LEARNING ANALYTICS FOR PERSONAL LEARNING ENVIRONMENTS: DETERMINING JOURNAL PUBLICATION TRENDS

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ABSTRACT

The e-learning domain has witnessed a shift from the traditional behavioral approach to an individual-centered learning approach based on learning analytics, with the aim of creating personalized and learner-sensitive designs. A systematic literature review of 284 articles published between 2011 and 2022 in 133 different journals was conducted to investigate this trend. Bibliometric analyses were performed. The results of the analysis show that there is an increasing trend towards the implementation of learning analytics and the use of these analytics for personalized learning environments. The results also show that the output levels of learning analytics have progressed from description and diagnosis to prediction and perspective building. This has the potential to improve the fields of learning analytics and personal learning environments.

Keywords: Learning analytics, personal learning environments, bibliometric analyze, learning design.

INTRODUCTION

Learning is a unique process that takes place as individuals perform certain activities at many different stages. This uniqueness brings with it the need to personalize learning and organize it by considering individual needs and goals (Firat, 2015). Learners attach great importance to personalized learning to recognize their own processes and competencies and to obtain more information (Kleimola & Leppisaari, 2022). In this regard, learning analytics is a crucial opportunity to individualize teaching in line with data obtained by analyzing learner behaviors (Zilinskiene, 2022).

In recent years, learners have had higher demands for online learning environments that increase their motivation and academic performance (Kowitlawakul et al., 2017). In parallel with this increase in learners' demands for online learning environments, learner data also accumulates (Krishnan et al., 2022; Naranjo et al., 2019). This data consists of digital footprints, defined as a set of unstructured personal data that learners leave behind in online learning environments (Donmez & Yegin, 2021; Pozdeeva et al., 2021). As learner behaviors in the learning environment are recorded, learning processes have become much easier to follow (Ulfa et al., 2019). Still, discovering learners' digital data and transforming them into usable information is a challenging process (Krishnan et al., 2022).

The interaction between the learner, teacher, and content results in the creation of big data, a rich resource for identifying the elements needed to sustain the learning process (Misiejuk et al., 2021). Such large-scale digital datasets are analyzed by data mining methods, providing a better understanding and improvement of learning-teaching processes (Kazanidis et al., 2021; Jivet et al., 2020). To obtain the desired information from big data, learning analytics needs to process this data in the desired direction. In this context, learning analytics allows for to analyze and interpret learners' digital footprints, including their learning experiences. Learning analytics, therefore, plays a key function in recording and evaluating the activities in the learning process and monitoring and improving the teaching process with opportunities for both learners and teachers (Klasnja-Milicevic et al., 2017).

Learning Analytics

Learning analytics (LA) study on collecting, measuring, analyzing, interpreting, visualizing, reporting, and evaluating the data obtained during learning and predicting learning performance (Firat, 2021; Siemens & Baker, 2012; Siemens & Long, 2011). Moreover, LA focuses on recording, analyzing, and discovering learners' digital footprints to reveal their cognitive characteristics and to give insights into their decision-making styles (Kazanidis et al., 2021). LA allows to assess learner behaviors in online learning environments, identify their needs, identify learners who are more likely to drop out, predict academic success, design efficient learning environments, and provide personalized opportunities (Cagliero et al., 2021; Kokoc & Altun, 2019; Ulfa et al., 2019). LA can also be used at various stages of education, including creating teaching materials, preparing suitable curricula, identifying learning resources, forming study plans, determining teaching strategies, and making institutional and national education policies (Klasnja-Milicevic et al., 2020).

To further improve its potential, learning analytics needs to go beyond providing one-way, source-based feedback to students (Pardo et al., 2018). A personalized learning system can provide students with individual learning support and individual adaptation to eliminate the disadvantages of a single model prepared for everyone in technology-enabled learning systems (Shemshack & Spector, 2020). The feedback to be obtained from monitoring and evaluating this process could make positive contributions to learning. This has made it possible to obtain individual results and to provide feedback and guidance in this direction.

LA is complex by nature since it involves generally large datasets and these datasets can come from numerous curricular data sources like Learning Management Systems (LMS), student information systems (SIS), Personalized Learning Environments (PLE), user data entries, interactions, logs, operation history, and other student behavior records (Pelletier et al., 2021). The process of LA abstracted in Figure 1.

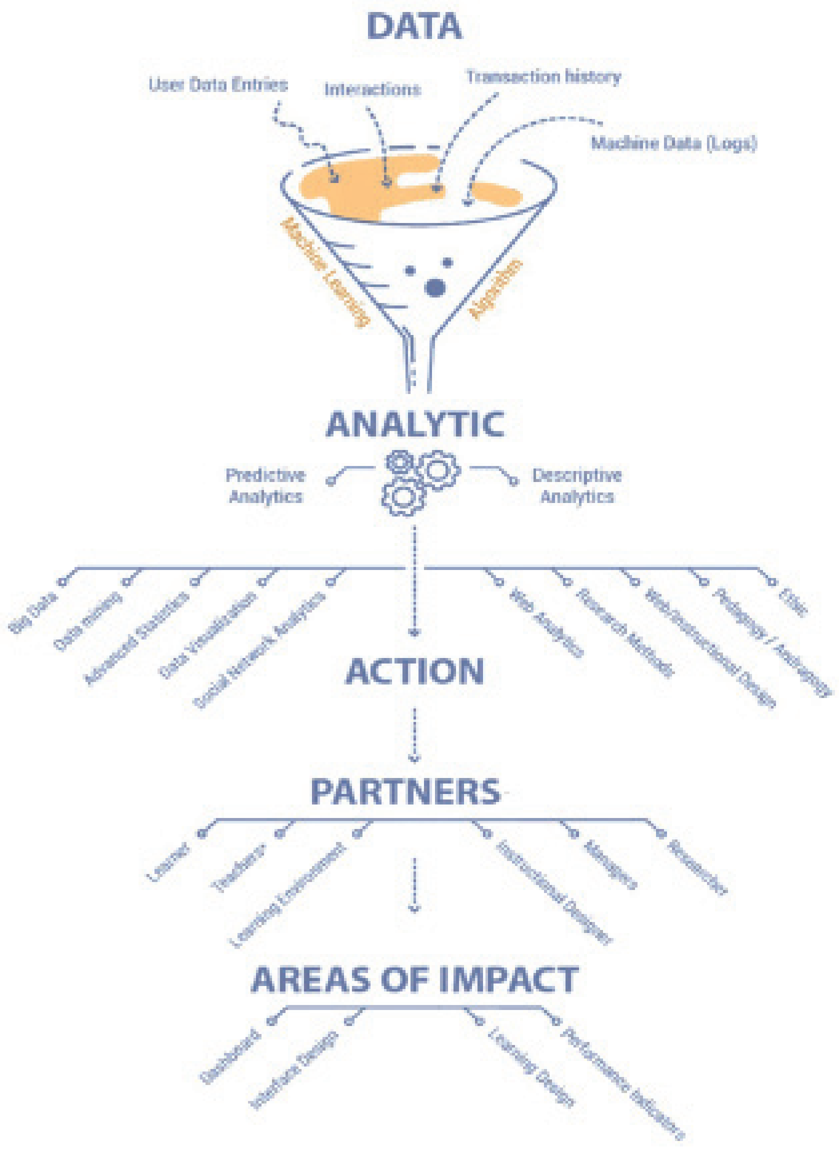

Figure 1. The Process of Learning Analytics

Aside from descriptive analytics, which optimizes future learning processes by shedding light on the past, we need to employ predictive analytics, which estimates the outcomes of ongoing learning processes and allows us to take proactive actions to optimize these processes (Omedes, 2016; Omedes, 2018). Institutions that can transition from descriptive/diagnostic analytics to predictive/perspective analytics will take the lead in learning (Omedes, 2017).

Personalized Learning Environments

With an increased amount of digital data obtained from learners, e-learning environments have transformed from a joint design for many students to one or more personalized designs for each student (Altun, 2012). This is an indication of personal learning environments. The structure of personalized learning eliminates the limitations of time and place, adapting to the individual's learning history and abilities (Sampson et al., 2002; Devedzic, 2006). PLE is a new generation e-learning environment where learners learn at their own pace and preferences, focused on self-regulated learning, with personalized navigation, guidance, and evaluation through hyper-environments (BartolomÃ & Cebrian-de-la-Serna, 2017; Montebello, 2021; Raj & Renumol, 2022). In a PLE, the learner actively participates in their own learning, has a say in how they learn best, and knows how to show and prove what they learned (Bray & McClaskey, 2015).

With a learner-centered approach and effective LA use, PLE offers Artificial Intelligence (AI)-supported, adaptive, intelligent learning management systems with personalized support in line with the learner's profile (Klasnja-Milicevic et al., 2020; Maseleno, et al., 2018; Montebello, 2021; Oliveira et al., 2021). Learners interact and communicate with other learners through personalized learning environments, finding the opportunity to control their learning resources, manage the learning activities they participate in, access re-curated learning content in line with their personalized learning needs, and ensure ethical use and ownership of their learning activity data (BartolomÃ & Cebrian-de-la-Serna, 2017).

Personalized learning (PL) can be adapted to learners' strengths, interests, preferences, and needs, allowing them to regulate their own learning processes (Keci & Qosja, 2021; Kuppusamy, 2019). In other words, PL focuses on the learners' background, needs, skills, and perceptions (UNESCO, 2017). PL demonstrates how each learner's pace, preferences, and resources are tailored to their needs. Adaptation is the system's ability to adapt to the changing learner needs as they progress (Dorca et al., 2017). PL can be preferred for numerous purposes, including strengthening the learning experience, preventing dropouts, increasing interaction, and providing access to the right resources.

PLEs are online environments tailored to learners' preferences and interests, including how they use resources, and participate in activities and communities, providing a learning experience suitable for learners' needs (Zwartjes, 2018; Fournier et al., 2019). Getting to know learners based on their digital footprints is a key part of designing PLE. Here, the digital footprints of learners need to be interpreted and inferred through LA. Hence, LA can play a crucial role in designing PLE. Because, LA offers significant opportunities to encourage learners' ability to manage, monitor, and reflect on their own learning. So, e-learning environments should be adapted to increase learners' performance and satisfaction (Hwang et al., 2020). With the rapid advances in AI, cloud computing, wearable technologies, and virtual reality technologies, PLE has gained a much more comprehensive sphere of influence (Xie et al., 2019). The improvements and transformation of LA technologies have impacted the design, development, improvement, and dissemination of PLEs.

Relevant Literature

The related literature of this study is limited to the systematic literature reviews on LA and PLE. A literature search did not identify any direct systematic reviews on the use of LA for PLE. One of the most recent studies was conducted by Wong, Li and Cheung (2022) to analyze learning analytics practices to achieve personalized learning. Except for this, the relevant literature includes systematic reviews on LA in seamless learning environments (Moon et al., 2023), LA for engagement and learning performance (Johar, et al., 2023), LA in higher education (Viberg et al., 2018), LA in m/u-learning (Pishtari et al., 2020), dashboards and self-regulated learning (Matcha et al., 2019), multimodal LA (Crescenzi-Lanna, 2020), effective LA approaches to measuring learning outcomes (Blumenstein, 2020), determining the thematic structure and trends of LA research (Chen et al., 2022), LA indicators (Ahmad et al., 2022), and LA support to teachers' design (Amarasinghe et al., 2022).

Wong, Li and Cheung (2022) analyzed 144 studies. The results of the review showed that the studies were largely focused on tertiary education and online learning. The data used for learning analytics were generally related to learning activities, academic performance, educational background and learning outcomes. Improving the learning experience, providing personalized recommendations and meeting personal learning needs were identified as the most common learning analytics and personalized learning goals. It was emphasized in this study that more research is needed on learning analytics for personalized learning.

In their systematic literature review, Moon et al. (2023) analyzed 27 emprical articles to investigate the trends and issues of learning analytics in seamless learning environments. The analyses revealed that in order to map students' learning profiles and trajectories in seamless learning environments, existing research has largely focused on extending multimodal data collection and analysis. In addition, researchers are able to systematically drive adaptive learning through the emerging use of automated data collection and computational metrics.

Johar et al. (2023) analyzed 42 articles with the help of PRISMA, highlighting the types of learner engagement that the use of learning analytics can indicate, in the hope of improving learner performance in online learning. The results showed that some studies measured multifaceted engagement to improve student learning. However, the number of studies was limited. The inclusion of social, cognitive, collaborative, behavioral and emotional engagement in online learning was therefore recommended for future research.

Viberg et al. (2018) analyzed 136 reports and 116 articles on "LA in higher education" from 2012 to 2018. Accordingly, the relevant literature dealt with using LA in higher education, the methods adopted for LA, whether LA improves learning outcomes, whether LA supports learning and teaching, and whether it is used ethically. The authors have emphasized that LA has a high potential in improving learning outcomes, supporting teaching and learning, and ethical use of personal data, with great expectations for it, though the use of LA in higher education, is not yet at the desired level. Hence, they drew attention to the scarcity of research to support these expectations. However, with the widespread use of LA in higher education, future research can provide a deeper understanding of students' learning experiences and the potential impact of LA on learning outcomes.

Pishtari et al. (2020) performed a systematic review on learning design in m/u-learning and LA. The authors provided an overview of the current research trend. Besides, based on similar learning contexts and research gaps, they suggested that m/u learning should be explored beyond higher education, the link between physical and virtual learning environments should be strengthened, and learning design and learning analytics should be integrated more systematically.

Matcha et al. (2019) conducted a systematic review of empirical findings regarding the effects of learning analytics dashboards (LADs) on learning and teaching. The authors highlighted LAD designs based on experiments and research should be preferred, instead of a priori designs. Therefore, they recommended the "user-centered learning analytics systems (MULAS)," which consists of four dimensions that are cyclically and iteratively interconnected, including theory, design, feedback, and evaluation.

Crescenzi-Lanna (2020) performed a systematic review of multimodal learning analytics studies to identify useful tools and strategies for assessing learning progress and behaviors among children below the age of 6 years. The aim was to guide multimodal learning analytics research with children 6-year-old children to assess their participation in tasks, emotions, attention, understanding, and achievements. The author found that the current knowledge in the literature showed how to use performance analytics, facial and speech recognition systems, eye tracking, kinetic analytics, and wristbands in children. Crescenzi-Lanna highlighted that ethical issues were the focus of multimodal data obtained from audio, visual, biometric, and quantitative behavior measurements.

Blumenstein (2020) conducted a systematic review on the effect sizes of 38 key studies following effective LA approaches to measure learning outcomes. Accordingly, learning designs that support socio-collaborative and independent learning skills were found to have positive effects on student achievements. Recent trends in personalizing student feedback have revealed the need to integrate student-specific factors into improving student experiences and academic outcomes. As a key finding, the author drew attention to the LA Learning Gain Design (LALGD), a new three-level model that synchronizes capturing significant data with pedagogical goals and learning outcomes. The author reported the model to be suitable for face-to-face and online environments, or a mix of both, contributing to data-based learning in higher education.

Chen et al. (2022) analyzed 3900 articles on LA to identify the thematic nature and trends of LA research. The main questions were "what research topics are the LA community interested in?" and "how have these research topics evolved?" The authors made use of structural topic modeling and bibliometrics. Major journals, countries/regions, institutions, and scientific collaborations were examined and visualized. According to their findings, the country that contributed the most to the LA literature was the USA, followed by the UK and Australia. Besides, the USA, the UK, Australia, Spain, and Germany collaborated the most, while the most LA collaborations were made between Australia and the UK. The most collaborations in LA research by institutions were observed in Open University (UK), University of Technology Sydney, Carnegie Mellon University, and the Open University of the Netherlands. Also, the University of Edinburgh and the University of South Australia collaborated on most articles. By publications, the most prominent institution was the Open University. Moreover, most citations with regards to LA were observed for Educational Technology and Society, Internet and Higher Education, and Computers and Education. The most prominent topics were combining various innovative technologies like visual dashboards, neural networks, multimodal technologies, and open learner models to support learning experiences, personalized suggestions/feedback, self-regulated learning in flipped classrooms, game-based exercises, and interaction practices in social learning.

Ahmad et al. (2022) analyzed 161 articles on LA, to identify the indicators of learning design (LD). Two important results stood out in the study. First result is that the researchers proposed a reference framework in which they present the possible connections between these two concepts to achieve a good fit between LA and LD; second, the researchers demonstrated how LA indicators and metrics have been studied in the past. According to the study, learning activities are the key factor for both LA and LD, therefore, the basic indicator and link in both is learning activity. The first conclusion that the researchers reached when they examined the articles of the past decade was that there was no clear definition of LA indicators and measures. It was also pointed out that there some conflicting definitions of learning activities and the consideration of some activities as learning activities such as mouse clicks were not pedagogically correct. As a result, the researchers proposed a framework that determines the LA indicators and their measurement.

Amarsinghe et al. (2022), in their study, aimed to fill the literature gap on whether teachers can use the same LA indicators in both LD and learning management of learning activities. For this purpose, they shared the results of 17 articles in their study. As a result of the literature review, it has been seen that the LA indicators used in the learning design and the LA indicators used in the orchestrating of learning activities differ from each other. Accordingly, the researchers presented the indicators that can be used for LD and the LA indicators that can be used for the management of learning activities as two different categories in a single framework.

Table 1. Systematic reviews regarding LA and PLE

Authors, year	Which years were included (from - to)	Main points of the systematic reviews
Viberg et al. (2018)	2012-2018	LA in higher education
Pishtari et al. (2020)	2008-2019	LA in m/u-learning
Matcha et al. (2019)	2010-2017	Dashboards and self-regulated learning
Crescenzi-Lanna, (2020)	2014-2019	Multimodal LA
Blumenstein, (2020)	2011-2016	Effective LA approaches to measuring learning outcomes
Chen, Zou and Xie, (2022)	2010-2019	determining the thematic structure and trends of LA research
Ahmad et al. (2022)	2011-2020	LA indicators
Amarasinghe et al. (2022)	2012-2020	LA support to teachers' design
Moon et al. (2023)	No time limit	LA in seamless learning environments
Johar et al. (2023)	2011-2021	LA for engagement and learning performance
Wong, Li and Cheung (2022)	2012-2019	LA practices to achieve personalized learning environments

As can be inferred from the literature review and Table 1., there are systematic literature reviews on the different aspects of LA. However, no systematic literature review could be found regarding to determine the trends and tendencies of LA to the formation of PLE, which is one of its ultimate goals. Therefore, this systematic literature review will contribute to filling this gap in the related literature.

Research Purpose

The purpose of this research was to determine trends and tendencies of the articles on Learning Analytics for Personalized Learning Environments from the Scopus database. To identify trends in the field, we addressed the following research questions:

1. What are the leading countries and institutions conducting research on LA for PLE?
2. What/who are the leading journals and authors of research on LA for PLE?
3. What is the LA for PLE research trend?

METHODOLOGY

This study designed as an systematic literature review. The identified keywords for the systematic literature review were "Learning Analytics" and "Personalized Learning Environments." Data collected from Scopus database. Elsevier Scopus is recognized as the world most comprehensive and qualified database due to its extensive coverage across various disciplines, rigorous selection process, and global reach. It offers comprehensive citation analysis, enabling researchers to assess the impact of scholarly work.

In our attempts for a pilot search with the keywords of "Learning Analytics" AND "Personalized Learning Environments.", we could not reach sufficient articles. To extend the number of results, we added the keyword "Personal Learning Environments" as an alternative phrase to "Personalized Learning Environments." The final search phrase is given below.

(TITLE-ABS-KEY ("Learning Analytics") AND TITLE-ABS-KEY ("Personal Learning Environment") OR TITLE-ABS-KEY (ple) OR TITLE-ABS-KEY ("Personal Learning Environment") OR TITLE-ABS-KEY (personal*)) AND (LIMIT-TO (DOCTYPE , "ar"))

As can be understood from the phrase, the search covers all years and is limited to journal articles. This search listed 329 documents including all article types. The 329 articles were further checked with the following criteria for inclusion:

1. articles on personalized learning through learning analytics (screening process conducted by 7 researcher),
2. the articles were written in English and
3. the full text of the article could be accessed.

Only the articles which fully met all the criteria were selected. Thus, 284 articles that met all criteria were included in the analysis. Figure 2 shows the distribution of documents by year.

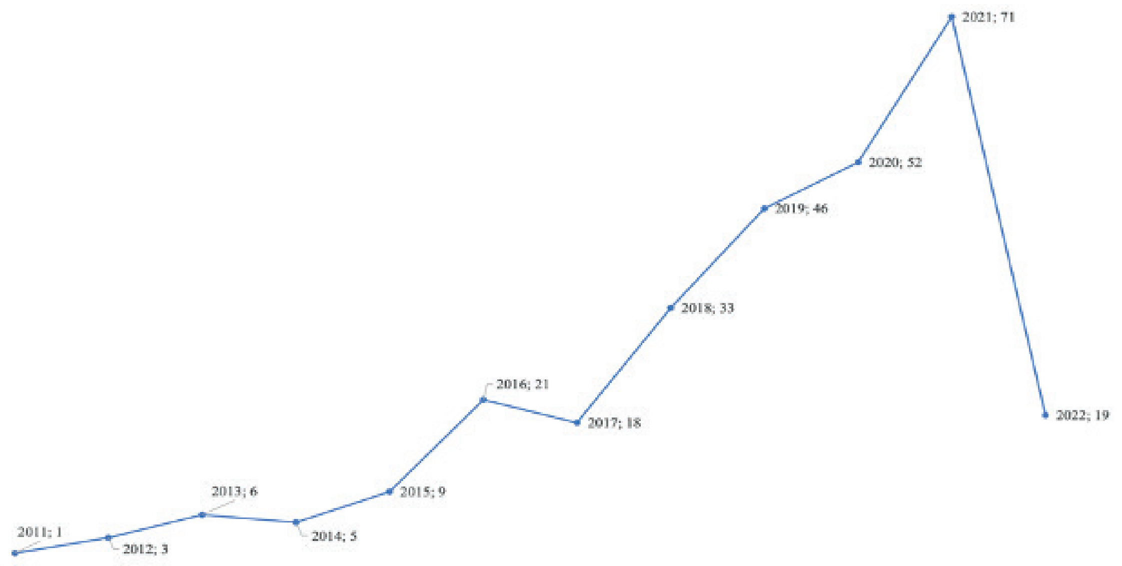

Figure 2. Publications by Year

The number of publications on LA for PLE seems to have increased from 2011 to 2022. Since the screening was carried out before the end of 2022, the number of articles published in this year is lower in the graph compared to the previous few years.

Data Analysis

Bibliographic data of 284 articles were exported from Scopus as a CSV file. The selected bibliometric information included the author(s), document title, source title, number of citations, affiliations, and keywords. We performed a data cleaning for each file, leaving only the names of institutions and countries in affiliations. The rest of the address information was removed from the file. We used the VOSviewer software to determine the most frequently used keywords in AI and LA studies and to visualize the results. Also, the network map of co-authorships, co-occurrences, co-citations, coupling analysis was created with the full counting method. VOSviewer 1.6.18 was used to visualize the similarities of articles on LA for PLE. VOSviewer is a software tool for constructing and visualizing bibliometric networks. The data collection and data analysis processes were reviewed by 7 different researchers. The researchers enhanced validity and reliability by implementing data cleaning techniques according to specific criteria, utilizing specialized software tools, involving multiple researchers for review and validation. These measures contribute to the trustworthiness of the study.

RESULTS

The findings obtained from the bibliographic data analysis are presented under the relevant headings for each research question.

Leading Countries and Institutions

To determine the countries of the publications, we downloaded their country data from Scopus and visualized them in a bubble graph in the Tableau data visualization software. Figure 3 shows the distribution of publications by country.

As seen in Figure 3, the USA was in the lead with 67 publications on LA for PLE, followed by Australia, Spain, and the UK with more than 30 publications each. 284 articles were produced by researchers from 67 different countries. Figure 4 below gives the co-authorship network by country. While creating the map, we selected the type of analysis as co-authorship and the unit of analysis as a country. The minimum number of publications from one country was 2. Of the 67 countries, 48 met the threshold.

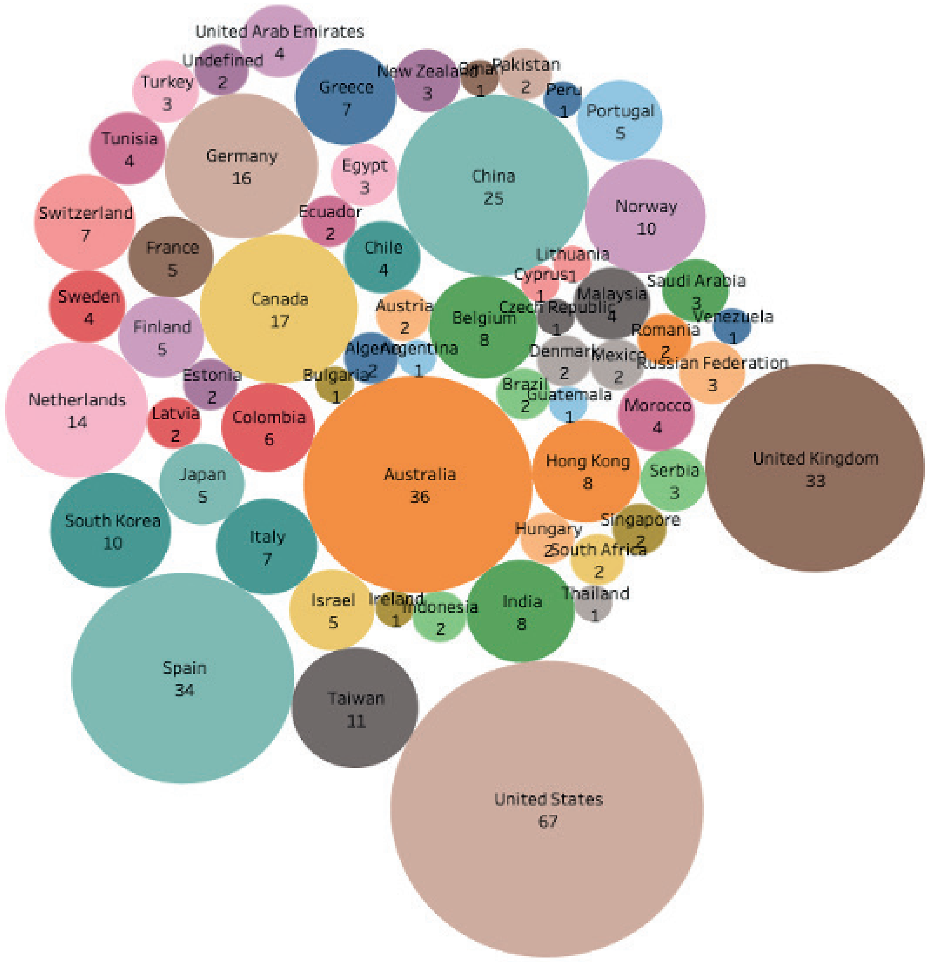

Figure 3. Bubble Graph of The Distribution of Publications by Country

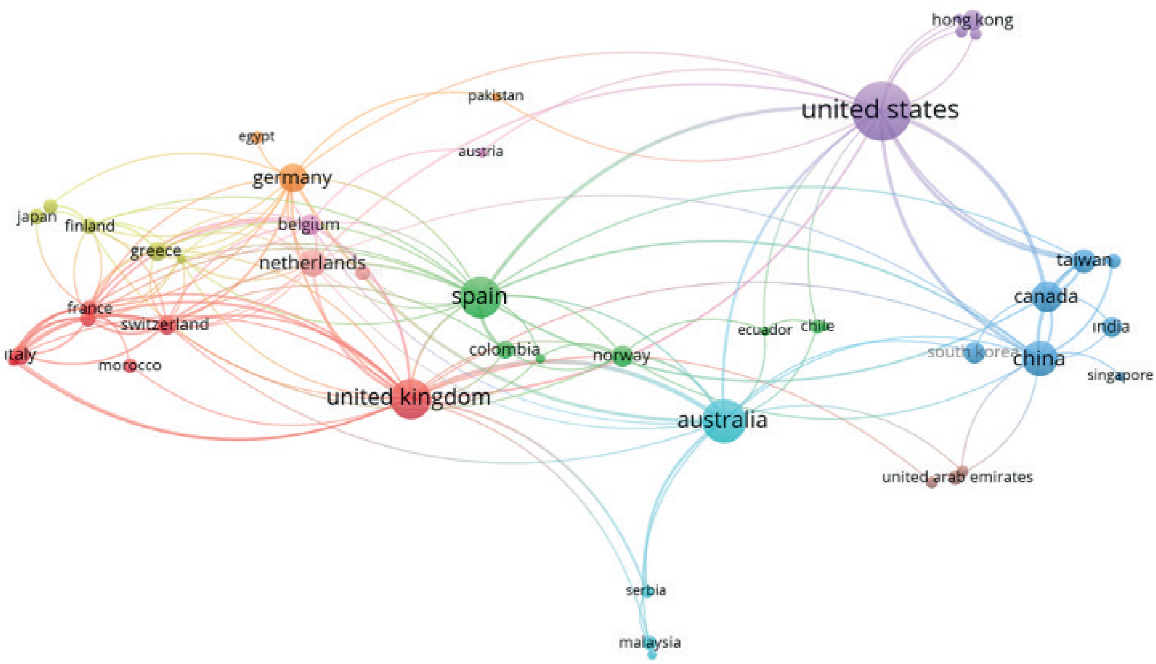

Figure 4. Co-Authorship Network Map of Leading Countries

Each node in the network is proportional in size to the number of publications. Thicker links between nodes represent a higher number of co-authorships. As seen in the network, there were 10 clusters. The leading countries in these clusters were the USA (NDocuments=67, NCitations=1712), Australia (ND=37, NC=932), Spain (ND=34, NC=423), the UK (ND=32, NC=524), China (ND=25, NC=219), Canada (ND=18, NC=599), Germany (ND=16, NC=413), the Netherlands (ND=15, NC=650), and Taiwan (ND=11, NC=241). Spain, the UK, and Australia acted as connectors in the network.

We created another VOSViewer network map from bibliographic data to identify the leading institutions. Figure 5 shows the network map of institutions. When creating the network map, we selected the type of analysis as co-authorship and the unit of analysis as a country. The minimum number of publications from one country was 5. Of the 440 institutions, 9 met the threshold.

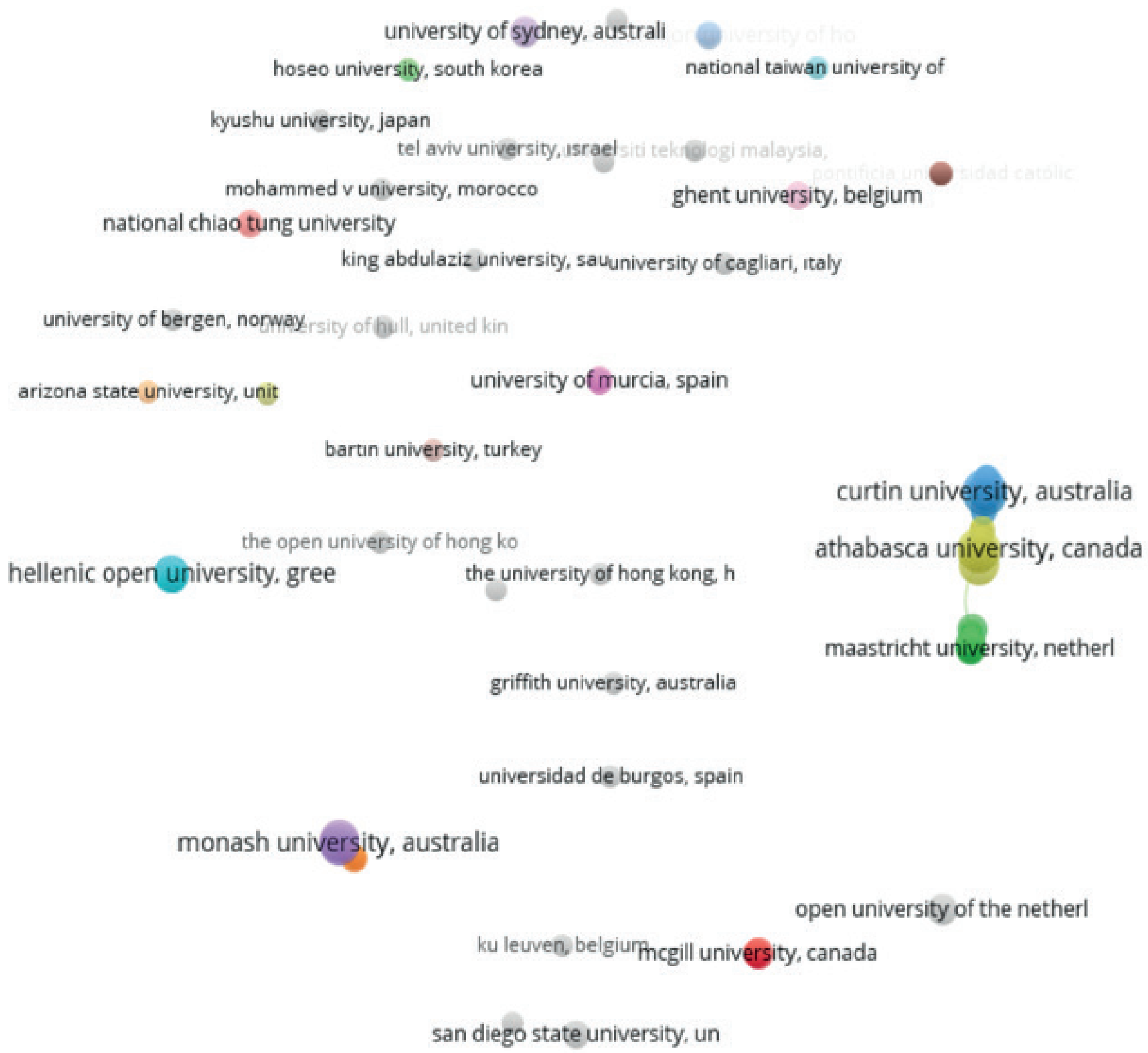

Figure 5. Co-Authorship Network Map of Leading Institutions

We observed that only 19 out of 86 institutions had co-authorship links. According to the number of publications, the leading institutions in terms of research on LA for PLE were Curtin University (ND=9, NC=298), Athabasca University (ND=8, NC=536), University of South Australia (ND=7, NC=168), Monash University (ND=7, NC=90), Beijing Normal University (ND=7, NC=34), University of Mannheim (ND=6, NC=243), and University of North Texas (ND=6, NC=60).

Leading Journals and Authors

The 284 articles were published in 133 different journals. When ranked according to the number of publications, 82 journals made only 1 publication, while the remaining 202 articles were distributed among the remaining 51 journals. Accordingly, 17 journals had 2 publications each, 12 journals had 3 publications each, 5 journals had 4 publications each, and 6 journals had 5 publications each, reaching a total of 120 articles by 40 journals. Table 2 below shows the ranking of 11 journals with 6 or more publications.

Table 2. Top 11 Journals by Number of Publications and Citations

Journals	Citations	Publications
	n	n
Interactive Learning Environments	145	14
Sustainability (Switzerland)	30	8
Technology, Knowledge and Learning	204	7
International Journal of Artificial Intelligence in Education	36	7
IEEE Transactions on Learning Technologies	190	7
Educational Technology Research and Development	121	7
Educational Technology and Society	558	7
Computers in Human Behavior	487	7
Journal of Universal Computer Science	72	6
Frontiers in Education	10	6
Australasian Journal of Educational Technology	26	6

According to Table 2, Interactive Learning Environments ranked first with 14 publications, followed by Sustainability (Switzerland) with 8 publications. The journals named Technology, Knowledge and Learning, International Journal of Artificial Intelligence in Education, IEEE Transactions on Learning Technologies, Educational Technology Research and Development, Educational Technology and Society, and Computers in Human Behavior had 7 publications each. The three journals with 6 publications each were the Journal of Universal Computer Science, Frontiers in Education, and Australasian Journal of Educational Technology. Considering the number of citations, Educational Technology and Society ranked first with 558 citations, followed by Computers in Human Behavior with 487 citations.

In the present research, we retrieved 284 articles published by 902 authors. Figure 6 shows the co-authorship network map of these articles. The minimum number of publications and citations by a single author was 2. Of the 902 authors, 110 met the threshold.

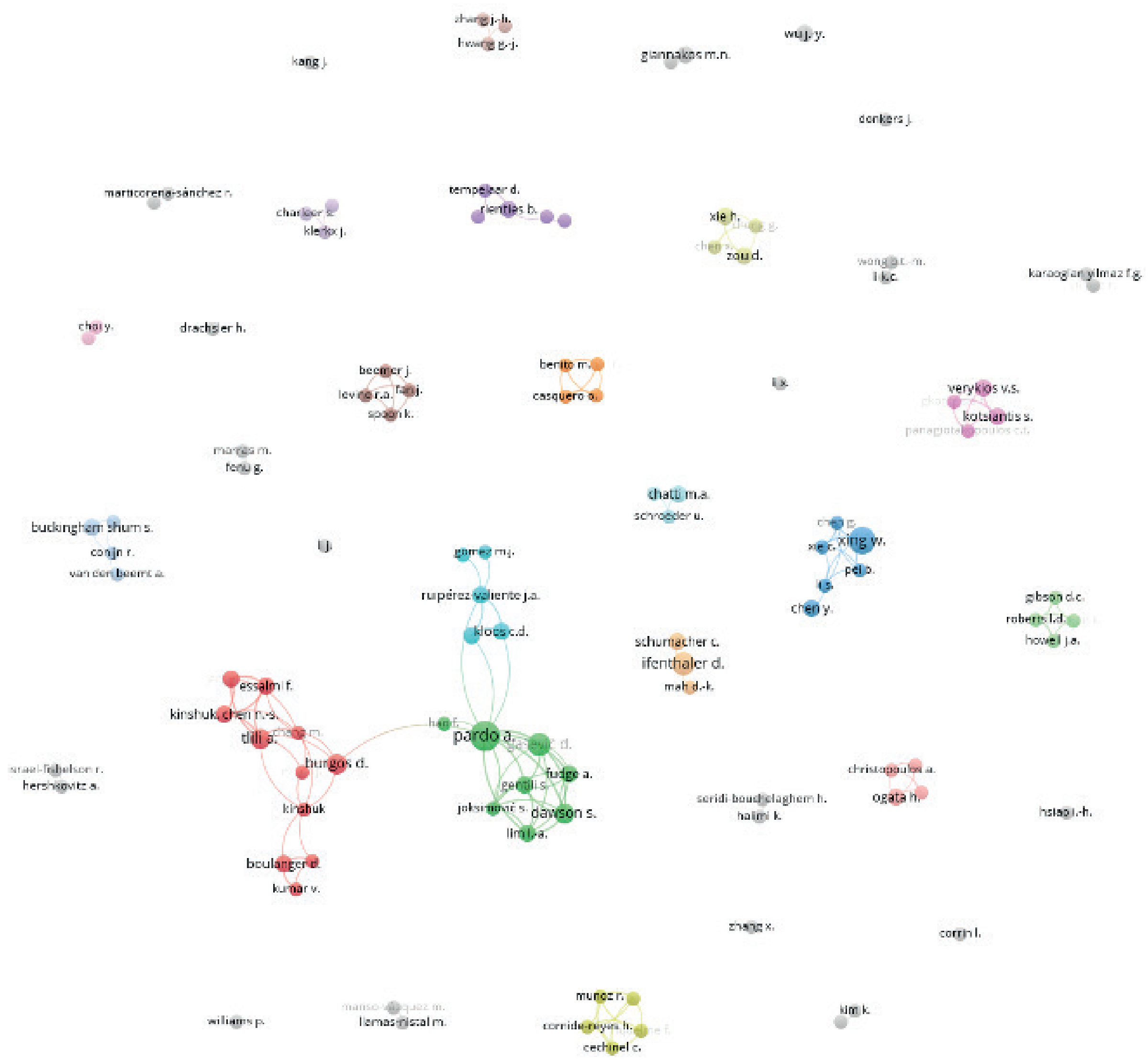

Figure 6. Co-Authorship Network Map of 110 Authors

As the graph shows, there were many co-authorship clusters among the authors. Table 3 below shows the 7 most prominent authors according to the number of publications and citations.

Table 3. Top 7 Authors by Number of Publications and Citations

Author	Institution and Country	Publications n	Citations n
Hendrik Drachsler	Leibniz Institute for Research and Information in Education, Netherlands	2	451
Abelardo Pardo	University Carlos III of Madrid, Spain	9	374
Wanli Xing	University of Florida, USA	7	286
Dirk Ifenthaler	University of Mannheim, Germany; Curtin University, Australia	5	237

Clara Schumacher	University of Mannheim, Germany	3	207
Dragan Gasevic	Monash University, Australia	5	183
Shane Dawson	University of South Australia, Australia	4	143

Abelardo Pardo had the most publications with 9 articles, while Hendrik Drachsler had the most citations at 451. Of the 110 authors who met the threshold of a minimum of 2 publications and 2 citations, 24 authors had a linked network. Regarding the prominent authors in the co-authorship cluster, there was a link between Abelardo Pardo and Burgos D. across co-authorship clusters. Also, there were links between Burgos and Tlili; Pardo, Dawson, and Gasevic; Ifenthaler, and Schumacher. Xing and Drachsler had a co-authorship cluster independent of the other prominent authors. Figure 7 shows the co-authorship network map of the 24 linked authors.

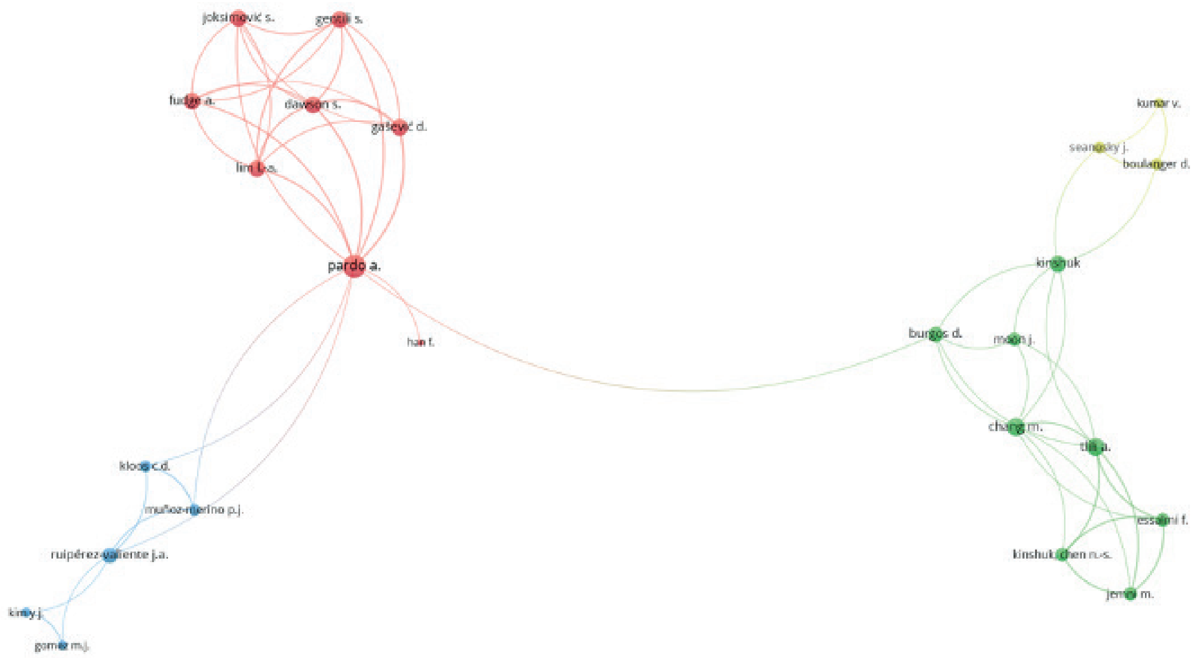

Figure 7. Co-Authorship Network Map of 24 Linked Authors

As can be seen in Figure 7, there were 4 clusters in the network. Pardo and Burgos had a central location and formed links between clusters. Han was linked to Pardo's cluster but was disconnected from all other clusters. Han's article with Pardo was titled "Combining University student self-regulated learning indicators and engagement with online learning events to Predict Academic Performance," with the following keywords: computer-assisted instruction; education; learning management systems; personalized e-learning.

LA for PLE Research Trend

The co-occurrence analysis of keywords was conducted with the full counting method. Figure 7 shows the network map of keywords. The minimum number of occurrences for a keyword was 4. Of the 856 keywords, 40 met the threshold. Also, the keywords "Learning Analytics," "Personalized Learning," "Personal Learning Environment," "Personalization," Personal Learning Environments," and "Personalised Learning" were removed from the analysis as they were the main subject of the research. Thus, Figure 8 shows the 36 keywords.

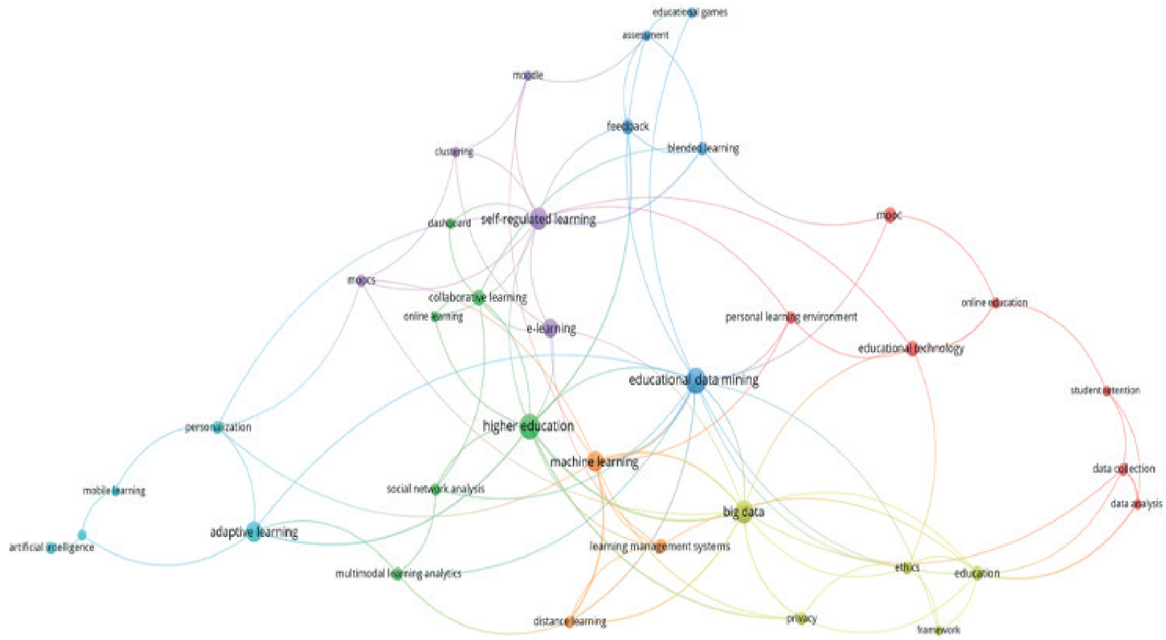

Figure 8. Co-Occurrence Map of Keywords

Figure 8 indicates 7 clusters in different colors. These clusters include the keywords that stood out according to the number of occurrences and the number of total link strength (NTLS). "Educational data mining" (Number of Occurrence=23, NTotal Link Strength=43) and "higher education" (NO=23, NTLS=43) were the most prominent keywords in terms of their centrality, overall weight, density, and degree of overlap with the other keywords. Other keywords with more than 10 occurrences were "big data" (NO=18, NTLS=34), "self-regulated learning" (NO=16, NTLS=26), "machine learning" (NO=14, NTLS=29), "adaptive learning" (NO=14, NTLS=25), and "e-learning" (NO=12, NTLS=13). Figure 9 gives an overlay visualization map of keywords by years to reveal the changes in LA for PLE research trends over time.

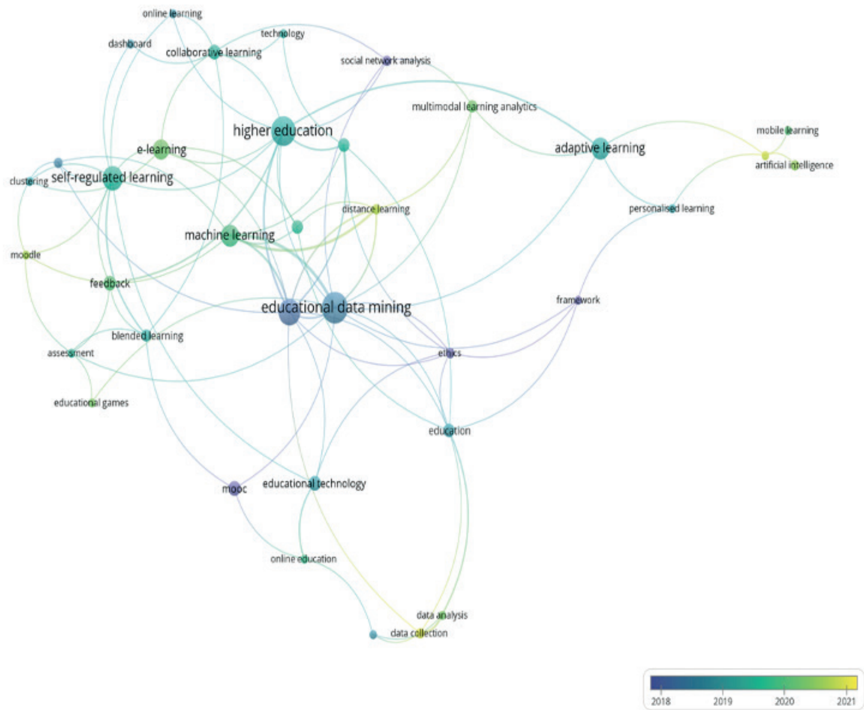

Figure 9. Overlay Visualization Map of Keywords

Given the changes throughout the years, “educational data mining,” “big data,” and “social network analysis” were prominent keywords before 2018-2022, while “adaptive learning,” “artificial intelligence,” and “smart learning environments” were more prominent in recent articles. Note that the former keywords were mostly associated with data and analysis phases, while the more recent ones are associated with the action phase. This indicates that LA research has recently focused on practical studies. To see a holistic network map of articles, we conducted a bibliographic coupling analysis. Figure 10 shows the overlay visualization map of the bibliographic coupling analysis.

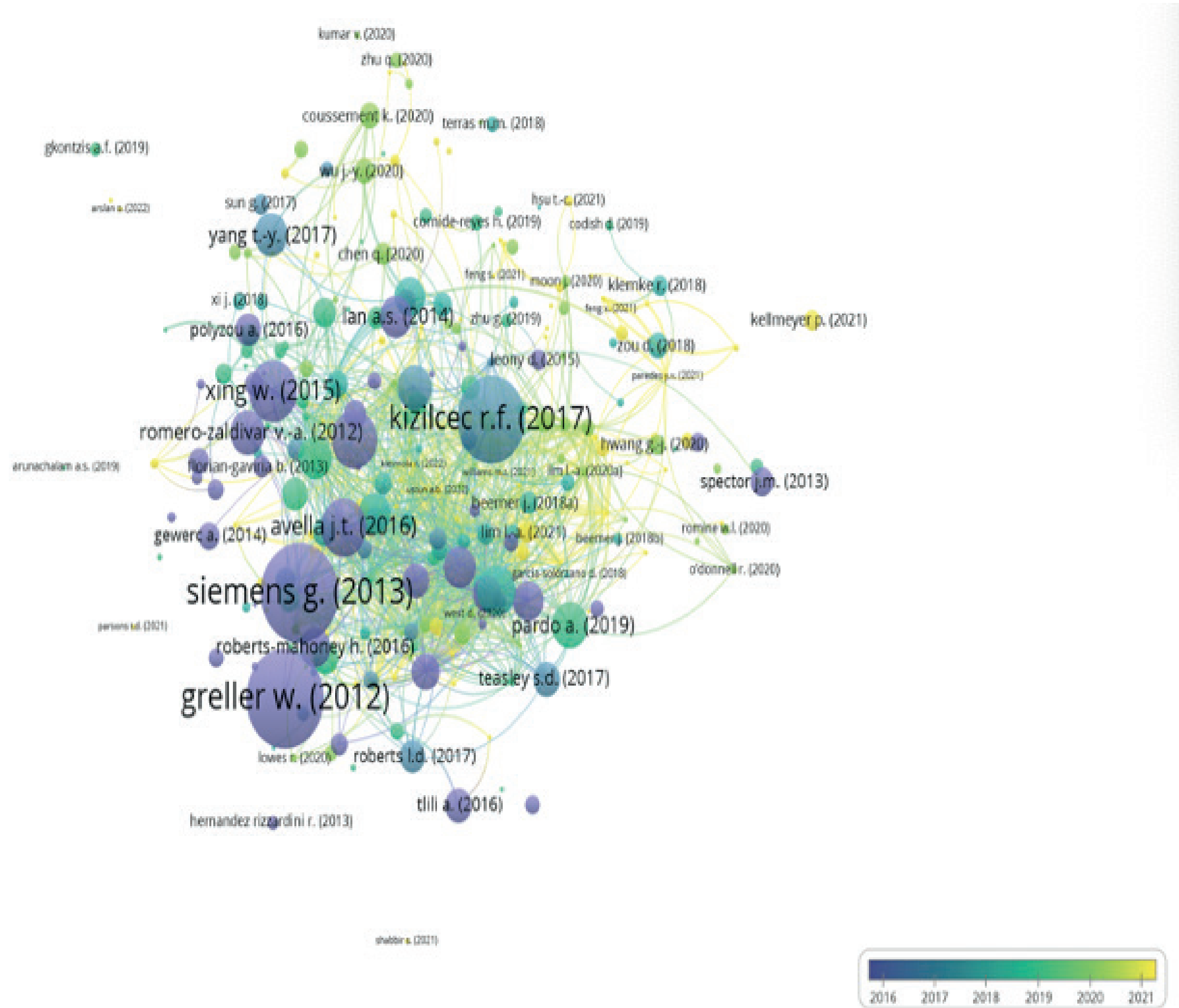

Figure 10. Bibliographic Coupling Analysis of Articles

Bibliographic coupling, like co-citation, is a similarity measure that uses citation analysis to establish a similar relationship between publications. As expected, older articles were cited more, as evident in Graph 9. Table 4 shows the most cited articles (100+).

Table 4. Most Cited Articles (100+)

Authors	Title	Year	Source title	Cited by
Greller W., Drachsler H.	Translating learning into numbers: A generic framework for learning analytics	2012	Educational Technology and Society	451
Siemens G.	Learning Analytics: The Emergence of a Discipline	2013	American Behavioral Scientist	450

Kizilcec R.F., Perez-Sanagustin M., Maldonado J.J.	Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses	2017	Computers and Education	345
Xing W., Guo R., Petakovic E., Goggins S.	Participation-based student final performance prediction model through interpretable Genetic Programming: Integrating learning analytics, educational data mining and theory	2015	Computers in Human Behavior	178
Avella J.T., Kebritchi M., Nunn S.G., Kanai T.	Learning analytics methods, benefits, and challenges in higher education: A systematic literature review	2016	Journal of Asynchronous Learning Network	158
Kay J., Reimann P., Diebold E., Kummerfeld B.	MOOCs: So many learners, so much potential.	2013	IEEE Intelligent Systems	157
Schumacher C., Ifenthaler D.	Features students really expect from learning analytics	2018	Computers in Human Behavior	118
Pardo A., Jovanovic J., Dawson S., Gasevic D., Mirriahi N.	Using learning analytics to scale the provision of personalized feedback	2019	British Journal of Educational Technology	102

The co-citation analysis of the cited references was conducted with the full counting method. The minimum number of citations for a reference was limited to 5. Of the 13617 cited references, 22 met the threshold. Figure 11 shows the co-citation network map of 21 linked articles.

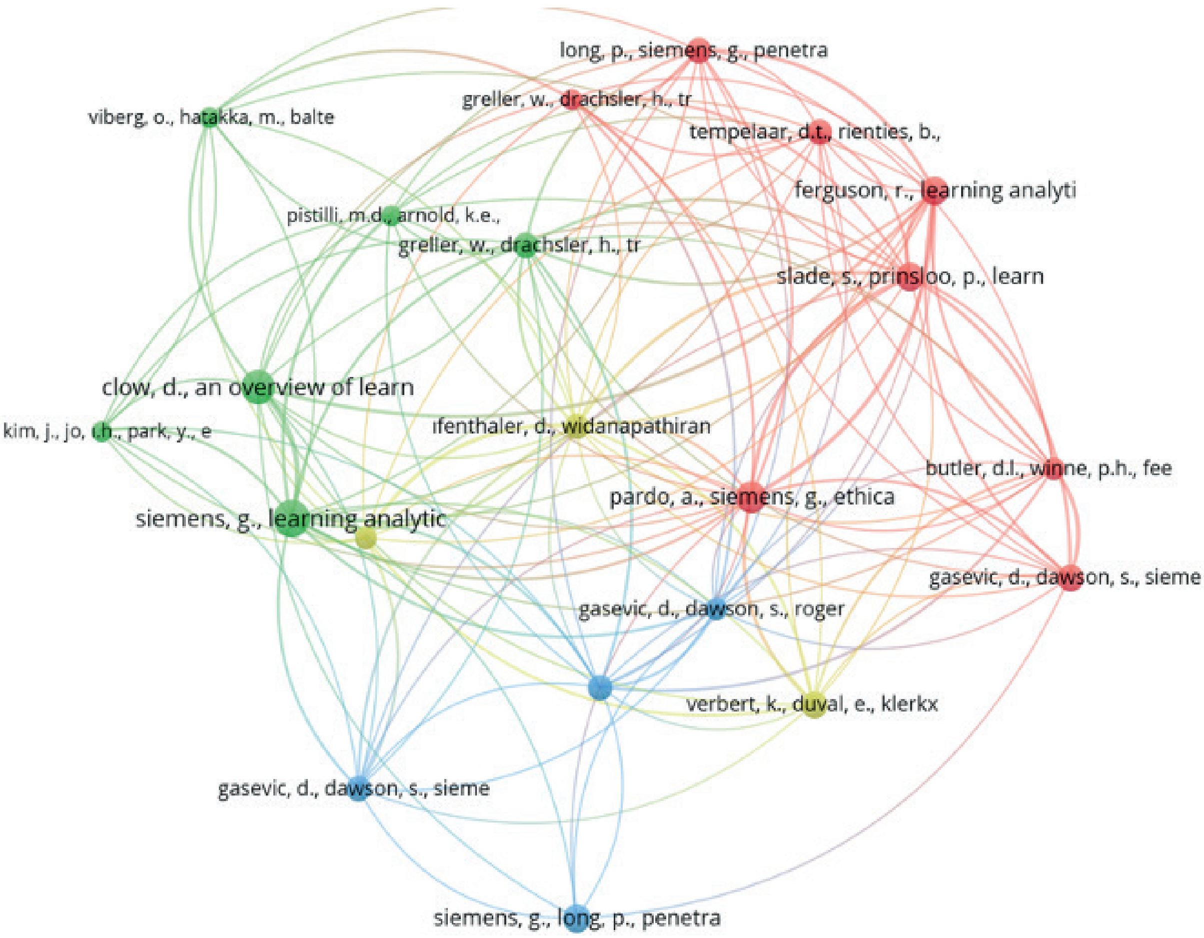

Figure 11. Co-Citation Analysis Map of Articles

The co-citation analysis map included 4 clusters. Table 5 gives the distribution of articles to clusters, weights of links, total link strength, and citations of articles.

Table 5. The Distribution of Articles to Clusters Based on Co-Citation

Article	Cluster	Weight <Links>	Weight <Total link strength>	Weight <Citations>
Butler, D.L., & Winne, P.H.(1995). Feedback and self-regulated learning: A theoretical synthesis.	Theory of LA	13	20	6
Ferguson, R.(2012). Learning analytics: drivers, developments and challenges.	Theory of LA	15	29	9
Gasevic, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning.	Theory of LA	12	19	8
Greller, W. & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics.	Theory of LA	11	16	5
Siemens, G. & Long, P. (2011). Penetrating the fog: Analytics in learning and education.	Theory of LA	15	20	7
Pardo, A. & Siemens, G. (2014). Ethical and privacy principles for learning analytics.	Theory of LA	18	31	11
Slade, S. & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas.	Theory of LA	15	29	9
Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context.	Theory of LA	12	13	7
Clow, D.(2013). An overview of learning analytics.	LA Overviews	15	23	13
Greller, W. & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics.	LA Overviews	15	21	7
Kim, J., Jo, I.H. & Park, Y. (2016). Effects of learning analytics dashboard: analyzing the relations among dashboard utilization, satisfaction, and learning achievement.	LA Overviews	9	10	5
Pistilli, M.D. & Arnold, K.E. (2010). Purdue Signals: Mining real-time academic data to enhance student success.	LA Overviews	11	13	5
Siemens, G. (2013). Learning analytics: The emergence of a discipline.	LA Overviews	17	32	16
Viberg, O., Hatakka, M., Balter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education.	LA Overviews	9	11	5

Gasevic, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success.	Why LA	14	17	6
Gasevic, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning.	Why LA	12	15	7
Hattie, J., & Timperley, H. (2007). The power of feedback.	Why LA	14	18	7
Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education.	Why LA	7	7	9
Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics.	LA in Action	12	18	6
Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications.	LA in Action	12	17	8
Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines.	LA in Action	18	29	7

Here, we analyzed the subjects of the articles in the aforementioned 4 clusters. Cluster 1, colored in red, was named "Theory of LA." Accordingly, Butler and Winne (1995) theorized the importance of using self-regulated learning and feedback together for effective learning; Ferguson (2012) examined the factors driving the development of LA; Gasevic et al. (2015) gave recommendations from research on LA for the realization of learning; Greller and Drachsler (2012) examined key dimensions and critical problem areas of LA, and potential dangers to the beneficial use of learning data; Siemens and Long (2011) investigated the benefits of using LA in higher education; Pardo and Siemens (2014) examined the ethical principles of using LA; Slade and Prinsloo (2013) gave recommendations for the ethical use of LA; Tempelaar, Rienties, and Giesbers (2015) highlighted the significance of informative feedback in the predictive modeling of student performance using LA.

Cluster 2, colored in green, was named "LA Overviews." Accordingly, Viberg et al. (2018) reviewed previous research on using LA in higher education from 2012 to 2018; Clow (2013) investigated the benefits, uses, and challenges of LA; Greller and Drachsler (2012) examined key dimensions and critical problem areas of LA, and potential dangers to the beneficial use of learning data; Kim et al. (2016) reviewed previous research on the effects of using LADs as personalized feedback tools on student satisfaction and learning achievements; Pistilli and Arnold (2010) investigated efforts for supporting learner success by mining real-time academic data; Siemens (2013) studied the research areas that contributed to the development of LA, models of LA, data ownership when using LA, and ethical privacy concerns.

Cluster 3, colored in blue, was named "Why LA." There were 4 prominent studies in this cluster. Accordingly, Gasevic et al. (2016) investigated the prediction of student achievements using LA; Gasevic et al. (2015) gave recommendations from relevant research on LA for the realization of learning; Hattie and Timperley (2007) investigated the effect of feedback on learning and achievement; Siemens and Long (2011) studied the benefits of using LA in higher education.

Cluster 4, colored in yellow, was named "LA in Action." Here, Schumacher and Ifenthaler (2018) investigated the expectations of university students regarding LA features; Verbert et al. (2013) researched examples of LAD applications; Ifenthaler and Widanapathirana (2014) examined the benefits and challenges of using LA.

DISCUSSION AND CONCLUSION

This study is limited with the bibliometric network analyses based on co-authorships, co-occurrences, co-citations and coupling analyzis of 284 articles published between 2011-2022. Here, we present a discussion of our findings and our conclusions under relevant sub-headings for each research question. The study in the relevant literature where the findings related to the first two research questions can be discussed is limited to Chen et al. (2022). This is because country-, institution-, author- and journal-based trend identification studies are limited to this study. Similarly, country-, institution-, author- and journal-based trend findings are presented from a more descriptive perspective without further evaluation, interpretation and practical implications.

What Are the Leading Countries and Institutions Conducting Research on LA for PLE?

The 284 articles about LA for PLE were written by researchers from 67 different countries. The USA, Australia, Spain, and the UK were the leading countries for several publications. This is similar to the findings of Chen et al. (2022). Chen et al. (2022) found that the USA had the most contributions to the LA literature with 24% of all relevant publications, followed by the UK and Australia. The co-authorship network map of leading countries formed 10 clusters, including the USA, Australia, Spain, the UK, the USA, China, Canada, Germany, the Netherlands, and Taiwan. Also, Spain, the UK, and Australia played a connector role in the network. This is again in parallel with the findings of Chen et al. (2022). Chen et al. (2022) reported that the USA, the UK, Australia, Spain, and Germany collaborated the most, while the most collaborations on LA occurred between Australia and the UK. The institutions with the most collaborations in LA were the Open University (UK), University of Technology Sydney, Carnegie Mellon University, and The Open University of the Netherlands. Besides, the University of Edinburgh and the University of South Australia collaborated on most articles (Chen et al., 2022). In terms of articles on LA for PLE by the number of publications, the leading institutions in descending order were Curtin University, Athabasca University, University of South Australia, Monash University, Beijing Normal University, University of Mannheim, and the University of North Texas. The Open University, on the other hand, was the leading institution in terms of LA research (Chen, et al., 2022).

What/who are the Leading Journals and Authors of Research on LA for PLE?

Interactive Learning Environments was the leading journal on LA for PLE with 14 publications, followed by Sustainability (Switzerland) with 8 publications. Regarding the number of citations, the leading journals were Educational Technology and Society and Computers in Human Behavior. Chen et al. (2022) observed the most cited journals on LA as Educational Technology and Society, Internet and Higher Education, and Computers and Education. Our findings correlate with theirs with regards to the journal with the most citations, i.e., Educational Technology and Society. The 284 articles were published by 902 authors. 110 of these authors had at least 2 publications. Abelardo Pardo was the leading author with 9 articles, while Hendrik Drachsler led the ranking of most citations at 451. Also, Pardo and Burgos stood out in terms of centrality and linking between clusters. However, Hendrik Drachsler was not linked to any of the clusters despite having a high number of citations.

LA for PLE Research Trend

To reveal the LA for PLE research trend, we conducted a keywords co-occurrence analysis, an overlay visualization of keywords, and a bibliographic coupling analysis of articles. According to the keywords co-occurrence analysis, the leading keywords were “educational data mining” and “higher education” in terms of their centrality, overall weight, density, and degree of overlap with the other keywords. We also analyzed the changes in keywords by year. Accordingly, the most prominent keywords in 2018 (data mining and big data) were mostly aimed at the data and analysis phases of LA. In 2021 and 2022, the most prominent keywords shifted to “adaptive learning,” “artificial intelligence,” and “smart learning environments,” relating more to the action phase of LA. This shows that LA has rapidly completed its development and passed into the application and adaptation phases. This finding highlights the "need for integrating student-specific factors" as also previously identified by Blumenstein (2020) and Pishtari et al. (2020). According to Pishtari et al. (2020), most publications on learning design (LD) and LA focused on formal education in higher education and on physical and virtual environments. Although, "the effects of monitoring time devoted to learning" was one of the main topics covered regarding LA and LD research. One of the most prominent subjects in LA research was the subject of usefulness. Also, the most cited studies revolved around the subject of "the usage of LA for evidence-based decision making" (Pishtari et al., 2020). Hence, our findings of the research trend indicate a shift from theory to practice, supporting the systematic review of Chen et al. (2022). Our co-citation analysis of the articles revealed 4 clusters, named "Theory of LA," "LA Overviews," "Why LA," and "LA in Action." Accordingly, the articles on LA for PLE have mostly been theoretical, until now; in recent years, however, authors have been ready to put it into practice. Moreover, the book titled "Learning Analytics: Fundaments, Applications, and Trends" by Leitner et al. (2017) states that LA research has mostly focused on "the usage of massive online open courses (MOOCs), enhancement of learning performance, student behavior, and benchmarking of learning environments." Finally, Matcha et al. (2019) investigated the literature about LADs and found that "self-regulated learning" has been the focus of LA and LAD research.

Suggestions

Based on our findings and understandings from this study, we have made the following suggestions:

- Future research on LA for PLE can comfortably deal with practical applications rather than theoretical and conceptual studies. The contributions of using AI and NLP in LA to form PLEs is a particularly interesting subject and is deserving of experimental investigation.
- Since online learning environments are rather suitable for LA, these environments should make much greater use of LA, beyond just LADs, to help achieve PLEs. We believe that this necessitates the production and dissemination of advanced LA components, software, and plug-ins that can be integrated into LMS and other e-learning environments. The usage of LA should be able to go beyond dashboards.

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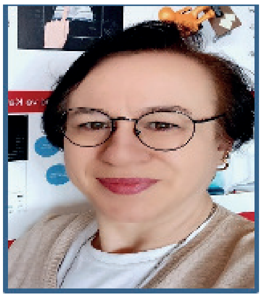

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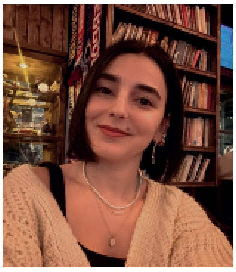

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