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Exploring the Learning Analytics Equation: What About the *Carpe Diem* of Teaching and Learning?

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Abstract: Humans have always been lured by the idea that they can use data to understand a phenomenon and make predictions about it. Learning analytics, in this sense, promise to understand and optimize learning and the environments in which it occurs by collecting data from learners and learning contexts. In this regard, this study systematically examines research on learning analytics through bibliometric, data mining, and analytics approaches. This paper argues that research interest in learning analytics is increasing steadily; some countries, higher education institutions, and researchers have a specific research agenda that indicates their intention to specialize in that field. It is also noted that there is a need for more interdisciplinary studies on learning analytics and a further need to merge technological capabilities with pedagogy. Based on the findings of text-mining and social network analysis, the following themes were identified: (1) learning analytics to improve teaching and personalize learning, (2) hegemony of data-driven teaching and learning practices, (3) multimodal learning analytics as the next generation practice, (4) learning design for learning analytics, (5) formative assessment through learning analytics, (6) learning analytics for social online learning spaces, and (7) privacy and ethical concerns to overcome. This paper suggests focusing on issues such as ethics and privacy and warns researchers to pay attention to the risks of both an educational panoptic society and quantified decision-making processes. Furthermore, rather than relying on algorithms, it is suggested to incorporate social values and center the learners in the learning analytics processes. Finally, this paper asks the following: “If we quantify the learning processes, how can we benefit from the *carpe diem* of educational processes and then seize the beauty of teaching and learning?”

Keywords: learning analytics, learning design, educational data mining, adaptive and personalized learning, diagnostic and predictive analytics.

Highlights

What is already known about this topic:

- Learning analytics is an emerging, evolving, and data-driven field.
- Learning analytics promises understanding and optimizing learning and the environments in which it occurs.

What this paper contributes:

- This paper critically analyzes the state of the art in learning analytics research.
- This paper warns us about blindly adopted, data-dominated learning analytics strategies.

Implications for theory, practice and/or policy:

- There is a need for generating policies and strategies for data privacy and ethics.
- There is a need for more interdisciplinary studies, merging the use of technology and pedagogy in learning analytics research.
- Social aspects of teaching and learning should not be neglected in the learning analytics equation.
- The Carpe Diem moment of teaching and learning should not be ignored.

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Introduction: Data-Driven, Digitally-Shaped Educational Landscapes

If you torture the data long enough, it will confess to anything. –Ronald H. Coase

Digital transformation processes have been widely adopted in the higher education landscape (Bozkurt & Sharma, 2022), which further inspired higher education institutions to access and use the large volume of data that is available in online learning environments. Besides, as noted by Clow (2013) and Sclater et al. (2016), learning management systems are used as the default learning space by many higher education institutions, which allows higher education institutions to collect each single digital footprint; the amount of this type of data is increasing and is easy to access. Furthermore, there is a tendency to benchmark the performance of the learners through quantified metrics. Statistical and computational capacities, doubled with powerful diagnostic and predictive algorithms, are making it easier to analyze large volumes of educational data. Finally, there is growing interest in developing data-driven learning strategies and behaviors for adaptive, personalized learning. Consequently, learning analytics has emerged as a popular research area, yet there are still many unresolved questions, which requires examining the concept of learning analytics from a critical perspective.

The State of the Art in Learning Analytics Research

The overall purpose of learning analytics is to improve the quality of learning experiences (Pardo & Siemens, 2014) by analyzing different learning scenarios (Siemens & Long, 2011). It is also highlighted that "learning analytics is applied research, and as such, there is much potential in the theory it generates" (Joksimović et al., 2019, p. 53). There is a wide range of definitions of learning analytics (e.g., Johnson et al., 2011; Sharples et al., 2013); however, the most referenced definition is the one identified during the 1st International Conference on Learning Analytics and Knowledge (LAK11, 2011):

> "Learning analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs".

Learning analytics can help educators understand how their students are learning and identify areas where they may need additional support. By analyzing data on student performance, educators can gain insight into which teaching methods and strategies are most effective, and use this information to improve their teaching and better support their students. One of the key advantages of learning analytics is that it allows educators to track student progress in real-time and respond to any issues or concerns as they arise. This can help prevent students from falling behind and ensure that they are able to keep up with their studies and reach their full potential. Additionally, learning analytics can help educators identify trends and patterns in student performance, which can inform the development of new teaching strategies and resources. For example, if a particular teaching method is found to be particularly effective at helping students improve their performance on a certain type of assignment, this information can be shared with other educators to help them improve their teaching as well. Overall, learning analytics is an important tool for educators, as it allows them to track student progress and identify areas for improvement in real-time, ultimately helping to enhance the learning experience for all students. However, it is still a relatively new research area and there is a need to fully explore its promises and risks.

The related literature on learning analytics reports different issues. For instance, while some argue that learning analytics "lacks a coherent, articulated epistemology of its own" (Clow, 2013, p. 686), others argue that, with multiple and well-established disciplinary roots (Gašević et al., 2017; Siemens, 2013), learning analytics is maturing (Knobbout & van der Stappen, 2020), evolving, and emerging as a bricolage field (Ferguson, 2012; Joksimović et al., 2019; Siemens, 2013). Considering its promises "ranging from pedagogical to technological perspectives, and from elementary to higher education level," it can be applied to a wide range of learning settings (Lee et al., 2020, p. 5).

The rise of learning analytics is not a coincidence. Along with the aforementioned issues, learning design practices (Mangaroska & Giannakos, 2018; Viberg et al., 2018), as an extension of instructional design, fuel the advancement of learning analytics. “The convergence and synergies between [learning design and learning analytics] are becoming an important area for research” (Mangaroska & Giannakos, 2018, p. 516) and themes such as design thinking and user experience-driven approaches; online learning-informed designs and online environments; analytical approaches for assessment and evaluation; and engagement-based learning design characterize the learning design processes (Saçak et al., 2022a).

Learning analytics research is a trending hot topic in higher education (Pelletier et al., 2021; 2022) and there is a wide range of articles aiming to depict the state of the art in learning analytics research. These papers report that learning analytics interventions enhance students’ learning, identify their problems early, and offer timely, personalized support (Wong & Li, 2020). Earlier studies on learning analytics found some evidence that learning outcomes improved, mostly in three areas: knowledge acquisition, such as getting better test scores and grades; skill development; and cognitive gains (Viberg et al., 2018). Meta-analysis studies argue that learning analytics can provide an effective walkthrough for designing effective smart learning environments; they can provide accurate and statistically significant critical insights into the individual and collective learning processes, the processes of identification and scaffolding of struggling students, the motivational effects of different parameters on achievement behaviors, increasing (self and contextual) awareness, and understanding the factors that make adaptation effective for learners (Papamitsiou & Economides, 2016).

On the other hand, it is noted that most of the cited learning analytics research papers are conceptual (Dawson et al., 2014), and ethical concerns and privacy issues are still heavily debated topics (Sclater et al., 2016; Slade & Prinsloo, 2013). Though the positive features of learning analytics are promoted, some still warn us of the seductive promises of learning analytics (Selwyn, 2020) and ask critical questions such as “what is being measured, why it might be useful, [and] how it relates to learning” (Wilson et al., 2017, p. 995). In such a context where there are divergent opinions and ambiguity regarding the future of learning analytics, this paper examines the research on learning analytics to identify research patterns and trends.

Methodology

To identify and better understand the research themes, this paper used data mining and analytics approaches (Fayyad et al., 2002) to systematically review (Gough et al., 2012) research on learning analytics and used analytics techniques such as text mining (Feldman & Sanger, 2007) and social network analysis (Scott, 2017). This study used Scopus, the largest abstract and citation database of peer-reviewed literature and home to a wide range of publications from different research areas (Scopus, n.d.), to collect the sampled publications. The publications sampled in this research were identified by using one single search string, “learning analytic*.” Because the term *learning analytics* manifests itself, we did not use any other search strings or narrow down our search to get a complete panoramic view. The justification for including only the publications with the search string in their title was to build a more concentrated, robust research corpus by identifying the most representative findings that reflect the state of blended learning research. After adopting the PRISMA Framework (Page et al., 2021), a total of 1,963 publications were included in the final research corpus (see Table 1). During the screening process, the researchers removed irrelevant publications and included peer-reviewed publications in order to form a sound research corpus.

Table 1. Search Strings and PRISMA Framework Protocol

Search String	"learning analytic*"
Database	Scopus
Identification	2,491 document results
Screening	• Limited to period between 2011 and 2021 (*n* = 2,215) • Non peer-reviewed publications were removed (*n* = 2,021) • Publications in other languages were removed (*n* = 1,963)
Included	A total of 1,963 records were included in the final research corpus

It is important to note that this study did have certain strengths and limitations. Starting with the study's strengths, the results were presented through data visualization techniques, which made it easier for other researchers to find new ways to look at the results. Moreover, the different analysis techniques used to examine the data offer a more comprehensive view of the subject in question. Regarding the limitations of the study, only the publications indexed by Scopus were used to create the study corpus, and though Scopus is the largest database and allowed for a large volume of data to be analyzed, the findings are still partial, considering that no publications from the gray literature were examined. Additionally, this paper also acknowledges that publications in the gray literature could provide complementary insights to better understand the state of blended learning research.

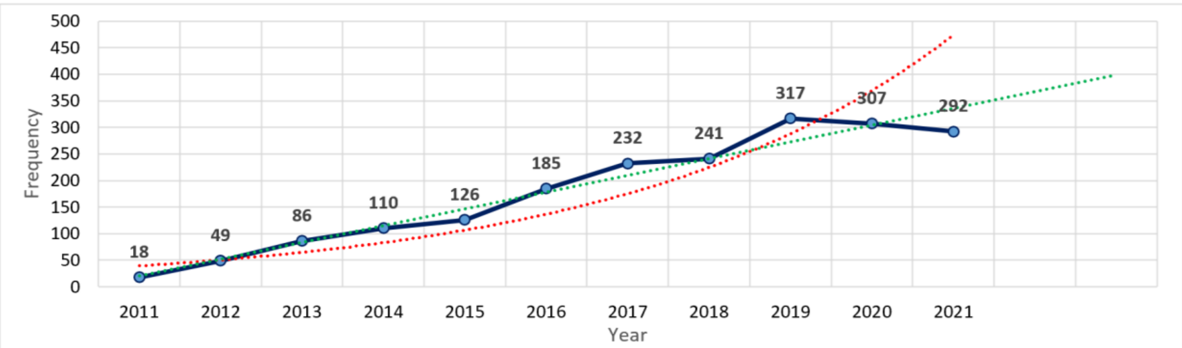
Findings and Discussions

This section presents findings and discussions of the descriptive data, text-mining, and social network analysis.

Research Model/Design

From 2011 to 2021, this review study covers a decade of learning analytics research. Accordingly, the research corpus includes a total of 1,963 studies (1,207 conference papers and 756 articles) published in 577 sources. The year 2011 is purposefully selected as a starting point because LAK11 occurred that year, and the most commonly used definition was identified during that event. A total of 4,033 authors contributed to the research corpus, which includes 177 single-authored papers. International co-authorship is 27% and the average age of the documents in the research corpus is 4.24 years, which means that most of the ideas presented are relatively new and reflect recent practices. A total of 3,429 keywords were used, and 56,922 references were cited in the papers included in the final research corpus. Time trend analysis (see Figure 1) indicates a steady increase in the number of learning analytics papers.

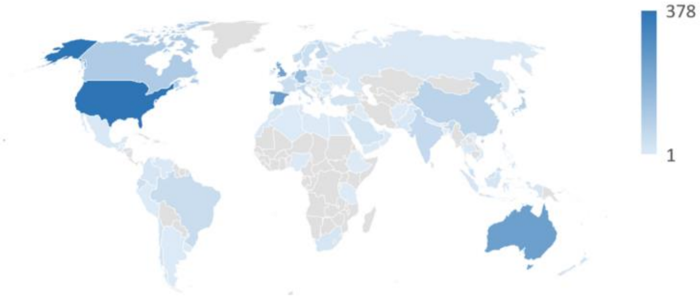
Figure 1. Time Trend Analysis of Research on Learning Analytics



The countrywide distribution (see Figure 2) suggests that more than half of the contributions come from 10 countries (60.5%), and developed countries with concrete digital transformation visions (e.g., United States, Spain, Australia, and United Kingdom) dominated the research on learning analytics.

Figure 2. Countrywide Distribution of Research on Learning Analytics

Country	n	%
United States	378	13,6
Spain	249	8,9
Australia	240	8,6
United Kingdom	236	8,5
Germany	144	5,2
Netherlands	113	4,1
Canada	102	3,7
Japan	88	3,2
China	76	2,7
Italy	59	2,1
Other	1101	39,5



The leading universities (see Figure 3), as expected, appear to be in countries with the most contribution (see Figure 2), and the top 10 contributing institutions constitute 20.9% of overall participation. Besides, most of the leading authors are affiliated with these higher education institutions, and 18.3% of the contribution is from these authors. This finding implies that some higher education institutions, as well as some of the lead authors, have specialized in learning analytics research and that these institutions could serve as learning analytics research hubs.

Figure 3. Institutional and Author-Based Distribution

University	n	%
The Open University	84	3,9
Monash University	52	2,4
Open Universiteit	50	2,3
Athabasca University	41	1,9
The University of Edinburgh	41	1,9
University of South Australia	40	1,8
Kyushu University	39	1,8
Universidad Politécnica de Madrid	37	1,7
Tallinna Ülikool	35	1,6
Technische Universitat Graz	34	1,6
Other	1715	79,1

Authors	n	%
Gašević, D.	55	3,3
Ogata, H.	41	2,4
Drachsler, H.	36	2,1
Rienties, B.	32	1,9
Dawson, S.	29	1,7
Pardo, A.	26	1,5
Kinshuk	24	1,4
Ochoa, X.	22	1,3
Worsley, M.	22	1,3
Ifenthaler, D.	21	1,2
Other	1375	81,7

In terms of the technological dimension of learning analytics research, computer science, engineering, and mathematics account for 59.8% of total research, while social sciences, which include education and educational field disciplines, account for 26.9% of total research, accounting for 86.7% of total research in learning analytics. This finding suggests that more cross-disciplinary research is needed to move forward, and the contribution from the social sciences can be increased if the learning analytics field expands beyond technological solutions to provide solutions that grow from the theoretical and practical knowledge of the social sciences and, by extension, educational disciplines. Interestingly, it seems that research on learning analytics is mostly led by conferences organized by prominent associations (see Figure 4). The Learning Analytics and Knowledge (LAK) proceedings, which were published by ACM, are the leading contributor of overall publications with 17.6%.

Figure 4. Distribution of Subject Areas and Sources of Learning Analytics Research

Subject Area	n	%
Computer Science	1555	43,4
Social Sciences	963	26,9
Engineering	364	10,2
Mathematics	221	6,2
Decision Sciences	102	2,8
Psychology	74	2,1
Arts and Humanities	57	1,6
Business, Management and Accounting	43	1,2
Medicine	42	1,2
Physics and Astronomy	36	1,0
Other	125	3,5

Source	n	%
ACM International Conference Proceeding Series	267	17,6
Lecture Notes In Computer Science	126	8,3
Ceur Workshop Proceedings	125	8,3
Journal Of Learning Analytics	33	2,2
Computers In Human Behavior	32	2,1
British Journal Of Educational Technology	31	2,0
Communications In Computer And Information Science	28	1,9
IEEE Global Engineering Education Conference Educon	25	1,7
Advances In Intelligent Systems And Computing	23	1,5
Computers And Education	23	1,5
Other	800	52,9

Bibliometric Patterns in Learning Analytics Research

For the co-citation analysis, the researchers analyzed a total of 50 references that hold strategic positions in the learning analytics research network (Figure 5). Accordingly, Greller and Drachsler (2012) and Ferguson (2012) are the central publications, followed by Slade and Prinsloo (2013), Arnold and Pistilli (2012), and Siemens and Long (2011). All these studies are conceptual and support the view that learning analytics is an emerging field that needs its own theoretical bases. The most-cited references (Figure 6) also show a similar pattern in that most of the papers are conceptual, explaining the field of learning analytics and showing an effort to explain its scope and provide justification for its presence in the educational landscape.

Figure 5. Analysis of the Co-Citation Network

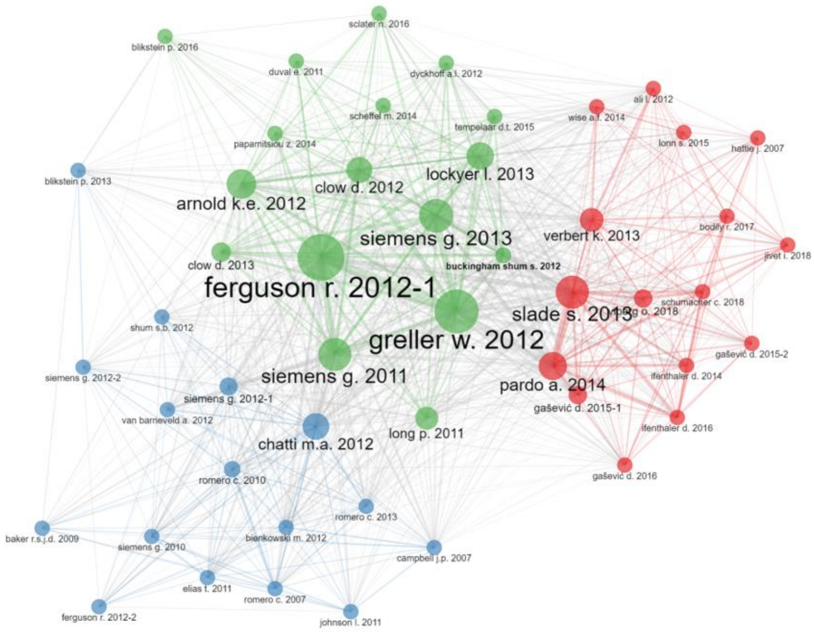


Figure 6. Most-Cited Reference Dashboard

Title	Author(s)	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Trend	Total
Learning analytics: Drivers, developments and challenges	Ferguson R. (2012)	0	1	12	34	55	85	83	89	90	112	81		642
Learning analytics: The emergence of a discipline	Siemens G. (2013)	0	0	2	13	23	41	49	57	79	81	93		438
Translating learning into numbers: A generic framework for learning analytics	Greller W., Drachsler H. (2012)	0	0	11	24	28	51	64	66	68	62	57		431
Learning analytics and educational data mining: Towards communication and collaboration	Siemens G., Baker R. S. J .D. (2012)	0	0	15	26	48	60	48	56	64	58	60		435
Course signals at Purdue: Using learning analytics to increase student success	Arnold K. E., Pistilli M. D. (2012)	0	0	7	22	31	50	62	63	72	72	52		431
Let's not forget: Learning analytics are about learning	Gasevic D., Dawson S., Siemens G. (2015)	0	0	0	0	6	35	48	59	84	90	68		390
Learning Analytics: Ethical Issues and Dilemmas	Slade S., Prinsloo P. (2013)	0	0	5	18	15	39	35	51	58	68	51		340
Learning analytics and educational data mining in practice: A systemic literature review of empirical	Papamitsiou Z., Economides A. A. (2014)	0	0	0	0	6	22	40	51	69	84	58		330
A reference model for learning analytics	Chatti M. A., Dyckhoff A. L., Schroeder U., Thus H. (2012)	0	0	6	22	35	51	44	56	43	52	44		353
Learning analytics dashboard applications	Verbert K., Duval E., Klerkx J., Govaerts S., Santos J. L. (2013)	0	0	9	16	28	52	52	48	49	47	39		340
Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting	Gasevic D., Dawson S., Rogers T., Gasevic D. (2016)	0	0	0	0	0	16	31	37	72	64	75		295
Social learning analytics	Shum S. B., Ferguson R. (2012)	0	0	18	34	40	54	34	37	40	35	31		323
Informing pedagogical action: Aligning learning analytics with learning design	Lockyer L., Heathcote E., Dawson S. (2013)	0	0	3	11	12	24	48	38	44	50	40		270
Can we predict success from log data in VLEs? Classification of interactions for learning analytics and	Agudo-Peregrina A. F., Iglesias-Pradas S., Conde-Gonzalez M. A.,	0	0	2	6	22	23	24	49	35	31	42		234
In search for the most informative data for feedback generation: Learning analytics in a data-rich context	Tempelaar D.T., Rienties B., Giesbers B. (2015)	0	0	0	0	4	19	32	42	38	45	34		214
Ethical and privacy principles for learning analytics	Pardo A., Siemens G. (2014)	0	0	0	3	10	29	18	28	36	41	46		211
The evolution of big data and learning analytics in American higher education	Picciano A. G. (2012)	0	0	3	5	7	26	39	41	37	31	30		219
The current landscape of learning analytics in higher education	Viberg O., Hatakka M., Balter O., Mavroudi A.	0	0	0	0	0	0	0	4	26	68	84		182
Design and implementation of a learning analytics toolkit for teachers	Dyckhoff A. L., Zielke D., Bultmann M., Chatti M. A., Schroeder U. (2012)	0	1	14	20	20	29	34	24	31	21	23		217
Educational data mining and learning analytics: An updated survey	Romero C., Ventura S. (2020)	0	0	0	0	0	0	0	0	0	21	96		117

Thematic Patterns in Learning Analytics Research

Data is not intelligence. –William Binney

This section provides findings from text-mining (Figure 7) and social network analysis (Figure 8) and uses these findings to identify research patterns in learning analytics research. The titles, abstracts, and keywords are the essence of any scholarly paper, and they are considered to be a meta-section that represent, summarize, and reflect the main ideas. In this regard, analyzing these sections can be extremely beneficial in determining research patterns, and the following section provides emerging research patterns in learning analytics.

- **Learning analytics to improve teaching and personalizing learning** (see the paths in Figure 7: *improve, teaching, learning analytics and personalized, learning* and *information, dashboard, teachers, students, courses, performance, academic, behaviors*; see the connected nodes in Figure 8: *technology enhanced learning higher education, learning design, learning analytics, personalized learning, academic analytics)*. As stressed in its definition, personalized learning is one of the promises of learning analytics (Klašnja-Milićević et al., 2020), and strategies such as customizable dashboards (Roberts et al., 2017) help learners manage the level of their learning and improve the effectiveness of teaching practices.
- **The hegemony of data-driven teaching and learning practices** (see the paths in Figure 7: *modeling, recommendation, learning, classification, machine,* and *dashboards, support, tools, learning analytics, and analysis, data, mining*; see the connected nodes in Figure 8: *educational technology, big data, educational data mining, learning management systems, machine learning, data visualization, learning dashboards*). Datafication and reliance on metrics are criticized because authority is given to third parties, and there is also the possibility of being exposed to biased algorithms (Carter & Egliston, 2021). Besides, such a view raises if we center datafication to the center of the learning processes, how can we humanize it and, if driven by algorithms, ensure that these practices are in their ideal form?
- **Multimodal learning analytics as the next-generation practice** (See the paths in Figure 7: *multimodal, learning, learning analytics, decision-making*; See the connected nodes in Figure 8: *learning design, multimodal learning analytics*). Multimodal learning analytics (Blikstein, 2013) is proposed to be a solution for complex learning processes (Blikstein, & Worsley, 2016) by bringing sensory data from real-world teaching and learning environments (Ochoa, 2017). In theory, while such an approach multiplies the positive outcomes of learning analytics, it would definitely lead to new challenges because it, again, intersects with privacy and ethical concerns.
- **Learning design for learning analytics** (see the paths in Figure 7: *design, learning analytics, educational, pedagogical*; see the connected nodes in Figure 8: *learning design, social learning analytics, learning analytics*). Though learning analytics has a clear focus on learning, there is a need to “holistically characterize learners, their needs, and their expectations” (Mangaroska & Giannakos, 2018, p. 528) where learning design can contribute through technology-informed design (Saçak et al., 2022a) in which the “design” aspect is prioritized and the focus is more on the experience of the learners (Saçak et al., 2022b).
- **Formative assessment through learning analytics** (see the paths in Figure 7: *evaluation, learning, formative, assessment*; see the connected nodes in Figure 8: *formative assessment, feedback, learning analytics, evaluation, assessment*). It is, perhaps, the best promise of learning analytics that it can provide working solutions for process-based formative analysis (Tempelaar et al., 2018). In this way, instructors can focus on the progress of the learners rather than on outcomes and can provide timely feedback that would further improve the quality of teaching and learning.
- **Learning analytics for social online learning spaces** (see the paths in Figure 7: *students, online, learning, e-learning*; see the connected nodes in Figure 8: *higher education, blended learning, distance learning, online learning, MOOCs*). Social media is highly used in online learning spaces to bridge formal and informal learning (Bozkurt, 2022) and it is argued that learning analytics can address these issues (Ferguson & Buckingham Shum, 2012). With the

emergence of blended learning due to the forced effects of the COVID-19 pandemic (Bozkurt et al., 2022), there is increasing use of online web tools and social media and learning analytics can carry the data in these social online spaces to increase the effectiveness of learning analytics.

- **Privacy and ethical concerns to overcome** (see the paths in Figure 7: *higher, education, institution, practices, privacy, learning analytics, ethical*; see the connected nodes in Figure 8: *big data, higher education, learning analytics, ethics, privacy*). Privacy and ethical concerns were articulated in many earlier publications (Clow, 2013; Sclater et al., 2016; Slade & Prinsloo, 2013; Viberg et al., 2018) and are highly related to further issues such as trust, accountability, and transparency (Pardo & Siemens, 2014). However, generating solutions for these issues is linked to many ideological assumptions and epistemologies (Slade & Prinsloo, 2013), which makes the task challenging and implies that learning analytics practices should develop solutions in their own context because the issues of privacy and ethics can be relative and interpreted differently by different parties.

Figure 7. Text-Mining Analysis of the Titles and Abstracts

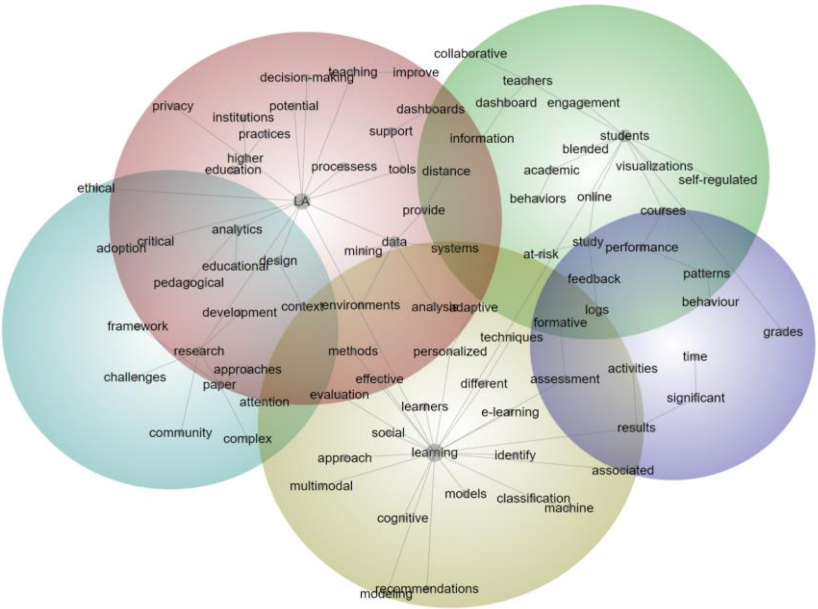
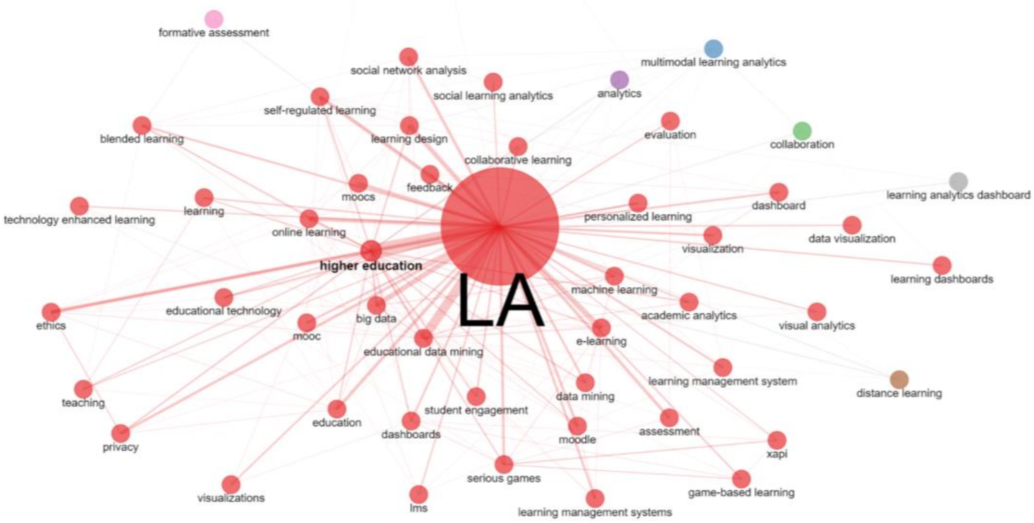


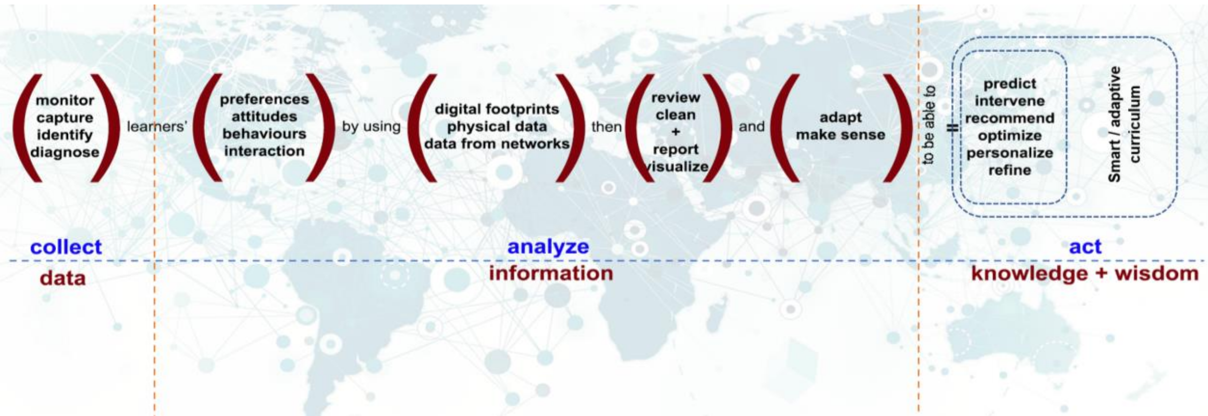
Figure 8. Social Network Analysis of the Keywords



Conclusion and Suggestions

This study analyzed a decade of learning analytics research and found that the field is maturing, and it is expected to see more studies in the future. It is also interesting to see that some countries demonstrate a special interest, and some higher education institutions along with some authors seem to have a special focus on learning analytics research, which implies their intention to specialize in that field. In terms of research areas, technology-related disciplines dominated learning analytics research, with a promising contribution from the social sciences. This point of view shows that there is a need for more cross-disciplinary research and hints at a hidden need in learning analytics research for the convergence of technological and pedagogical dimensions. The analysis of co-citations and most-cited papers suggests that the learning analytics field should move beyond conceptual discussions and concentrate on the field's theory and practice. On examination of the learning analytics research, the following themes were identified: (1) learning analytics to improve teaching and personalize learning, (2) hegemony of data-driven teaching and learning practices, (3) multimodal learning analytics as the next generation practice, (4) learning design for learning analytics, (5) formative assessment through learning analytics, (6) learning analytics for social online learning spaces, and (7) privacy and ethical concerns to overcome. Based on the reviewed papers and insights gained from related literature, we propose the learning analytics equation framework, which can be used to frame learning analytics practices. We referred to it as an equation because learning analytics is still maturing, which means that new variables can be added and it can be updated based on the developments in the field.

Figure 9. Learning Analytics Equation



Though the purpose of this paper is to depict the trends and patterns in learning analytics research, there are still some concerns, and the examination of the learning analytics research revealed further questions. For example, there is a concern about being an educational panoptic society, and there are ethics and privacy issues to be solved. The heavy reliance on quantitative data also risks making education a standardized process and leading to a quantified higher education. It is still an open debate that, without quantifiably assimilating human values and feelings, how can we transform social aspects of teaching and learning into learning analytics? If learning analytics has a huge potential to primarily serve learning, where are the learners during the decision-making processes, and who uses analytical dashboards, and for what purposes?

Carpe diem quam minimum credula postero –Horace (23 BCE), from Odes (I.11).

As a final remark, one may wonder where the social part is and how we can humanize learning processes if we heavily quantify them? Why are we so obsessed with predicting the future and why do we not prefer the *carpe diem* moment of teaching and learning? Beyond quantifying teaching and learning, how can we reach learners and encourage them to finish their journey, which begins in their hearts and minds and continues through lifelong learning networks? If we identify a vision based on the quantified measures, how can we seize the beauty of teaching and learning and how can we improvise our educational practices? After all, teaching and learning processes are all about social interactions and, that being so, heavily quantified processes can assimilate them.

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Aras Bozkurt: Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing; Ramesh C Sharma: Writing – original draft, Writing – review & editing.

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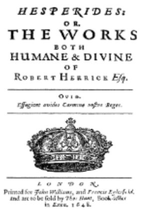
We pay tribute to the movie *Dead Poets Society*, directed by Peter Weir (1989) and written by Tom Schulman, which introduced the first stanza of Robert Herrick's (1648) poem "To the Virgins, to Make Much of Time":



Gather ye rose-buds while ye may,
Old Time is still a-flying;
And this same flower that smiles today
Tomorrow will be dying.

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Ethics Statement

Because this study doesn't involve any living entities, an ethics review is not applicable.

Conflict of Interest

The authors do not declare any conflict of interest.

Data Availability Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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