0.03636364
Mean of geodesic distance among reachable pairs	4.078184
Maximum geodesic distance	10

for analysis. This number acted as a natural cut-off as there were three clusters that included five or more publications.

Cross-Cluster Themes Across all three major clusters, four major themes emerged as central to interdisciplinary learning analytics research. First, little or no research was conducted in K-12 education. All research in all three clusters was performed in either higher education, adult education, or informal learning contexts (i.e. MOOCS). Second, learning analytics research did not appear to be concerned with the construction of interventions. This is not to say that learning analytics methods aren't being used to implement or track interventions, however, if this was the case, it could be present in literature other than that reviewed within this study. Third, there did not appear to be a pattern in the type of content being studied. Research instead focused on general principles of learning, with individual research studies taking place in various subject areas. Finally, most empirical research performed across the studies was not experimental or large-scale. Research tended to be case-based and contextualized in a specific learning context.

Cluster 1: Prediction of Student Success or Failure Cluster 1 is the largest cluster and contained the two publications with the highest centricity. Research in this cluster tended to focus mostly on higher education, especially online undergraduate courses. The goal of most publications in this cluster was to predict student success or failure. A good example of a typical publication in this cluster is Gasevic et al. (2016, id #5 in Fig. 1). This publication compared predictive models of student success in nine undergraduate blended learning courses by using data from the learning management system at a large university to determine if a generalized model for predicting student success across all nine courses was possible, or if individualized models were necessary for each class.

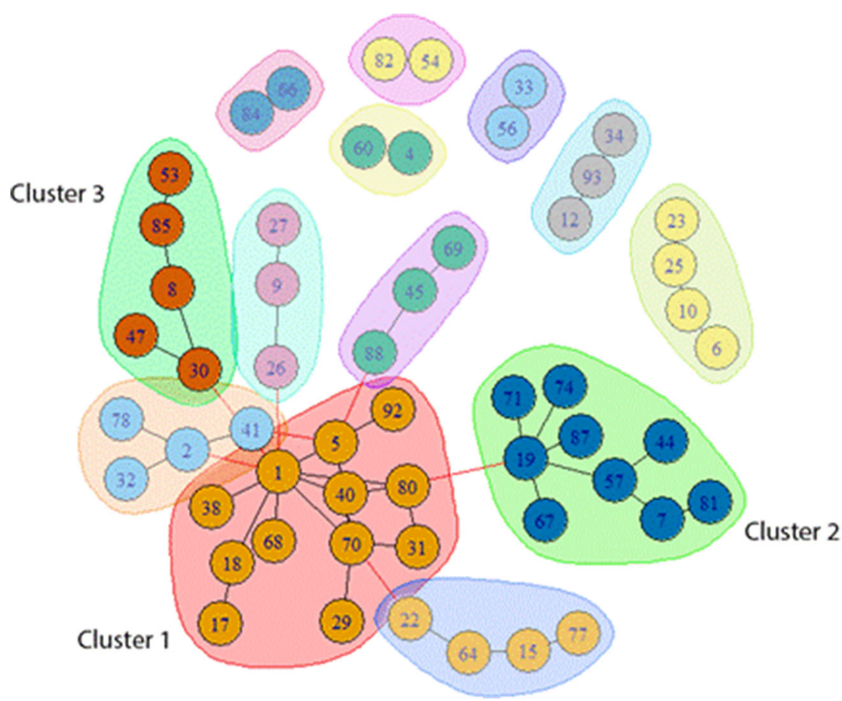

Fig. 1 Learning analytics network with clusters highlighted

This cluster was the most diverse in topic, as it included several literature reviews and theoretical pieces (e.g. Drachsler and Greller 2016; Gasevic et al. 2015, id #1). However, these reviews were also focused on the topic of predicting student achievement. Most original research in this cluster attempted to predict student achievement through available online data, almost always in an undergraduate course. This research seemed to be the central core of learning analytics in this cluster.

Cluster 2: Analytics to Inform Instructional Design Cluster 2 focused on how learning analytics can inform the design of instructional material. In this cluster's publications, there were a number of approaches suggested for a relationship between learning analytics and course design. Many publications focused on making learning analytics research accessible to teachers so they can make ad-hoc decisions during class (McKenney and Mor 2015), while other focused on more holistic design (Toetenel and Rienties 2016). This focus on teachers also meant that these studies were not as clearly focused on prediction, as pure predictive models are often not interpretable. Instead, the focus of these models may be more aptly characterized as attempting to understand student learning. It is noteworthy that cluster 2 was almost a distinct component within the network, connected by only one publication to the largest component in the network. This showed that while researchers were aware of the need to include instructional design as a central component of learning analytics, it was not a concern that is integrated into the wider learning analytics research community. It is also important to clarify that research in this cluster focused on the design of course material as well as giving teachers tools for better understanding their students learning, but gave little suggestion as to how this information might be utilized to perform real-time interventions.

Cluster 3: Policy Implementation Concerns Cluster 3 contained one piece of original research (You 2016, id #30). The other four publications in cluster 3 offered opinions on pragmatic and ethical concerns on the implementation of learning analytics systems across K-12, higher education, and Massive Online Open Courses (MOOCs). Again, Cluster 3 is nearly a distinct component within the network, connected only by You's (2016) original research.

Discussion

This study offered an overview of both the structure and content of research in interdisciplinary learning analytics publications. While other reviews have focused on specific methods used in learning analytics research and theoretical frameworks for future research (e.g. Gasevic et al. 2015) this study focused on the topicality of research, giving a more high-level overview of research and its relationship to other fields. As the three most common publications for interdisciplinary learning analytics publications (Computers & Education, British Journal of Educational Technology, and Internet and Higher Education) are closely related to educational technology, this research seems particularly pertinent to Educational Technology researchers and practitioners. If learning analytics is to succeed as an interdisciplinary field, the data seem to suggest that it will be through collaboration with the educational technology field. This research aims to add clarity to what interdisciplinary learning analytics research looks like currently, and what opportunities educational technology research and practitioners may have to participate in this growing field.

Implications for Educational Technology Research and Practice

While several well-cited studies give extensive guidelines on what defines quality learning analytics systems, most are highly theoretical or technical and aimed mainly at researchers (e.g. Scheffel et al. 2014a, b). Based on the three clusters discovered in this research, the authors developed a simplified structural framework of the current state of learning analytics interdisciplinary research and practice (Fig. 2).

This simple framework centers on the prediction of student success and failure. The exact methods for prediction are outside the scope of this paper, as they tend to be highly technical and mathematical. This core cluster focused on predicting student success is informed by implementation concerns, as well as instructional design principles. In general, these instructional design principles focus on the creation and improvement of instructional tools for teachers, not on real-time interventions for students. While there is some literature on designing real-time interventions (Bart et al. 2016), this responsibility still seems to rest mainly on the practitioner. While there are more concerns when designing a learning analytics system, this is the emergent conceptual framework found in this study. The time may be right for practitioners interested in analytics to collaborate with researchers in order to move the field forward.

Implications for Research

Close Ties to Instructional Technology While SoLAR acts as a nexus for learning analytics researchers, the results of this study have shown that there is beginning to be learning analytics research published in more interdisciplinary journals, such as Computers & Education. Currently, learning analytics research must balance encouraging the growth of the *Journal of Learning Analytics* and submitting publications to other journals where their publications tend to be more highly cited,

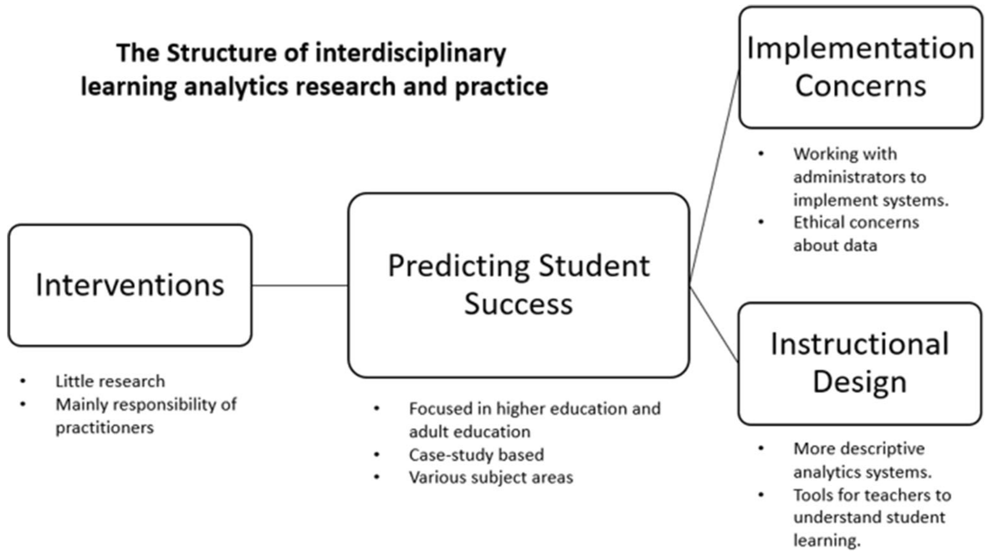

Fig. 2 A structural model of interdisciplinary learning analytics research and practice

such as *Computers & Education*, and *The British Journal of Educational Technology* (Table 1). Luckily, this growth of interdisciplinary learning analytics research reveals opportunities for educational technology researchers to get involved without being experts in learning analytics. Specifically, Fig. 2 suggests several research gaps that may be best filled by instructional technology research, including taking the many predictive models and instructional tools being created and using them to perform instructional interventions. The learning analytics community as frequently called for grounding of learning analytics systems in instructional design best-practices (Scheffel et al. 2014a, b; Wise 2014), and surely would welcome collaboration. K-12 contexts are not yet frequently utilized for learning analytics research. This may be due to several factors. First, restrictions around student data make research in K-12 settings much more difficult than in university or online settings. Second, there is evidence that the movement to integrate learning analytics into K-12 research is being led mainly by corporations to the exclusion of academic researchers (Roberts-Mahoney et al. 2015). If true, this could seriously impede collaboration and the spread of quality learning analytics systems. Either way, researchers have an imperative to be involved in K-12 research wherever possible, despite the obstacles currently in place. Instructional technology research may be uniquely positioned to better introduce learning analytics to K-12 research.

Limitations & Future Research

The main limitation of this study was the number of publications included in the final analysis. When faced with the tradeoff between a larger, more diverse data set, and a smaller more easily analyzed dataset, the researcher preferred the latter for this study. While this may mean the study is less generalizable to the entirety of learning analytics research, the inclusion of only the most cited publications lead to an internally valid and intrinsically valuable study. As was noted in the results sections, Clusters 2 and 3 were nearly completely separate from the main component of the network when measuring the relationships between citations. Future research may also look at the relationship between authors and research topic to investigate whether these research areas are truly distinct from each other, or if authors fluidly move between these topics, offering greater cohesion between the three clusters. It is also noteworthy that the predetermined methodology for this study ended up select papers authored by a very small group of researchers. It is unclear whether this is a large group of research synonymous to learning analytics that is using terminology, or if the interdisciplinary research is truly confined to this select group of researchers. Whichever is true, there does appear to be outsized impact by a small number of researchers. Future studies may cast a broader net and attempt to determine if there is other research in the general field of educational technology that is utilizing learning analytics methods and principles.

Conclusion

In this study the authors conducted an empirical, bibliometric analysis of current literature in learning analytics. The authors performed a citation network analysis and found three dominant clusters of research. A qualitative thematic review of publications in these clusters revealed distinct context, goals, and topics. The largest cluster focused on predicting student success and failure, the second largest on using analytics to inform instructional design, and the third on concerns in implementing learning analytics systems. The authors suggested that further collaboration with educational technology researchers and practitioners may be necessary for learning analytics to reach its interdisciplinary goal. The authors also noted that learning analytics currently does not often take place in K-12 settings, and that the burden of creating learning interventions still seemed to reside mainly with practitioners.

Compliance with Ethical Standards

This study did not include data from human subjects, and so was given exempt status by the institutional research board at the university of the researchers. This research did not receive any external or internal funding, and the authors do not have any conflicts of interest that need to be reported.

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