Let's Shine Together! A Comparative Study between Learning Analytics and Educational Data Mining

Guanliang Chen
Monash University
Melbourne, Victoria, Australia
guanliang.chen@monash.edu

Vitor Rolim
Universidade Federal de Pernambuco
Recife, Pernambuco, Brazil
victor.b.rolim@gmail.com

Rafael Ferreira Mello
UFRPE
Recife, Pernambuco, Brasil
rafaelflmello@gmail.com

Dragan Gašević
Monash University
Melbourne, Victoria, Australia
dragan.gasevic@monash.edu

ABSTRACT

Learning Analytics and Knowledge (LAK) and Educational Data Mining (EDM) are two of the most popular venues for researchers and practitioners to report and disseminate discoveries in data-intensive research on technology-enhanced education. After the development of about a decade, it is time to scrutinize and compare these two venues. By doing this, we expected to inform relevant stakeholders of a better understanding of the past development of LAK and EDM and provide suggestions for their future development. Specifically, we conducted an extensive comparison analysis between LAK and EDM from four perspectives, including (i) the topics investigated; (ii) community development; (iii) community diversity; and (iv) research impact. Furthermore, we applied one of the most widely-used language modeling techniques (*Word2Vec*) to capture words used frequently by researchers to describe future works that can be pursued by building upon suggestions made in the published papers to shed light on potential directions for future research.

CCS CONCEPTS

• **Information systems** → *Web mining*; • **Applied computing** → *Education.*

KEYWORDS

Learning Analytics, Educational Data Mining, Hierarchical Topic Detection, Language Modeling

ACM Reference Format:
Guanliang Chen, Vitor Rolim, Rafael Ferreira Mello, and Dragan Gašević. 2020. Let's Shine Together! A Comparative Study between Learning Analytics and Educational Data Mining. In *Proceedings of the 10th International Conference on Learning Analytics and Knowledge (LAK '20), March 23–27, 2020, Frankfurt, Germany.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3375462.3375500

LAK '20, March 23–27, 2020, Frankfurt, Germany

ACM ISBN 978-1-4503-7712-6/20/03…$15.00
https://doi.org/10.1145/3375462.3375500

1 INTRODUCTION

With the growing interests in utilizing the abundant data collected by various educational systems and tools to facilitate teaching and learning, LAK and EDM emerged as two mainstream conferences[1] for researchers and practitioners to report and share findings that are gained from such data-intensive research practices [42, 43, 49]. After the development of about a decade, both of the two communities have yielded many invaluable findings and continued pushing forward the boundaries of research in technology-enhanced education and learning. Most importantly, these research findings have been translated into practices in the real world and demonstrated great impacts on both teachers and learners.

As early as in their initial development stage, LAK and EDM had been compared by researchers in terms of their similarities and dissimilarities across several dimensions such as research interests and frequently-adopted techniques. For instance, Siemens and Baker [45] pointed out that both LAK and EDM aimed at developing efficient and effective methods to make use of educational data to assist teaching and learning practices. However, LAK stressed more on using data to better inform and empower instructors and learners, while EDM put a greater emphasis on using data to automate learning adaptation. Though such comparison was useful, it only enabled people to grasp a rather general understanding of the connection and distinction between the two conferences.

Given that both LAK and EDM have passed their initial development stage and become increasingly impactful, it is necessary to compare the two conferences systematically and thoroughly for the following reasons. Firstly, previous works (such as [45, 49]) did not detail the topics investigated by the two conferences in a fine-grained manner. Hence, it remains an open question how to consistently profile and compare their research focuses and impact over the years. This also hinders gaining insights about potential directions for future research. Secondly, both LAK and EDM have been expanding largely. However, the development process of the two communities remains largely unknown. For instance, who were the contributing researchers? Where were those researchers from? Were researchers from one community also attracted to the other? Have both LAK and EDM embraced a diverse set of participants to foster communication and collaboration among researchers of

[1] In this work, we used *venue*, *conference*, and *community* interchangeably to address LAK and EDM.

different demographics? As a result, we have little knowledge in guiding the future development of the two communities. We expect that, with a more nuanced comparison, relevant stakeholders (e.g., researchers in the field, conference committee) can be equipped with a better understanding of the unique characteristics of LAK and EDM in the past development, potential rewarding directions for future research, and possible actions to boost the future development of the two communities.

Formally, our work is guided by the following research questions:

RQ1 What topics are commonly investigated in LAK and EDM?

RQ2 To what extent do LAK and EDM differ from each other with respect to the following perspectives?
(a) investigated topics;
(b) community development;
(c) community diversity; and
(d) research impact.

RQ3 What are the potential directions for future research as derived from the work published in LAK and EDM?

It is worth noting that both LAK and EDM are two fast-developing research fields, which have incorporated a variety of educational topics in the past decade. To effectively and accurately identify such topics (**RQ1**), we designed an approach combining the power of topic modeling techniques and human expertise. We firstly employed a hierarchical topic detection method to analyze the text of the papers published in LAK and EDM, which returned the set of detected topics organized as a hierarchical tree with nodes from lower levels of the tree representing more fine-grained topics and nodes from upper levels representing more general topics. Then, a specific upper level of the tree, which had a relatively small and reasonable number of nodes, was selected and three experienced experts in the field were recruited to manually choose proper names indicative of the topics behind those nodes. With the topics detected, we further performed several analyses to answer **RQ2**, including (a) the definition and calculation of *T-Score* (see Sec. 3.3 for details), which can be used as a proxy to describe the communities' efforts devoted to investigating a topic; (b) the analysis of distinguishing authors according to their previous involvement in LAK and EDM; (c) the measurement of diversity in terms of contributing authors' gender, nationality, and ethnicity as well as regions of the contributing authors' affiliations; and (d) the analysis of the citations received by authors and papers. As for **RQ3**, we assumed that words, which the authors frequently used to describe potential future works in latter sections of the papers (e.g., Discussion and Conclusion) of a specific topic, are informative to describe future directions for the research on the topic. We adopted one of the most popular language modeling techniques, *Word2Vec*, to analyze the text collected from sections where authors might discuss future works.

In summary, the main findings derived by our study include:

- Eleven topics were commonly investigated in LAK and EDM, which received different emphases from authors of the two communities, e.g., the investigation of *Engagement Patterns & Resource Use* was observed in a larger fraction of papers in LAK, while *Predictive & Descriptive Analytics* appeared more frequently in EDM.
- Compared to LAK, authors in EDM stayed slightly closer to their peers and thus constituted a more connected community. Noticeably, a steady number of EDM authors were attracted to LAK in recent years.
- Overall, LAK was highly similar to EDM in terms of their diversity in contributing authors' gender and nationality as well as the world regions of the contributing authors' affiliations. However, EDM was more diverse to LAK in terms of their authors' ethnicity.
- LAK papers, especially those investigating *MOOCs & Social Learning*, attracted a larger number of citations than those published in EDM.
- Future research directions for *Affect Modeling* may include more efforts on the capture and exploitation of the data used to model learners' affect states, while *Reading & Writing Analytics* may demand for developing more advanced techniques to model learners' comprehension.

2 RELATED WORK

2.1 Bibliometric Studies in Educational Research

Bibliometrics refers to the use of statistical methods to analyze books, articles, and other publications, whose goal is to explore the impact of a research field, a publication venue (e.g., conference and journal), or a (set of) researcher(s) [39]. Given that (i) educational research is a very broad field, which consists of a variety of topics; and (ii) there could be up to a few hundreds or even thousands of papers published every year revolving around each of those topics, bibliometric methods have been widely used to capture the general trend of educational research. For example, Chiang et al. [12] explored the trends of e-learning literature by analyzing 1,944 papers retrieved from the SSCI database between 1967 and 2009 with keywords such as "e-learning" and "distance learning". They found that the quantity of e-learning literature was expanding remarkably and researchers in the field often worked with others to publish papers. To name a few, other representative works of this research strand include [21, 25, 36, 57, 58].

There are a few studies relevant to our work [15, 16, 32, 49], which used different data sources (e.g., the Scopus database [49], conference proceedings [15, 16, 32]) and techniques (e.g., authorship analysis [32], citation analysis [15], epistemic network analysis [16]) to reveal different aspects related to the research on learning analytics and educational data mining. For instance, Dawson et al. [16] found that the impact of learning analytics research on practice, theory, and frameworks was relatively limited. It is also worth noting that bibliometrics has been recognized as an important instrument to diagnose the health of the learning analytics field [31]. Compared to these studies, our work distinguished itself from the following aspects. Firstly, we chose LAK and EDM as our data source, in which the most relevant cutting-edge research is published every year. Secondly, we applied text analysis methods to automatically conduct a nuanced detection on the topics investigated by researchers in the field. Thirdly, with the aid of language modeling techniques, we further explored and discussed potential research directions for certain topics in the field.

2.2 Topic Modeling

Topic modeling is widely adopted in bibliometric studies because of its strong ability in discovering abstract topics in a collection of documents, which, typically, is achieved by measuring the possibilities of the co-occurrence between topics and documents [50]. In particular, Latent Dirichlet Allocation (LDA) [6] and its variants are most popular among various topic modeling techniques [14, 20, 30]. Though being widely used, LDA has two inherent limitations. Firstly, LDA assumes the number of topics is pre-fixed and known to people beforehand, which is rather impractical for fields where new topics keep occurring. Though techniques such as log likelihood [23] and perplexity [3] can be applied to determine the number of topics automatically, these techniques, still, may return a large number of topics (could be up to a few hundred), which poses great challenges to people to efficiently interpret those topics. Secondly, as LDA models the topic distribution among documents via the Dirichlet distribution, the returned topics are uncorrelated to each other, which further hinders capturing the underlying relationship between different topics. Similar to [13, 55], we also adopted a topic modeling method based on hierarchical latent tree analysis to account for the fast-changing topical variance in LAK and EDM. Specifically, this method is capable of identifying topics in different granularity levels (thus do not require people to be aware of the number of topics in advance), and more importantly, the identified topics are returned as a hierarchical tree describing the interconnected relationship between different topics. We describe the details of this method in Sec. 3.2.

3 METHODS

In this section, we first detail our data collection process, followed by the introduction of the method we adopt to uncover the investigated topics in LAK and EDM. Then, we introduce the metrics and techniques used in comparing the two communities. Lastly, we describe how *Word2Vec* was applied to explore future research directions.

3.1 Data Collection

Our data collection was mainly assisted by Database systems & Logic Programming[2] (DBLP) and Microsoft Academic[3]. DBLP is an online reference for bibliographic information of publications in academic conferences of computer science, and Microsoft Academic is a free web search engine for academic publications and literature, which has indexed over 220 million publications. In details, we collected the publication data of LAK and EDM in two steps: (i) we first obtained the titles of all publications in LAK (between 2011 and 2019) and EDM (between 2008 and 2019) by scraping their corresponding HTML pages in DBLP; and then (ii) we further used the title of each paper to retrieve its metadata via the Microsoft Academic API, including the abstract, the authors, the affiliations to which the authors belong, the number of citations, the list of referenced papers, etc. Note that we only included publications that are full or short papers from the main conference proceedings into our study because these two types of publication existed in both of the two conferences in almost every year and they carried most of the prominent research works that should be considered when portraying the development trends of the fields. By doing this, we expect to deliver a more fair comparison between the two communities.

[2]https://dblp.org

[3]https://academic.microsoft.com/

3.2 Hierarchical Topic Detection

As indicated before, both LAK and EDM are developing rapidly and embrace research on new topics. This continuous change makes it difficult to capture the relationship between these new topics and the old ones and further maintain a holistic understanding of the communities, e.g., what are the main research interests in LAK or EDM? To deal with this challenge, our work adopted the Hierarchical Latent Tree Model (HLTM) [29] to identify the investigated topics and assign papers to those topics. The key idea of HLTM is to model both the patterns of word co-occurrence in documents and the co-occurrence of those patterns by using a hierarchy of discrete latent variables. The hierarchy of discrete latent variables can be viewed as a tree, in which each node is interpreted as a topic. That means the nodes at lower levels in the tree represent more fine-grained topics, while those at higher levels represent more general topics as they are created by measuring the co-occurrence of those more fine-grained topics. Another noticeable property of HLTM is that, when modeling the patterns of word co-occurrence, it mainly takes into account characteristic words, i.e., words that are of high frequency in one topic but are of low frequency in other topics, which is not supported by LDA. Similar to LDA, HLTM allows each document to be simultaneously assigned with more than one topic, and each topic is returned with a set of characteristic words specific to it.

Compared to LDA, the most significant benefit brought by HLTM is its ability in discovering the investigated topics as well as the relationship between these topics as a hierarchical topic tree, which enables us to learn about both the fine-grained topics and the general trends in the field by inspecting different levels of the tree. In this study, we focused on the topics from upper levels of the tree as our goal was to detect the general research focuses of LAK and EDM. With a specific tree level selected, we recruited three experts, who have been involved in both of the two communities for years, to manually scrutinize the characteristic words of each topic in that tree level as well as the papers belonging to the topics, especially those containing characteristic words in their titles, and then determine a name to represent the topic.

In line with [10, 20, 30], we only used the titles and the abstracts of the collected papers as input to HLTM, which are expected to carry enough information to indicate the topics investigated in each paper. Before serving as input to HLTM, we pre-processed the textual data by (i) lowering cases, removing numbers, punctuation marks, and stopwords, and lemmatization, and (ii) only keeping the top 1,000 most frequent terms. We ran HLTM with different random seed parameters as suggested by the original work for 50 times and evaluated the resulted hierarchical topic trees by computing their *topic compactness* [11], i.e., the average similarity between pairs of terms in topics, and selected the one with highest value for analysis.

3.3 Community Comparison

With the research topics identified by applying HLTM described above, we applied different analysis methods to answer **RQ2**, so as to underline the difference between LAK and EDM with respect to (a) investigated topics, (b) community development, (c) community diversity, and (d) research impact.

Investigated topics. Here, we aim at measuring and comparing the rough amount of researchers' efforts allocated to different topics in LAK and EDM in different years. Our intuition is that, for a specific topic, the set of accepted papers that are specific to the topic in a conference in a year can be regarded as a proxy for the total amount of efforts invested by researchers in that year. It should be noted that (i) LAK and EDM may accept different numbers of papers in different years; and (ii) different number of topics may be observed in different papers. To enable a fair comparison, we define the metric of *T-Score*. For a conference $c \in \{\text{LAK}, \text{EDM}\}$ in year $y \in [2008, 2019]$, we denote the set of papers accepted by c in year y as $P_{c,y} = \{p_1, p_2, ...\}$. Assume that there is a total K topics investigated by LAK and EDM, i.e., $T = \{T_1, T_2, ..., T_K\}$, and the set of topics contained in a paper $p_i \in P_{c,y}$ is represented as T_{p_i}. If we represent the total amount of efforts from all authors in conference c in year y as 1, then the amount of efforts allocated by those authors to a specific topic T_k (i.e., $\text{T-Score}_{c,y,T_k}$) can be computed as follows:

$$\text{T-Score}_{c,y,T_k} = \sum_{p_i \in P_{c,y}} \frac{1}{|P_{c,y}| \cdot |T_{p_i}|} \quad \text{where} \quad T_k \in T_{p_i} \tag{1}$$

Similarly, we can slightly revise Equation 1 to compute the total amount of efforts allocated by authors to the topic T_k in conference c across all the years, i.e., $\text{T-Score}_{c,T_k}$, as follows:

$$\begin{aligned} \text{T-Score}_{c,T_k} &= \sum_{p_i \in P_c} \frac{1}{|P_c| \cdot |T_{p_i}|} \\ \text{where} \quad T_k \in T_{p_i} \quad &\text{and} \quad P_c = \sum_{y \in [2008, 2019]} |P_{c,y}| \end{aligned} \tag{2}$$

Note that, compared to Equation 1, Equation 2 represents the total amount of efforts devoted by all authors in conference c (instead of the efforts from a specific year) as 1. In experiments, we calculated both Equation 1 and Equation 2 to answer **RQ2 (a)**.

Community development. To gain a better understanding of the development of LAK and EDM, we are mainly interested in: (i) whether LAK and EDM have attracted more and more authors over the years and who those authors are and (ii) whether the authors in the two communities are connected with each other differently. For (i), we first calculated the number of authors who published in LAK and EDM in every year. Then, we further delved into the composition of those authors by distinguishing:

- authors that had never published in LAK or EDM before;
- authors that had published in the same conference before;
- authors that had published in the other conference before;
- authors that had published in both LAK or EDM before.

For (ii), we constructed two networks of authors based on their co-authorship in published papers of LAK and EDM, respectively. Specifically, each author was represented as a node in the network. If two authors had co-authored at least one paper, an edge was created to connect these two authors. The weight of the edge was determined based on the number of papers that the two authors had co-authored. Then, we borrowed a set of metrics from network science [2] to inspect whether there exists any obvious difference between the two communities, including:

M1 *# Nodes*, i.e., the total number of authors in a community;
M2 *# Edges*, i.e., the total number of author pairs who had co-authored at least one paper;
M3 *Average degree*, i.e., the average number of authors that are adjacent to a specific researcher;
M4 *Average weighted degree*, i.e., the average number of co-authorship that an author had;
M5 *Diameter*, i.e., the maximal distance between all pairs of authors;
M6 *Average path length*, i.e., the average distance between all pairs of authors;
M7 *Average clustering coefficient*, i.e., the measure of how complete the neighborhood of an author was;

We used Gephi[4] to compute the above metrics.

Community diversity. Quite some previous works, such as [26, 33], have well recognized that a diverse and inclusive scientific community is likely to be more productive, innovative, and impactful. This motivated us to measure the community diversity of LAK and EDM, which was achieved by taking into account (i) the contributing authors and (ii) the affiliations to which the contributing authors belong. Specifically, we quantified the diversity of the contributing authors in terms of their demographic including *gender*, *ethnicity*, and *nationality*. These demographic attributes were inferred from authors' names with the aid of open-source tools, i.e., genderize[5] and NamePrism [56]. As for the diversity of the affiliations, we considered the regions in which the affiliations reside. To attain this information, we utilized the Wikipedia API as follows: (i) we first checked whether an affiliation has a corresponding Wikipedia page by searching with its name; (ii) if yes, we further queried relevant metadata about the affiliation, which contained its regional information.

With such demographic and regional information identified, we used Simpson's index [47] to measure the diversity of a community, which takes into account not only the number of species (e.g., authors of different gender, nationality, or ethnicity, or affiliations of different regions) but also the relative abundance of each species. The value range of Simpson's index is [0, 1], with 0 represents no diversity and 1 represents infinite diversity.

Research Impact. As suggested by previous works [44, 51], the number of citations that a paper receives can be treated as a proxy of its research impact. In line with this, we measured the research impact of the two communities by calculating the following metrics:

M8 Avg. # of citations that LAK/EDM authors received[6];
M9 Avg. # of citations that LAK/EDM papers received;
M10 Avg. # of citations that LAK/EDM papers of a topic received;

3.4 Future Research Direction Exploration

Potential rewarding directions for future research in a scientific field, more often than not, are given by experienced researchers in

[4] https://gephi.org/
[5] https://genderize.io/
[6] Only the citations received by papers of LAK/EDM were considered here.

the field through manually surveying and summarizing relevant research works, such as [42, 43]. Instead of solely relying on the human efforts, we suggested that methods used for automatic text analysis can help answer **RQ3**. Notice that authors often discuss current research gaps and provide potential directions for future work in sections whose titles contain keywords like "discussion", "limitation", and "future work" (referred as future-work sections in the following). For a specific topic, if researchers frequently use certain words to discuss its potential research directions in the future-work sections across different papers of a topic, we assume that such frequently-used words can be used to shed some light on the future directions of the topic. We referred these frequently-used words as future-work words.

Recall that each topic can be described with a set of characteristic terms after applying HLTM described in Sec. 3.2, which is given in Table 1 in Sec. 4. We proposed to apply *Word2Vec* to capture the future-work words for each topic. *Word2Vec* takes a large text corpus as its input and produces a set of vectors for words in the corpus. In particular, if two words co-occur closely and frequently in the corpus, their vectors are positioned closely in the vector space of the corpus. Therefore, if words that are positioned closely relate to the characteristic words of a specific topic in the vector space of the future-work sections, these words can be retrieved as the corresponding future-work words. Specifically, our approach consists of three main steps to identify the future-work words for a specific topic:

(1) We adopted the same pre-processing steps as described in Sec. 3.2 to the text of the future-work sections of the published published in the past five years and then used them to train the *Word2Vec* model;
(2) For each characteristic word of a topic, we retrieved the top-K closest words in the vector space by calculating the cosine similarity between word vectors;
(3) Among the sets of retrieved close words, we computed the occurrence of each word and returned the top-K with the highest occurrence as the future-work words for the topic.

4 RESULTS

4.1 Published papers

In total, we collected 1,018 papers for our study, in which 436 were from LAK and 582 from EDM. The number of papers accepted by LAK and EDM across the years was depicted in Figure 1, from which we observed: (i) in general, both LAK and EDM accepted more and more papers over the years; and (ii) EDM accepted more papers than LAK in almost every year at the early stage of development, while, in recent years (2017-2019), LAK had a higher (or even) number of papers than EDM.

4.2 Identified Topics

By applying HTLM on the collected data, we constructed a hierarchical topic tree consisting of two levels, in which the bottom level had 100 fine-grained topics and these topics were further clustered into 11 more general topics at the top level. The names of these 11 topics, as determined by the recruited experts, are given together with their characteristic terms and the representative papers of each topic cluster in Table 1. Based on Table 1, we had several interesting

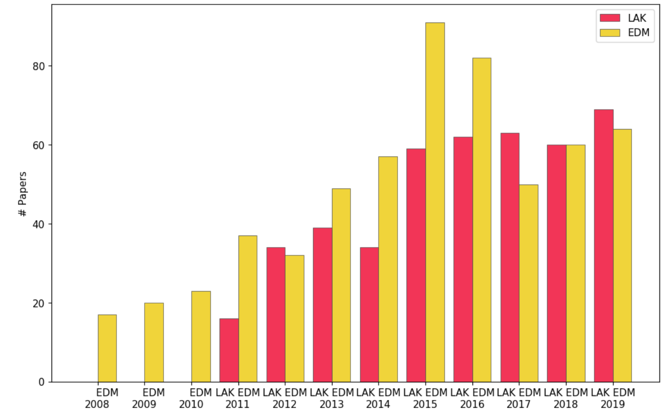


Figure 1: The number of accepted papers across the years.

observations. Firstly, the topic that was most widely investigated by researchers in the two communities was T1 (*Predictive & Descriptive Analytics*) with 673 papers, followed by T2 (*Engagement Patterns & Resource Use*) with 590 papers and T3 (*Multimodal Learning Analytics & Collaborative Learning*) with 488 papers. This is in line with our understanding as these topics were popular among authors in both of the two communities. The least attractive topic was T11 (*Affect Modeling*), which was only investigated by 60 papers. This is probably due to the lack of necessary resources to afford the equipment required for such research, e.g., eye trackers and EEG. Recall that each paper could belong to multiple topic clusters simultaneously (e.g., [27] being assigned to both T1, T2, and T8). In our results, on average, there are 3.69 topics contained in each paper, and over 65% papers covered from 3 to 5 topics.

4.3 Community Comparison

Difference of the investigated topics. The results of the overall *T-Scores* (Figure 2) show that the LAK authors dedicated more attention to the research of T2 (*Engagement Patterns & Resource Use*) and T6 (*Effects on Teaching & Learning Practices*), while EDM researchers put more emphasis on T1 (*Predictive & Descriptive Analytics*) and T4 (*Knowledge & Skill Modeling*). This is in line with the difference between the two communities highlighted by [45]. That is, one of the main goals of LAK is to better support instructors and learners, which can greatly benefit from research of T2 and T6. EDM focuses on the automated adaptation driven by techniques like machine learning, which, more often than not, is powered by the research of T1 and T4. However, when delving into the *T-Scores* of different topics across the years (Figure 3), we did not observe much obvious difference between LAK and EDM. However, one obvious increase in the research of T2 is observed in both LAK and EDM. In addition, the research on T6 in LAK increased gradually over the years, while its counterpart in EDM remained relatively steady over the years.

Difference of community development. We plot the total number as well as the composition of the authors in LAK and EDM across the years in Figure 4. Noticeably, both communities grew bigger and bigger over the years. This growth in the numbers of authors is a strong indicator of their increasing influence in the data-intensive

Table 1: The 11 topics that were commonly investigated by LAK and EDM between 2008 and 2019. The topics are ordered according to the number of papers that included them.

ID	Name	Characteristic words	Representatives	# Papers
T1	Predictive & Descriptive Analytics	learn-analytic, predict, feature, tutor, prediction, compare, train	[18, 27]	673
T2	Engagement Patterns & Resource Use	access, platform, resource, associate, material, semester, choose	[7, 27]	590
T3	Multimodal LA & Collaborative Learning	multimodal-learn, multimodal, collaborative-learn, analytic, collaboration, collaborative, technique	[8, 54]	488
T4	Knowledge & Skill Modeling	knowledge-trace, bayesian-knowledge-trace, student-knowledge, student-model, parameter, bkt, student-modeling	[35, 41]	438
T5	Recommender Systems & LA Adoption	recommendation, recommend, filter, recommender, evaluation, trajectory, learn-paper	[38, 48]	369
T6	Effects on Teaching & Learning Practices	effect, positive, randomize, negative, treatment, condition, engagement	[4, 52]	340
T7	Reading & Writing Analytics	text, write, word, essay, natural-language-processing, linguistic, student-write	[19, 46]	268
T8	MOOCs & Social Learning	mooc, forum, discussion-forum, massive-open-online-mooc, post, participation, discussion	[27, 37]	261
T9	Assessment	item, real-datum, irt, testing, simulated, response, mastery	[5, 37]	124
T10	Game-based Learning & Study Strategies	game, problem-solve, behavior, educational-game, gameplay, player, problemsolving	[9, 24]	116
T11	Affect Modeling	affective-state, affect, frustration, confusion, boredom, affective, detector	[17, 22]	60

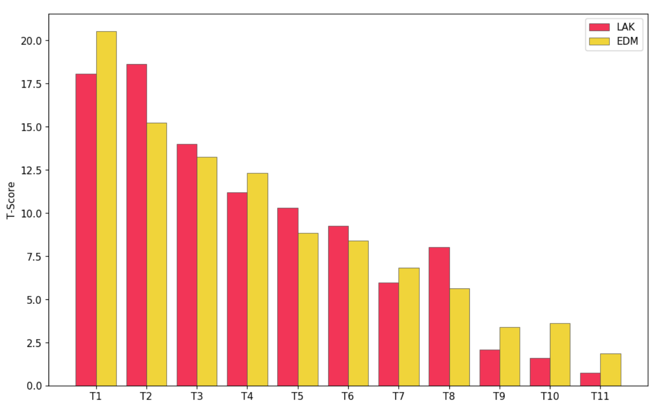


Figure 2: The overall *T-Scores* of different topics.

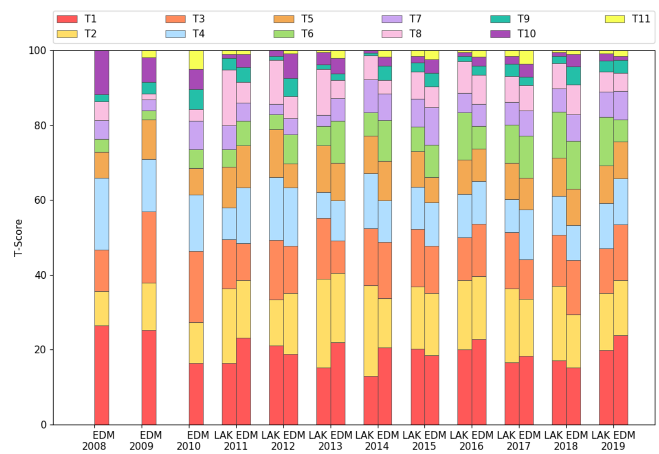


Figure 3: The *T-Scores* of different topics across the years.

research of education. Every year, the majority of the authors were those who had no paper accepted in neither of the two communities before. For the first edition EDM that as inevitable as it started first 2008, but that was necessarily the case for LAK that started in 2011. However, this also indicates that the first LAK conference edition did not have any authors who had previously published at EDM. Moreover, this also indicates a relative youth of the fields and general openness to new authors to join the two communities. In recent years (starting from 2015), we observe that the number of EDM authors who were attracted to LAK were constantly higher than that of LAK to EDM. To make this more obvious, we repeated the analysis by dividing the years into four periods, as shown in Figure 5. This figure clearly demonstrates the increasing attractiveness of LAK to the EDM authors in recent years (P2 and P3).

As for the measurement of the closeness between authors, we computed the metrics M1-M7 as shown in Table 2, which indicates that the EDM authors were slightly closer and more connected to their peers than their LAK counterparts. For example, the EDM authors were connected to an average of 4.70 peers, while it was 4.46 peers for the LAK authors.

Difference of community diversity. With Genderize, we successfully identified the gender of 90.24% authors in LAK and EDM, with about 10% unknown. Among the authors with identified gender, 58.84% were male and 31.40% were female. The respective gender distributions of the authors in the two communities were highly similar to this overall distribution. This large gender discrepancy indicates that, similar to many other science and engineering communities, both LAK and EDM were dominated by male researchers, though EDM was slightly gender-balanced as compared to LAK in

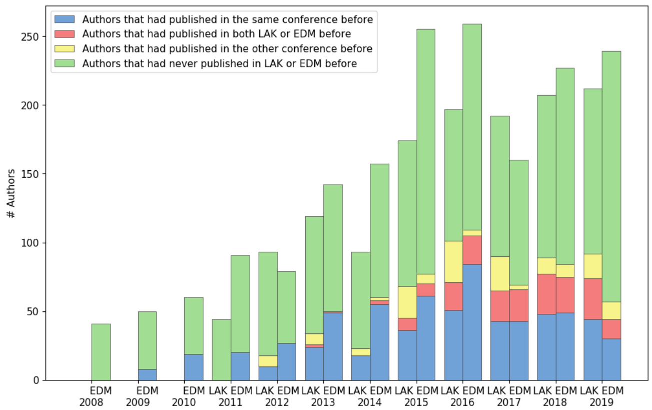


Figure 4: The composition of authors across the years.

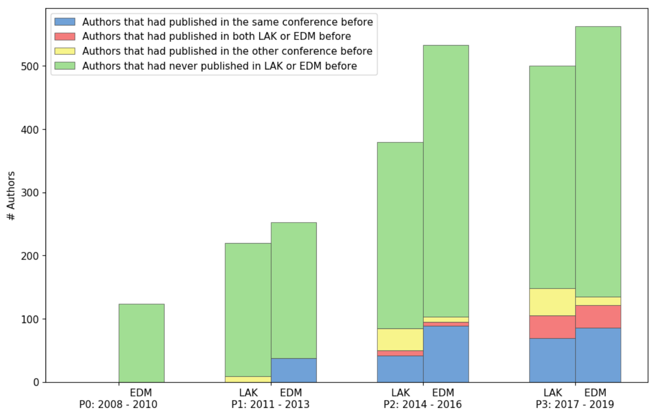


Figure 5: The composition of the authors across four aggregated periods: P0 - 2008–2010; P1 – 2011–2013; P2 – 2014–2016; and P3 – 2017–2019.

Table 2: The results of network analysis for LAK and EDM.

ID	Network Metrics	LAK	EDM
M1	# Nodes	935	1,205
M2	# Edges	2,086	2,832
M3	Average Degree	4.46	4.70
M4	Average Weighted Degree	5.11	5.34
M5	Diameter	19	13
M6	Average Path length	5.61	4.80
M7	Average Clustering Coefficient	0.85	0.88

terms of the overall diversity measured by Simpson's index (0.46 vs. 0.43). As for the difference of authors' nationality (Figure 6 (a)), we found that LAK had a larger fraction of Celtic English (i.e., people from immigration countries like U.S., Canada, and Australia), European, and Hispanic, while the fraction of Asian and Muslim was much larger in EDM. When it comes to ethnicity (Figure 6 (b)), LAK was more attractive to White and Hispanic, while EDM embraced more Asian and Pacific Islanders. As for the regions of the affiliations (Figure 6 (c)), we observe that there were more affiliations from North America and East Asia in EDM, while more affiliations from Europe and Oceania in LAK. When considering the overall diversity, EDM was slightly better than LAK in authors' nationality (0.79 vs. 0.78) and obviously outperformed LAK in authors' ethnicity (0.50 vs. 0.42). On the contrary, LAK was slightly more diverse than EDM in terms of the regions of the contributing affiliations (0.67 vs. 0.66). Similar observations can also be found when inspecting the yearly diversity of the two communities regarding authors' nationality and ethnicity as well as affiliations' regions (Figure 7), while LAK, compared to EDM, achieved slightly higher diversity in authors' gender in recent years.

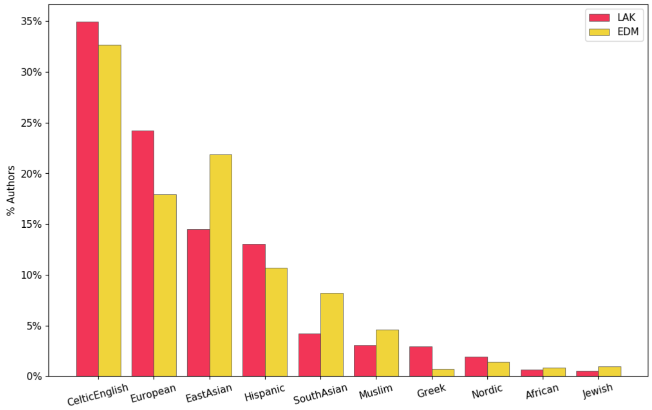
Difference of research impact. Based on Table 3, we observed that both authors and papers of LAK received a much larger number of citations than those of EDM. This difference is also observed when calculating the average number of citations received by papers of different topics in the two communities. In particular, the largest difference in the average values is 12.31 for the citations of the papers on topic of T8 (*MOOCs & Social Learning*).

Table 3: The average number of citations received by authors and papers. Significant differences (according to Mann-Whitney test) are marked with * ($p < 0.01$) and ** ($p < 0.001$).

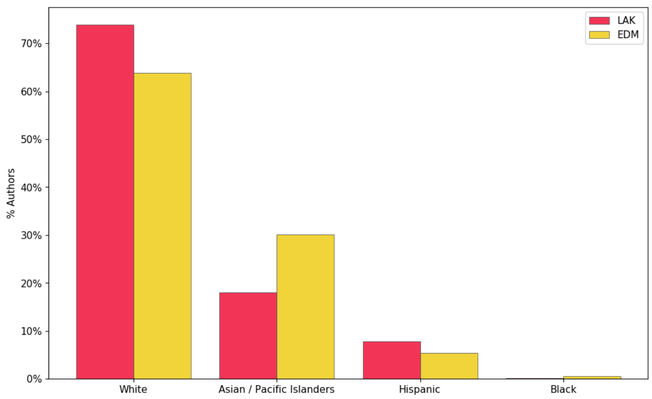
	Metrics	LAK	EDM
M8	# Avg. citations that a researcher has **	28.68	19.00
M9	# Avg. citations that a paper has **	14.63	8.63
	T1: Predictive & Descriptive Analytics **	16.03	9.54
	T2: Engagement Patterns & Resource Use **	13.76	7.15
	T3: Multimodal LA & Collaborative Learning **	15.56	7.97
	T4: Knowledge & Skill Modeling *	16.38	8.13
	T5: Recommender Systems & LA Adoption **	16.67	9.71
M10	T6: Effects on Teaching & Learning Practices *	13.84	6.20
	T7: Reading & Writing Analytics *	14.80	7.96
	T8: MOOCs & Social Learning **	22.27	9.96
	T9: Assessment	6.61	9.91
	T10: Game-based Learning & Study Strategies	20.30	10.91
	T11: Affect Modeling	22.75	9.70

4.4 Exploration of Future Research Direction

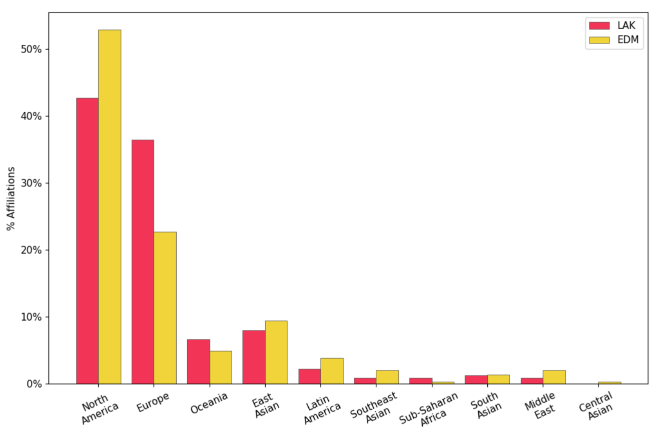
The most indicative words of each topic derived by analyzing future-work sections in the EDM and LAK papers are given in Table 4. Interestingly, Table 4 provides several insights about the potential research directions for a few topics. Take T3 (*Multimodal LA & Collaborative Learning*) as an example, the most relevant words derived from future-work sections include "*posture*" and "*gaze*", which may imply that more research efforts should be revolved with the capture and utilization of such data. To verify whether this implication exists, we further manually checked the future-work sections of papers in this topic cluster, and we found the authors indeed made similar suggestions in the papers, e.g., "*... In future work, I intend to examine how incorporating audio, head pose, gaze and electro-dermal activation data may complement the video segment selection process ...*" [53] and "*... Future work with regards to prototypical postures would also explore both participants in a dyad at once, clustering on both joint angles simultaneously ...*" [40]. Similarly, when inspecting



(a) The nationality of the authors



(b) The ethnicity of the authors



(c) The regions of the authors' affiliations

Figure 6: The fraction of authors of different nationality and ethnicity and the fraction of affiliations of different regions in EDM and LAK.

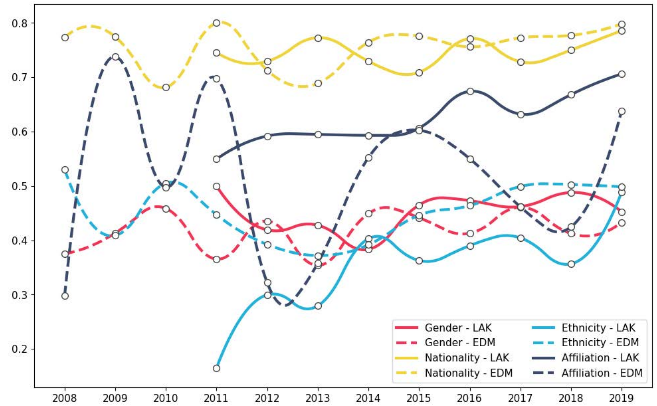


Figure 7: The diversity of the authors and affiliations across the years.

T7 (*Reading & Writing Analytics*), we found that there were several papers suggesting that research on this topic required more efforts in modeling learners' comprehension, e.g., "*... the application of dynamical systems theory to reading comprehension assessment is still in its infancy. Our future efforts will involve leveraging this vast theoretical and methodological framework in order to model comprehension processes more directly and at more fine-grained levels ...*" [28]. However, it should be noted that, for most of the other topics, we could not derive much useful insights about the directions of future work, e.g., T8 (*MOOCs & Social Learning*). This calls for more research efforts to be devoted to exploring more robust approaches to achieve this goal.

5 DISCUSSION

Implications for LAK and EDM. A few implications can be drawn from this study. Firstly, our analyses revealed that the most under-explored topic in EDM and LAK is *Affect Modeling*, though it has been widely recognized as essential for the personalization of learning experience. This is possibly due to the costs of experimental devices needed to capture relevant data, which could not be afforded by many researchers. To facilitate the research of this topic, it would be necessary to develop effective practices to share those experimental devices as well as the collected data.

Secondly, we demonstrated that the authors of LAK and EDM spent different amounts of effort on various research topics. Though the observed difference is in line with the two communities' original focuses (as stated in [45]), it would be beneficial for them to pay attention to the research published in the other community and learn from each other. For instance, we noticed that there was an obvious increase in the research of T6 (*Effects on Teaching & Learning Practices*) in LAK while its counterpart in EDM remained rather steady, it would be interesting to scrutinize the works presented in LAK and search for possible driving factors behind the increase, e.g., have there been many new learning analytics systems, e.g., OnTask [34], developed to support both teachers and learners in recent years? Are these systems different from those (e.g., Intelligent Tutoring Systems) developed in EDM in the early years? What are the fine-grained topics within T6 in LAK and EDM?

Thirdly, though the LAK authors and papers generally received more citations than those in EDM, we should note that citation cannot fully reveal the quality and impact of research work (as demonstrated in [1]). Therefore, additional information should be collected to better indicate their research impact, e.g., the number

Table 4: The identified future-work words of different topics.

ID	Topics	Future-work words
T1	Predictive & Descriptive Analytics	chance, train, outperform, classifier, lesson, kappa, auc
T2	Engagement Patterns & Resource Use	participate, watch, advisor, preparation, service, signal, literacy
T3	Multimodal LA & Collaborative Learning	posture, gaze, exploration, methodology, interview, trace, coding
T4	Knowledge & Skill Modeling	procedure, refine, kc, mastery, factorization, matrix, refinement
T5	Recommender Systems & LA Adoption	optimization, effectiveness, competency, propose, functionality, widget, ensure
T6	Effects on Teaching & Learning Practices	completion, cause, fix, receive, ignore, certificate, motivation
T7	Reading & Writing Analytics	comprehension, property, cohesion, index, sentence, style, overlap
T8	MOOCs & Social Learning	participate, thread, medium, reply, quantity, moocs, forum
T9	Assessment	estimation, pfa, misconception, bkt, parameter, afm, procedure
T10	Game-based Learning & Study Strategies	regulation, progression, bridge, hypothesize, puzzle, solve, trajectory
T11	Affect Modeling	gaming, disengagement, correctness, detect, boredom, frustration, state

of attendees to the conferences every year, the number of papers that have been reported by news media, the number of systems and tools developed by LAK and EDM that have been put to use in the real world.

Fourthly, we noticed that, the participation in both LAK and EDM was mainly dominated by the authors who were (i) male, (ii) of nationality of Centlic English, European, or East Asian, (iii) of ethnicity of White or Asian/Pacific Islanders, and (iv) from affiliations residing in North American or Europe. Such apparent diversity should raise awareness among relevant stakeholders in the two communities. More importantly, effective strategies should be developed to increase the diversity of the two communities, e.g., providing travel grants for under-representative people to present their research in the conferences.

The limitations of our work. There were a few potential threats to the validity of the presented analyses in our work. Firstly, though enabling us to effectively identify a relatively small number of general topics investigated by both LAK and EDM, HLTM lacks the ability to deal with the polysemy of words, i.e., capturing the association of one word with two or more distinct meanings. For instance, *gaming* is widely used when described the research of *Game-based learning*, which refers to to the design of learning programs to trigger amusement or fun among learners during their learning process, but also frequently used in the research of *Study strategies*, which refers to the investigation of learners' attempts in completing the learning programs (e.g., submitting random guesses to assessment questions). This is also why the papers of these two topics were identified and combined into T10 in Table 1.

Secondly, we predicted the authors' gender, nationality, and ethnicity with the aid of Genderize and NamePrism. Though these tools seem robust in general, their prediction performance in our data remains unknown. To show the validity of our study, it is necessary to evaluate their prediction performance in our case. In addition, only authors' names were used by these tools to infer the demographic information, which, to a certain extent, limits the coverage of the prediction, e.g., the gender of about 10% authors could not be determined. Therefore, more information about authors should be collected and more advanced methods should be utilized for this prediction task.

Thirdly, we were only able to derive insights into potential research directions for a limited number of topics in Sec. 4.4. This is probably due to the fact that, more often than not, the authors mixed the description of future research directions with the conclusions of their work in future-work sections. This demands us to develop more robust approaches to answer **RQ3**, e.g., first applying pre-trained language models to distinguish sentences describing future research from those summarizing the completed studies, and then only utilizing the identified sentences related to future research directions as input to our method described in Sec. 3.4.

Fourthly, our attempt in exploring future research directions was solely based on the analysis of the proceedings of LAK and EDM in the past five years. In addition to these two venues, there exist other relevant communities such as Artificial Intelligence in Education, Learning@Scale, and Learning Science, which also play important roles in pushing the boundary of data-intensive educational research. Thus, it is also necessary to include these venues for analysis to better depict the future trends of educational research.

6 CONCLUSION AND FUTURE WORK

About a decade has passed since the establishment of the LAK and EDM conferences. To advance our understanding of the development of these two mainstream venues of data-intensive research on technology-enhanced education, this paper presented an extensive comparison between them and revealed their similarities and dissimilarities in terms of the investigated topics, community development, community diversity, and the impact of research works. In the future, we plan to (i) include the proceedings from other relevant venues for analysis to better depict the landscape of current research on technology-enhanced education, and (ii) explore other techniques to capture rewarding directions for future research.

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