

A SYSTEMATIC REVIEW OF LEARNING ANALYTICS IN HIGHER EDUCATION: METHODS, BENEFITS AND CHALLENGES (2017 - 2023)

Essa E. Almazroei

University of Jeddah, Jeddah, Saudi Arabia

ORCID: 0000-0001-9009-2348

Abstract

In our study we will be discussing a detailed analysis of the application of learning analytics in higher education from (2017-2023). As it Addresses the various methodologies that's being used in learning analytics while highlighting its strengths and weaknesses. By collecting data from a wide range of academic papers and reports the study focuses on the role of how learning analytics enhances to student's achievement, progress and overall, the quality of their education. It also provides a guideline for an effective execution of learning analytics, reaffirming the importance of data-driven, customized educational approaches. Eventually the study explores ethical implications and potential challenges related to learning analytics presenting an overview of their impact in the educational sector.

Keywords:

Challenges in Learning Analytics Educational Sector Impact Student Performance and Behavior
Systematic Review Benefits and Drawbacks
Deployment and Implementation

Introduction

In recent years, there has been a significant increase in the use of learning analytics in higher education, with the technology being used to generate data-driven insights regarding student performance, behavior, and engagement. This paper will provide a systematic review of the methodologies, benefits, and challenges of learning analytics in higher education from 2017 to 2023, as well as insights into the possible benefits and drawbacks of using such technology. This paper will examine the implications for the deployment of learning analytics in higher education, as well as recommended practices for future implementation. And this will happen by answering three main questions: the first one is: What are the primary methods used for learning analytics in higher education during this time period? And the second one is: What are the benefits associated with these methods? Finally, what are the challenges associated with these methods? To answer these questions, we will analyze existing literature on this topic including journal articles, reports from educational institutions/organizations related to learning analytics initiatives during this time (e.g., case studies). We anticipate that our findings will provide valuable insight into how best practices can be implemented when utilizing various forms of data analysis within academic settings such as universities or colleges.

Learning analytics

Learning analytics is an important emerging field in higher education and is proving beneficial to both students and instructors. [Avella et al. \(2018\)](#) state that “learning analytics is an important tool for improving student learning outcomes within university institutions. This technology utilizes data that can inform teaching and decision making in ways that provide improved student and institutional performance.” By leveraging the data provided by learning analytics, instructors can make data-driven decisions to form targeted interventions, provide and tailor information to individual student behavior, facilitate co-learning, and analyze overall student learning. This can help to optimize strategies, allocate resources, and guide teaching interventions appropriately and efficiently. As a result, both instructors and students can benefit from the use of learning analytics to inform teaching and learning.

Learning analytics, defined as 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” ([Crompton et al., 2020,1](#)). Learning analytics is a strong tool that educational institutions are increasingly using to measure and improve student learning. Learning analytics data has a positive impact on higher education by assisting in the identification of learning trends, delivering individualized educational experiences, linking students with resources, and decreasing administrative costs. ([Wong, 2017](#)).

By collecting and analyzing student data, educators can better understand how students interact with the materials, track the progress of the learning process, identify areas of improvement, and anticipate potential challenges faced by learners. Furthermore, the data collected can be used to tailor learning activities to individual needs or to implement interventions that maximize learning outcomes ([Clark, 2008](#)). To summarize, learning analytics enables educational institutions to actively engage with obtained data to encourage more effective pedagogical practice and maximize the educational experience for students.

Learning analytics defines itself with a focus on data from learners and learning environments, with corresponding goals of understanding and optimizing student learning [Motz et al. \(2023\)](#) express concern about the lack of alignment of learning analytics research with its stated goals, noting that many studies do not adequately analyze learner data, measure student learning, or intervene in learning environments.

Learning analytics is in the middle between learning theory and data analytics. [Vân Haastrecht et al. \(2023\)](#) emphasizes the need for holistic validation strategies in learning analytics, integrating both positivistic and interpretivist validity criteria. He suggests an argument-based validation approach for more meaningful-insights in the educational experiences.

Learning analytics has been opening new opportunities to support learning in higher education. [Divjak et al. \(2023\)](#) study students' preferences for learning analytics dashboard features, finding a preference for features related to short-term planning and organization of learning, with cautious attitudes towards features that encourage comparison and competition.

Learning analytic and higher education

Learning analytics can offer tremendous benefits in higher education by empowering faculty, administrators, and students with detailed information and data insights from student behavior. Learning analytics is the collection, measuring, and analysis of data to improve student success in higher education institutions ([Hantoobi et al., 2021](#)).

Educators can identify student behaviors using learning analytics insights to better understand how their students engage with content, how long they engage, and how effectively they master the subject. ([Muljana & Placencia, 2018](#)).

Administrators can better identify at-risk students and give targeted interventions to help these students acquire the skills and knowledge they need to succeed. Furthermore, by using student feedback generated by learning analytics, instructors can adapt lessons to improve student success, track progress more effectively, and educate more effectively. Learning analytics also helps to improve and expand higher education efficiency by providing comparison analyses, supporting students in better tracking their own progress, and allowing institutions to recognize and reward high levels of engagement. By unlocking the promise of learning analytics, higher education may begin to adopt revolutionary changes to redress historical inequities and improve outcomes for all students ([Martin & Thawabieh, 2017](#)).

A recent review of Learning Analytics in Higher Education from 2017 to 2023 reveals a variety of methods by which institutions can develop and measure educational outcomes. Challenges and barriers to implementing learning analytics in higher education remain, but research has identified potential areas of inefficiency that can be leveraged to make improvement. Adoption of learning analytics has the potential to improve not only the accuracy of predicting skill-acquisition assessment, but also to develop strategies that help personalize and individualize learning experiences. As more research is conducted on this topic, institutions will have access to a greater understanding of how to use Learning Analytics to effectively improve educational outcomes ([Ifenthaler et al., 2021](#)).

The systematic review uncovered several beneficial applications and positive implications for learners, institutions, and educators. However, the review also highlighted some of the challenges and ethical considerations associated with continued growth and usage of Learning Analytics. It is essential for Higher Education providers to stay informed, consider the various benefits and challenges, and use insights from Learning Analytics to implement sound strategies to benefit not only their students and institutions, but also the wider Higher Education landscape ([Larrabee, Hughes & Smith, 2019](#)).

Even though learning analytics benefit learning but its uptake by higher educational organizations stays low. [Knobbout et al. \(2023\)](#) discuss the challenges in adopting learning analytics at higher educational institutions. They evaluated a capability model for learning analytics, which showed that it aids participants in planning for the adoption of learning analytics at their organizations.

When higher education institutions have the potential to collect a decent amount of learner data, it is important to consider the most of stakeholders involved with and impacted using learning analytics. Heiser et al. (2023) explore the concerns about bias and equity in the use of learner data as perceived by different stakeholders in higher education institutions.

Methods

To address the research problem, researchers conducted a literature review using the systematic procedure which helped to:

1. Formulate the problem
2. Collect data
3. Evaluate the data
4. Analyze the data
5. Organize and write the results.

Formulating the problem

The problem is that incorporating Learning analytics into data evaluation in higher education diverts educators' focus away from openly detailing methodology, benefits, and limitations of using Learning analytics in higher education. These three important components require greater explanation for higher education stakeholders to effectively use learning analytics in higher education. Educators must navigate through a mound of literature to become acquainted with Learning analytics methods, benefits, and challenges. To help solve the problem, the following questions drove this review:

1. What are the primary methods used for learning analytics in higher education during this time?
2. What are the benefits associated with these methods?
3. What are the challenges associated with these methods?

Collect Data

The researcher undertook a systematic review of literature from the last 5 years to identify and describe methods used by universities to apply learning analytics to improve student outcomes. The researcher reviewed papers published between 2017 and 2023 in the following databases: EBSCOhost, ProQuest Education Journals, SpringerLink, ScienceDirect, JSTOR, Web of Science, Educational Resources Information Center (ERIC) and Google Scholar using keywords such as “learning analytics”, “student success”, “Learning analytics and approaches”, “learning analytics and advantages”, “learning analytics and problems” and “higher education.” A total of 150 articles were found, of which 61 were included in the final review.

Evaluate the data.

In this paper 61 articles were used. 43 of these were about learning analytics methodologies, 9 about benefits, and 9 about challenges. This review included only articles that were directly connected to LA methods, benefits, and challenge, and helped address the three research questions.

Cooper's (1988) technique was appropriate for guiding a systematic review of literature. The researcher used the above-described approach, keywords, and databases to search the literature. Furthermore, researchers limited their literature search to the chosen keywords and databases. This literature may not include sources not available via the searched criteria and databases. **Table 1** provides the source found corresponding to the research questions.

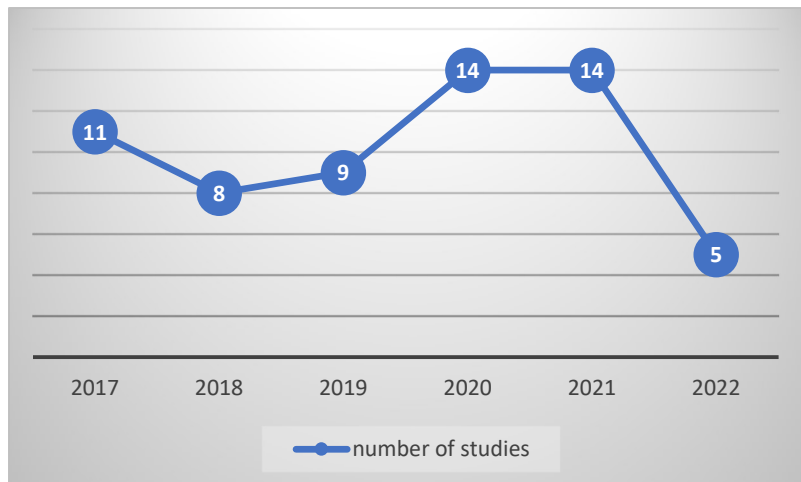
Table 1: Source found corresponding to the research questions.

Focus	Sources
Learning analytic methods	• Bodily & Verbert, 2017 • Gibson et al. (2017) • Perikos et al. (2017) • Charleer et al., 2018 • Dalla Valle et al. (2018) • Tempelaar et al. (2018) • Van Horne et al., 2018 • Yu et al. (2018) • Azcona et al. (2019) • Baneres et al. (2019) • Chaudy et al. (2019) • Leitner & Ebner, 2019 • Matcha et al. (2019) • Smith (2019) • Broos et al. (2020) • Choi et al. (2020) • Conijn et al. (2020) • Cornide-Reyes et al. (2020) • Hilliger et al., 2020 • Knight et al. (2020) • Lim et al. (2020) • Matcha, Gašević, & Pardo, 2020 • Shibani et al. (2020) • Yilmaz (2020) • Yılmaz, 2020 • Afzaal et al. (2021) • Hunt et al. (2021) • Iraj et al. (2021) • Karaoglan et al. (2021) • Lewis et al. (2021)

	• Lim, Dawson, et al. (2021) • Lim, Gasevic, et al. (2021) • Lim, Gentili, et al. (2021) • Misiejuk et al. (2021) • Tsai et al. (2021) • Wang et al. (2021) • Yilmaz et al. (2021) • Yousef et al. (2021) • Karaoglan Yilmaz (2022) • Kohnke et al. (2022) • Lu et al. (2022), • Ustun et al. (2022) • Zheng, Niu, and Zhong (2022). • Oh et al. (2023) • Oreski (2023) • Quick et al. (2023) • Khan et al. (2023) • Van Campenhout et al. (2023)
Learning analytic benefits	• Iam- on & Boongoen, 2017 • Jo et al., 2017 • Martin, & Nock, 2018 • Prieto et al., 2018 • Kaya, 2019 • Coussement et al., 2020 • Ndukwe & Daniel, 2020 • Vijayalakshmi, Panimalar & Janarthanan, 2020 • Yaseen et al., 2021 • Knobbout et al. (2023) • Divjak et al. (2023) • Aghaei et al. (2023) • Heiser et al. (2023) • Enodien et al. (2023)
Learning analytic challenges	• Leitner, 2017 • Lundie, 2017 • Sergis and Sampson, 2017 • Tsai and Gasevic, 2017 • Wilson et al., 2017 • Wintrup, 2017

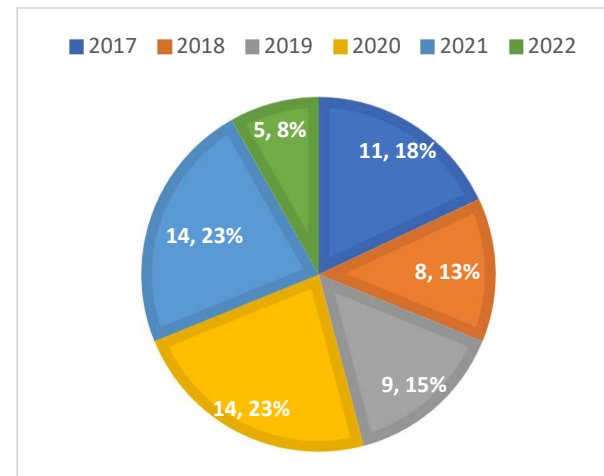
- Viberg et al., 2018
- Jones, 2019
- Selwyn, 2019
- Gadekar and Hiwarkar (2023)
- Grimm et al. (2023)
- Islam et al. (2023)
- Poellhuber et al. (2023)
- Nittas et al. (2023)
- Kitto et al. (2023)
- Gedrimiene et al. (2023)

Fig (1) the numbers of studies per year



the studies per year

Fig (2) the percentage of



Analyze the data

This section contains the results of the literature review that were used to address the three research questions.

Learning analytic methods and tools

Several methods and tools are used in the field of Learning Analytics in Higher Education from 2017-2020, including visual data analysis, educational data mining, text analysis and social network analysis. Additionally, many educational institutions have begun to use Learning Analytics dashboards to visualize the data, allowing for easier analysis and decision-making. There

are also several tools available for Learning Analytics, such as Learning analytics-based feedback approaches, and predictive analytics tools.

Table (2): Methods used by LA.

Category	Methods	Studies
Information visualization	Dashboard visualizations, influence graph, graph-based methods, knowledge graph, line chart, scatter plot, map, bar chart, map, pie chart, surface chart, histogram plot, flow chart	Gibson et al. (2017), Perikos et al. (2017), Dalla Valle et al. (2018), Tempelaar et al. (2018), Yu et al. (2018), Azcona et al. (2019), Baneres et al. (2019), Chaudy et al. (2019), Matcha et al. (2019), Smith (2019), Broos et al. (2020), Choi et al. (2020), Cornide-Reyes et al. (2020), Lim et al. (2020), Yilmaz (2020), Afzaal et al. (2021), Hunt et al. (2021), Karaoglan et al. (2021), Lewis et al. (2021), Lim, Dawson, et al. (2021), Lim, Gasevic, et al. (2021), Lim, Gentili, et al. (2021), Misiejuk et al. (2021), Tsai et al. (2021), Wang et al. (2021), Yilmaz et al. (2021), Yousef et al. (2021), Karaoglan Yilmaz (2022), Ustun et al. (2022), Zheng, Niu, and Zhong (2022).
Data mining	Predictive modelling, classification, clustering, Bayesian network analysis, process mining, behavior modelling, relationship mining, support vector machine, discovery model, neural network, machine learning	Perikos et al. (2017), Tempelaar et al. (2018), Yu et al. (2018), Azcona et al. (2019), Baneres et al. (2019), Matcha et al. (2019), Choi and Cho (2020), Afzaal et al. (2021), Iraj et al. (2021), Lim, Gasevic, et al. (2021), Tempelaar et al. (2021), Tsai et al. (2021), Yousef and Khatiry (2021), Zheng, Zhong, and Niu (2021), Karaoglan Yilmaz (2022), Kohnke et al. (2022), Lu et al. (2022), Ustun et al. (2022).
Text analysis	Thematic analysis, writing analytics, text mining, deductive analysis,	Gibson et al. (2017), Perikos et al. (2017), Yu et al. (2018), Conijn et

	natural language processing, sentiment analysis, content analysis, natural language processing	al. (2020), Knight et al. (2020), Lim et al. (2020), Shibani et al. (2020), Yilmaz (2020), Hunt et al. (2021), Lewis et al. (2021), Lim, Gasevic, et al. (2021), Misiejuk et al. (2021), Niu, and Zhong (2021), Zhong (2021), Ustun et al. (2022).
Social network analysis	Social network analysis, epistemic network analysis, network diagrams	Choi and Cho (2020), Lim et al. (2020), Misiejuk et al. (2021).

Fig (3) the numbers of studies for each method
Method

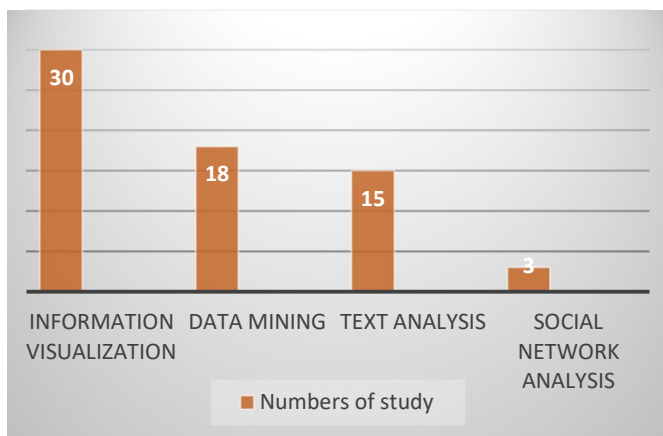
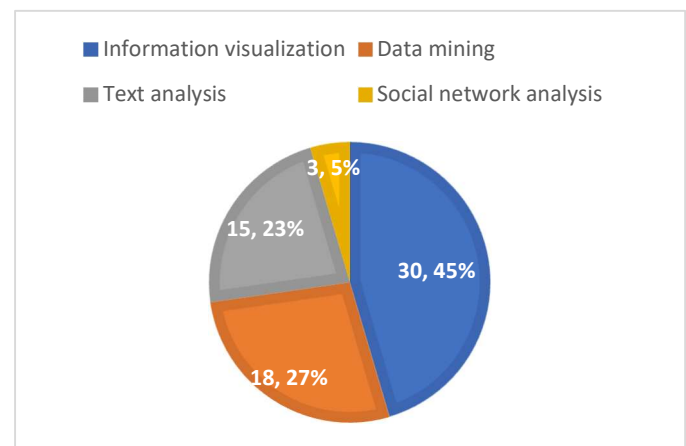


Fig (4) the percentage of each



The most used LA methods were information visualization and data mining methods. The information visualization approach was used in 30 studies and the methods used are dashboard visualizations, influence graph, graph-based methods, knowledge graph, line chart, scatter plot, map, bar chart, map, pie chart, surface chart, histogram plot, and flow chart.

Data mining was used in 18 studies, and its methods according to the studies used are predictive modelling, classification, clustering, Bayesian network analysis, process mining, behavior modelling, relationship mining, support vector machine, discovery model, neural network, and machine learning.

Text analysis was used in 15 studies and its methods according to the studies used are thematic analysis, writing analytics, text mining, deductive analysis, natural language processing, sentiment analysis, content analysis, and natural language processing.

and finally social network analysis was used in 3 studies and its methods according to the studies used are social network analysis, epistemic network analysis, and network diagrams.

The tools described below enlighten teachers, educators, and administrators in higher education who are not LA experts about the various methods and tools published in the literature. Such an

overview offers educators an integrative report and saves them from the overwhelming process of conducting a literature search to become acquainted with various LA approaches.

Learning analytic dashboard

LADs encourage students to set realistic objectives and track their progress in learning (Bodily and Verbert, 2017; Russell, Smith, and Larsen, 2020). The section that follows provides an overview of the dashboards that have been implemented to assist students, instructors, and student advisers.

LISSA (*Learning Dashboard for Insights and Support During Study Advice*) was developed by Charleer et al. (2018) to aid study advisers in assisting their first-year students in planning a more realistic curriculum. The visuals were created by analyzing historical data and student grades. However, the LISSA dashboard only displays the student's academic success when compared to their peers. As a result, this dashboard is only useful to students with sufficient advice from their study consultant. Furthermore, the LISSA dashboard does not offer students actionable insights.

Although some studies have indicated positive associations between the usage of LADs and academic success (Van Horne et al., 2018), little is known regarding the impact of LADs on the academic accomplishment of at-risk students (Russell, Smith and Larsen, 2020). Despite some positive findings, many flaws in existing LAD research have been identified (Matcha et al., 2020). Several research studies, for example, show that learners struggle to evaluate data visualized on dashboards and use dashboard feedback to guide their learning practices (Matcha, Gašević, & Pardo, 2020). To increase learning results, students require quality feedback and timely assistance (Hilliger et al. 2020). One problem that Learning Analytics has is determining the best visualization style to offer learning analytics feedback to students (Leitner and Ebner, 2019).

With the growth of educational data, increasing attention was given to student learning supported by learning analytics dashboards. Divjak et al. (2023) conducted a longitudinal study to understand what features students find most useful in learning analytics dashboards. They found a preference for features related to short-term planning and organization, with reservations about features that promote comparison with other students.

Learning analytics-based feedback approaches

LA-based feedback approaches appear to contribute to the community of inquiry of university students, namely their perceptions of cognitive, social, and instructional presence, as well as their reflective thinking skills (Ylmaz, 2020).

Research in learning analytics has long held a strong interest in improving student self-regulated learning and measuring the impact of feedback on student outcomes. Dawson et al. (2023) discuss an integrated model that combines feedback and assessment in learning analytics. They emphasize the need for capturing feedback and learning outcomes over a complete program of study, highlighting the importance of contextual factors in feedback diversity.

Predictive Learning Models

Predictive modelling has become a common research approach in LA. It provides future foresight and vision, which can aid improve learning efficacy and inspire remedial, timely, and suitable actions. Predictions are made by studying previous data and projecting it onto a model designed to foretell expected outcomes with a particular level of accuracy. Brooks and Thompson (2017) outlined the main steps to creating a predictive model, beginning with identifying the problem, collecting the data needed for analysis, and defining the predicted outcome, then selecting the predictor variables that perfectly correlate with the chosen output, and finally building the predictive model using one or more algorithms. To create predictive models, several algorithms are utilized, decision Tree, Bayesian Classifier, Neural Networks, Support Vector Machine, K-Nearest Neighbor, and Logistic and Linear Regression are the most common. (Kumar et al., 2018).

Learning analytics benefits

Based on the number of papers chosen for this review, it can be concluded that higher education institutions can benefit from using learning analytics in a variety of ways, including curriculum development and improvement, improved student learning outcomes, improved instructor performance, and monitoring of student dropout and retention. The following graph represent the numbers of studies for each benefit:

Fig (5) the numbers of studies for each benefit:

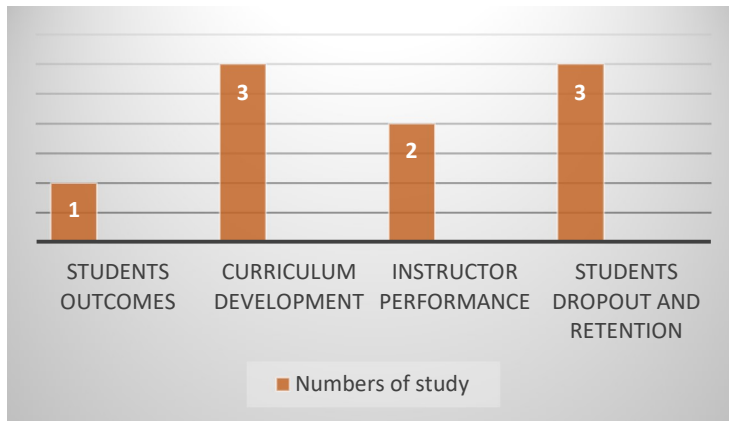


Fig (6) the percentage of each

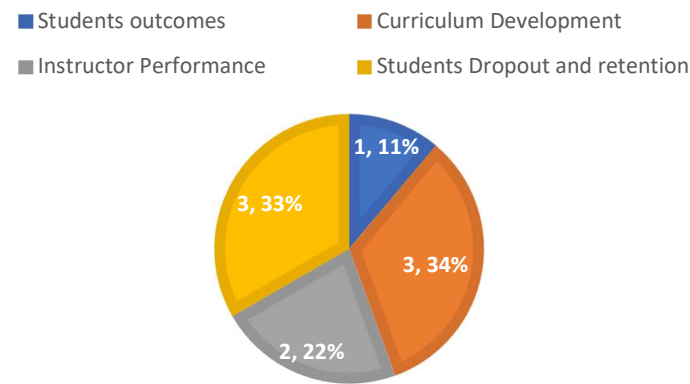


Table (3) The name of studies for each benefit:

The benefits	The study names
Students' outcomes	Jo et al., 2017
Curriculum developments	- Martin & Nock, 2018 - Kaya, 2019

	• Ndukwe & Daniel, 2020
Instructor performances	• Prieto et al., 2018 • Vijayalakshmi, Panimalar & Janarthanan, 2020
Students' dropout and retention	• Iam-On & Boongoen, 2017 • Coussement et al., 2020 • Yaseen et al., 2021

One of the most significant advantages of learning analytics is that it enables schools and instructors to identify *student learning outcomes* and how to improve student performance throughout the educational process. According to the study, the usage of data from learning analytics contributed to positive learning outcomes (Jo et al., 2017).

Learning analytics also gives a framework for predicting the performance quality level of teachers to improve students' learning outcomes in order to obtain improved *instructor performance*. The performance evaluation system aids universities in accomplishing their educational goals. The goal is to help teaching staff grow and develop by analyzing, monitoring, and utilizing pertinent information provided inside a model to improve their progress and efficiency (Prieto et al., 2018; Vijayalakshmi, Panimalar & Janarthanan, 2020).

For curriculum development and enhancement, learning analytics can also be utilized to provide further solutions on educational difficulties connected to curriculum design, primarily at the course level, with the purpose of improving learning and teaching processes and giving aid for program-level curriculum creation. It is critical to identify the relationships between courses within a program to organize them and ensure curriculum success. (Kaya, 2019). Using learning analytics in the curriculum development also assists teachers in better integrating content and responding to expressed dissatisfaction with extensive lists of standards that are frequently provided as collections of unrelated topics in prescribed courses of study (Martin & Nock, 2018). Learning analytics also improves instructors' diagnostic pedagogical abilities, allowing them to use data and evidence to improve teaching quality and uncover the best ways for increasing teaching performance. Learning analytics also allows teachers to use data to reflect on their teaching outcomes, which can subsequently be used to engage colleagues in meaningful dialogues to improve teaching quality. Instructors must also increase their data literacy and data inquiry skills to improve their teaching issues. As a result, providing teachers with analytics on their teaching practices and learning outcomes can assist them in improving the quality of their education. (Ndukwe & Daniel, 2020). Learning analytics also promotes accurate monitoring of *student dropout and retention*. Despite the numerous benefits of online courses, such as continuous access, high flexibility, extensive content, and low cost, significant dropout rates continue to hinder pedagogical and economic aims. Other research has discovered a considerable increase in dropouts and low attendance in online classes (Yaseen et al., 2021). Dropout detection tools for students, on the other hand, would allow educational institutions to identify students who are on the verge of dropping out and highlight areas that may be addressed to assist them in finishing their studies (Coussement et al., 2020). Learning Analytics technologies have been created to address the issue

of dropout in some universities' online distance education courses. Auxiliary features in such LA systems include, among other things, data visualization, dropout prediction, instructional action support, and textual analysis (Iam-On & Boongoen, 2017).

Learning analytics challenges

Fig (7) the numbers of studies for each concern

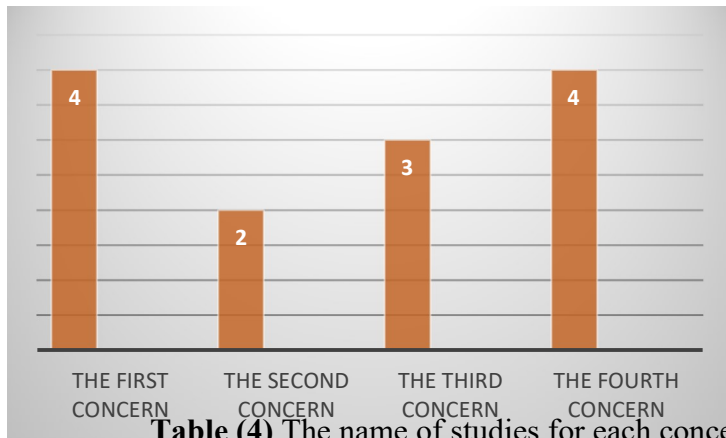
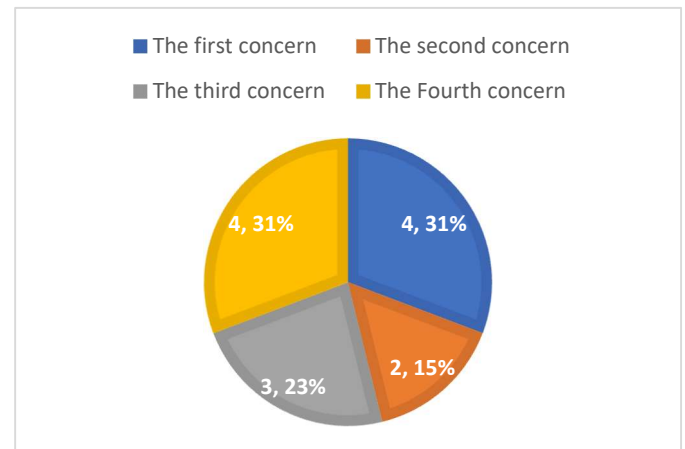


Table (4) The name of studies for each concern

Fig (8) the percentage of each concern



The concerns	The study names
The first concern	- Leitner et al., 2017 - Tsai and Gasevic, 2017 - Sergis and Sampson, 2017 - Selwyn, 2019
The second concern	- Lundie, 2017 - Wintrup 2017
The third concern	- Lundie, 2017 - Leitner et al., 2017 - Viberg et al., 2018
The fourth concern	- Lundie, 2017 - Wintrup 2017 - Viberg et al. 2018 - Jones 2019

Some researchers have critiqued LA for a variety of reasons. *The first concern* is that LA was created without the active participation of students and instructors (Sergis and Sampson 2017; Selwyn 2019). Typically, central institutional organizations oversee the processes of data collection and analysis, with students and teachers restricted to an observer position (Leitner et al. 2017; Tsai and Gasevic 2017) with limited awareness of the LA techniques used (Selwyn 2019).

The second concern is the students and their learning. Students appear to be underrepresented in the creation of LA systems in universities (Lundie 2017). Furthermore, identifying kids at risk is a core premise of LA methodologies, and there are worries in the research that doing so may promote labelling (Wintrup 2017) and operate as self-fulfilling prophecies, increasing the exact problems that LA is intended to alleviate. Academic personnel may become stuck in these processes as well, developing unrealistic expectations regarding students' academic achievement.

The third concern is that the institutions' interests in grades, persistence, and non-completion indicators tend to trump students' motivation, engagement, and pleasure, as well as more formative assessments of learning (Lundie 2017). As a result, it is unclear whether LA has a good impact on learning (Viberg et al. 2018). In this regard, Viberg et al. (2018) discovered, through a systematic literature review on LA in higher education, that only a small proportion of research papers (9%) show evidence that LA improves higher education students' learning outcomes, defined as knowledge acquisition, skill development, or cognitive gains. Furthermore, Leitner et al. (2017) discovered in their literature study that most of the publications were about academics and administrators making decisions rather than teachers and students.

Furthermore, some scholars believe that LA minimizes the complexities of teaching-learning processes (Lundie 2017; Selwyn 2019; Wilson et al. 2017). LA collects and measures what is readily available and easily examined and analyzed (Selwyn, 2019). Selwyn (2019) also mentions an incorrect use of LA.

The fourth concern is related to privacy and vulnerability (Jones 2019; Viberg et al. 2018). LA could be viewed as a monitoring instrument via which students are constantly monitored (Wintrup 2017). Additionally, this can be interpreted as a restriction on students' liberty (Wintrup 2017). Governments and institutions may use machine-learning algorithms to influence students' decisions throughout their lives (Lundie 2017).

Discussions

The review's findings indicate that learning analytics can be utilized to promote teaching staff productivity and efficiency, facilitate collaboration, and improve student happiness and engagement. However, the adoption of learning analytics is hampered by a lack of effective tools and analytical methodologies that enable educators to examine and comprehend complicated data sets and uncover important trends. As a result, the entire potential of learning analytics has yet to be realized, as has the full potential of these technologies, which has yet to be unlocked. There has been an upsurge in the usage of online technology for the delivery of teaching and learning activities in higher education over the last several years.

Acknowledgment:

This work was funded by the University of Jeddah, Jeddah, Saudi Arabia, under grant No. (UJ-23-SHR-46). Therefore, the authors thank the University of Jeddah for its technical and financial support.

References

- Afzaal, M., Nouri, J., Zia, A., Papapetrou, P., Fors, U., Wu, Y., ... & Weegar, R. (2021). Explainable AI for data-driven feedback and intelligent action recommendations to support students' self-regulation. *Frontiers in Artificial Intelligence*, 4.
- Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. *Online Learning*, 20(2), 13-29.
- Azcona, D., Hsiao, I. H., & Smeaton, A. F. (2019). Detecting students-at-risk in computer programming classes with learning analytics from students' digital footprints. *User Modeling and User-Adapted Interaction*, 29(4), 759-788.
- Azcona, D., Hsiao, I. H., & Smeaton, A. F. (2019). Detecting students-at-risk in computer programming classes with learning analytics from students' digital footprints. *User Modeling and User-Adapted Interaction*, 29(4), 759-788.
- Baneres, D., Rodríguez-Gonzalez, M. E., & Serra, M. (2019). An early feedback prediction system for learners at-risk within a first-year higher education course. *IEEE Transactions on Learning Technologies*, 12(2), 249-263.
- Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies*, 10(4), 405-418.
- Brooks, C., & Thompson, C. (2017). Predictive modelling in teaching and learning. *Handbook of learning analytics*, 61-68.
- Broos, T., Pinxten, M., Delparte, M., Verbert, K., & De Laet, T. (2020). Learning dashboards at scale: early warning and overall, first year experience. *Assessment & Evaluation in Higher Education*, 45(6), 855-874.
- Charleer, S., Moere, A. V., Klerkx, J., Verbert, K., & De Laet, T. (2017). Learning analytics dashboards to support adviser-student dialogue. *IEEE Transactions on Learning Technologies*, 11(3), 389-399.
- Chaudy, Y., & Connolly, T. (2019). Specification and evaluation of an assessment engine for educational games: Integrating learning analytics and providing an assessment authoring tool. *Entertainment Computing*, 30, 1- 31.
- Choi, Y., & Cho, Y. I. (2020). Learning analytics using social network analysis and Bayesian network analysis in sustainable computer-based formative assessment system. *Sustainability*, 12(19), 1- 13.
- Clark, I. (2008). Assessment is for learning: Formative assessment and positive learning interactions. *Florida Journal of Educational Administration & Policy*, 2(1), 1-16.
- Conijn, R., Martinez-Maldonado, R., Knight, S., Buckingham Shum, S., Van Waes, L., & van Zaanen, M. (2022). How to provide automated feedback on the writing process? A participatory approach to design writing analytics tools. *Computer Assisted Language Learning*, 35(8), 1838-1868.

- Cornide-Reyes, H., Riquelme, F., Monsalves, D., Noel, R., Cechinel, C., Villarroel, R., ... & Munoz, R. (2020). A multimodal real-time feedback platform based on spoken interactions for remote active learning support. *Sensors*, 20(21), 1- 27.
- Coussement, K., Phan, M., De Caigny, A., Benoit, D. F., & Raes, A. (2020). Predicting student dropout in subscription-based online learning environments: The beneficial impact of the logit leaf model. *Decision Support Systems*, 135, 1- 33.
- Crompton, H., Bernacki, M., & Greene, J. A. (2020). Psychological foundations of emerging technologies for teaching and learning in higher education. *Current Opinion in Psychology*, 36, 101-105.
- Dalla Valle, L., Stander, J., Gresty, K., Eales, J., & Wei, Y. (2018). Stakeholder perspectives on graphical tools for visualising student assessment and feedback data. *Research in Learning Technology*, 26, 1- 21.
- Gibson, A., Aitken, A., Sándor, Á., Buckingham Shum, S., Tsingos-Lucas, C., & Knight, S. (2017, March). Reflective writing analytics for actionable feedback. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 153-162).
- Hantoobi, S., Wahdan, A., Al-Emran, M., & Shaalan, K. (2021). A review of learning analytics studies. *Recent advances in technology acceptance models and theories*, 119-134.
- Hilliger, I., Ortiz-Rojas, M., Pesántez-Cabrera, P., Scheihing, E., Tsai, Y. S., Muñoz-Merino, P. J., ... & Pérez-Sanagustín, M. (2020). Identifying needs for learning analytics adoption in Latin American universities: A mixed-methods approach. *The Internet and Higher Education*, 45.
- Hunt, P., Leijen, Ä., & van der Schaaf, M. (2021). Automated feedback is nice and human presence makes it better: Teachers' perceptions of feedback by means of an e-portfolio enhanced with learning analytics. *Education Sciences*, 11(6), 61- 174.
- Iam-On, N., & Boongoen, T. (2017). Generating descriptive model for student dropout: a review of clustering approach. *Human-centric Computing and Information Sciences*, 7(1), 1-24.
- Ifenthaler, D., Gibson, D., Prasse, D., Shimada, A., & Yamada, M. (2021). Putting learning back into learning analytics: actions for policy makers, researchers, and practitioners. *Educational Technology Research and Development*, 69(4), 2131-2150.
- Iraj, H., Fudge, A., Faulkner, M., Pardo, A., & Kovanović, V. (2020, March). Understanding students' engagement with personalised feedback messages. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 438-447).
- Jo, I., Park, Y., & Lee, H. (2017). Three interaction patterns on asynchronous online discussion behaviors: A methodological comparison. *Journal of Computer Assisted Learning*, 33(2), 106-122.
- Jones, K. M. (2019). Learning analytics and higher education: a proposed model for establishing informed consent mechanisms to promote student privacy and autonomy. *International Journal of Educational Technology in Higher Education*, 16(1), 1-22.

- Karaoglan Yilmaz, F. G., & Yilmaz, R. (2021). Learning analytics as a metacognitive tool to influence learner transactional distance and motivation in online learning environments. *Innovations in Education and Teaching International*, 58(5), 575-585.
- Kaya, I. E. (2019). Artificial neural networks as a decision support tool in curriculum development. *International Journal on Artificial Intelligence Tools*, 28(4).
- Knight, S., Shibani, A., Abel, S., Gibson, A., & Ryan, P. (2020). AcaWriter: A learning analytics tool for formative feedback on academic writing. *Journal of Writing Research*.
- Kohnke, L., Fount, D., & Chen, J. (2022). Using Learner Analytics to Explore the Potential Contribution of Multimodal Formative Assessment to Academic Success in Higher Education. *SAGE Open*, 12(2).
- Kumar, A. D., Selvam, R. P., & Kumar, K. S. (2018). Review on prediction algorithms in educational data mining. *International Journal of Pure and Applied Mathematics*, 118(8), 531-537.
- Larrabee Sønderlund, A., Hughes, E., & Smith, J. (2019). The efficacy of learning analytics interventions in higher education: A systematic review. *British Journal of Educational Technology*, 50(5), 2594-2618.
- Leitner, P & Ebner, M. (2019). Learning analytics challenges to overcome in higher education institutions. In *Utilizing learning analytics to support study success*, 91- 104.
- Leitner, P., Khalil, M., & Ebner, M. (2017). Learning analytics in higher education—a literature review. *Learning analytics: Fundamentals, applications, and trends*, 1-23.
- Lewis, S., Heath, G., Lim, L., & Roberts, R. (2021). "I'm not a number, I'm someone to them": Supporting commencing university students' through technology-mediated personalized communication. *Student Success*, 12(1), 24-34.
- Lim, L. A., Dawson, S., Gašević, D., Joksimović, S., Fudge, A., Pardo, A., & Gentili, S. (2020). Students' sense-making of personalised feedback based on learning analytics. *Australasian Journal of Educational Technology*, 36(6), 15-33.
- Lim, L. A., Dawson, S., Gašević, D., Joksimović, S., Fudge, A., Pardo, A., & Gentili, S. (2020). Students' sense-making of personalized feedback based on learning analytics. *Australasian Journal of Educational Technology*, 36(6), 15-33.
- Lim, L. A., Gasevic, D., Matcha, W., Ahmad Uzir, N. A., & Dawson, S. (2021, April). Impact of learning analytics feedback on self-regulated learning: Triangulating behavioral logs with students' recall. In *LAK21: 11th international learning analytics and knowledge conference* (pp. 364-374).
- Lim, L. A., Gentili, S., Pardo, A., Kovanović, V., Whitelock-Wainwright, A., Gašević, D., & Dawson, S. (2021). What changes, and for whom? A study of the impact of learning analytics-based process feedback in a large course. *Learning and Instruction*, 72.
- Lu, C., & Cutumisu, M. (2022). Online engagement and performance on formative assessments mediate the relationship between attendance and course performance. *International journal of educational technology in higher education*, 19(1), 1-23.

- Lundie, D. (2017). The givenness of the human learning experience and its incompatibility with information analytics. *Educational Philosophy and Theory*, 49(4), 391-404.
- Martin, A. L., & Thawabieh, F. A. (2017). The role of Big Data management and analytics in higher education. *Business, Management and Economics Research*, 3(7), 85-91.
- Martin, J. D., & Nock, K. A. (2018). A Nonlinear, “sticky” Web of Study for Chemistry: A Graphical Curricular Tool for Teaching and Learning Chemistry Built upon the Interconnection of Core Chemical Principles. *Journal of Chemical Education*, 95(12), 2134-2140.
- Matcha, W., Gašević, D., & Pardo, A. (2019). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies*, 13(2), 226-245.
- Misiejuk, K., Wasson, B., & Egelanddsdal, K. (2021). Using learning analytics to understand student perceptions of peer feedback. *Computers in human behavior*, 117, 1-13.
- Muljana, P. S., & Placencia, G. (2018). Learning analytics: Translating data into “just-in-time” interventions. *Scholarship of Teaching and Learning, Innovative Pedagogy*, 1(1), 6.
- Ndukwe, I. G., & Daniel, B. K. (2020). Teaching analytics, value and tools for teacher data literacy: A systematic and tripartite approach. *International Journal of Educational Technology in Higher Education*, 17(1), 1-31.
- Perikos, I., Grivokostopoulou, F., & Hatzilygeroudis, I. (2017). Assistance and feedback mechanism in an intelligent tutoring system for teaching conversion of natural language into logic. *International Journal of Artificial Intelligence in Education*, 27(3), 475-514.
- Prieto, L. P., Sharma, K., Kidzinski, Ł., Rodríguez-Triana, M. J., & Dillenbourg, P. (2018). Multimodal teaching analytics: Automated extraction of orchestration graphs from wearable sensor data. *Journal of computer assisted learning*, 34(2), 193-203.
- Russell, J. E., Smith, A., & Larsen, R. (2020). Elements of Success: Supporting at-risk student resilience through learning analytics. *Computers & Education*, 152.
- Selwyn, N. (2019). What’s the problem with learning analytics?. *Journal of Learning Analytics*, 6(3), 11-19.
- Sergis, S., & Sampson, D. G. (2017). Teaching and learning analytics to support teacher inquiry: A systematic literature review. *Learning analytics: Fundaments, applications, and trends*, 25-63.
- Shibani, A., Knight, S., & Shum, S. B. (2020). Educator perspectives on learning analytics in classroom practice. *The Internet and Higher Education*, 46, 1-27.
- Smith, P. (2019). Engaging online students through peer-comparison progress dashboards. *Journal of Applied Research in Higher Education*, 1- 35.
- Tempelaar, D., Rienties, B., Mittelmeier, J., & Nguyen, Q. (2018). Student profiling in a dispositional learning analytics application using formative assessment. *Computers in Human Behavior*, 78, 408-420.

- Tsai, Y. S., & Gasevic, D. (2017, March). Learning analytics in higher education---challenges and policies: a review of eight learning analytics policies. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 233-242).
- Tsai, Y. S., Mello, R. F., Jovanović, J., & Gašević, D. (2021, April). Student appreciation of data-driven feedback: A pilot study on OnTask. In *LAK21: 11th international learning analytics and knowledge conference* (pp. 511-517).
- Ustun, A. B., Zhang, K., Karaoğlu-Yilmaz, F. G., & Yilmaz, R. (2022). Learning analytics based feedback and recommendations in flipped classrooms: an experimental study in higher education. *Journal of Research on Technology in Education*, 1-17.
- Van Horne, S., Curran, M., Smith, A., VanBuren, J., Zahrieh, D., Larsen, R., & Miller, R. (2018). Facilitating student success in introductory chemistry with feedback in an online platform. *Technology, Knowledge and Learning*, 23(1), 21-40.
- Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in human behavior*, 89, 98-110.
- Vijayalakshmi, V., Panimalar, K., & Janarthanan, S. (2020). Predicting the performance of instructors using Machine learning algorithms. *High Technology Letters*, 26(12), 694- 705.
- Wang, D., & Han, H. (2021). Applying learning analytics dashboards based on process-oriented feedback to improve students' learning effectiveness. *Journal of Computer Assisted Learning*, 37(2), 487-499.
- Wilson, A., Watson, C., Thompson, T. L., Drew, V., & Doyle, S. (2017). Learning analytics: Challenges and limitations. *Teaching in Higher Education*, 22(8), 991-1007.
- Wintrup, J. (2017). Higher education's panopticon? Learning analytics, ethics and student engagement. *Higher Education Policy*, 30(1), 87-103.
- Wong, B. T. M. (2017). Learning analytics in higher education: an analysis of case studies. *Asian Association of Open Universities Journal*.
- Yaseen, H., Alsoud, A., Nofal, M., Abdeljaber, O., & Al-Adwan, A. (2021). The effects of online learning on students' performance: A comparison between UK and Jordanian universities. *International Journal of Emerging Technologies in Learning (iJET)*, 16(20), 4-18.
- Yilmaz, R. (2020). Enhancing community of inquiry and reflective thinking skills of undergraduates through using learning analytics-based process feedback. *Journal of Computer Assisted Learning*, 36(6), 909-921.
- Yilmaz, R. (2020). Enhancing community of inquiry and reflective thinking skills of undergraduates through using learning analytics-based process feedback. *Journal of Computer Assisted Learning*, 36(6), 909-921.
- Yousef, A. M. F., & Khatiry, A. R. (2021). Cognitive versus behavioral learning analytics dashboards for supporting learner's awareness, reflection, and learning process. *Interactive Learning Environments*, 1-17.

- Yu, L. C., Lee, C. W., Pan, H. I., Chou, C. Y., Chao, P. Y., Chen, Z. H., ... & Lai, K. R. (2018). Improving early prediction of academic failure using sentiment analysis on self-evaluated comments. *Journal of Computer Assisted Learning*, 34(4), 358-365.
- Zheng, L., Niu, J., & Zhong, L. (2022). Effects of a learning analytics-based real-time feedback approach on knowledge elaboration, knowledge convergence, interactive relationships and group performance in CSCL. *British Journal of Educational Technology*, 53(1), 130-149.
- Van Haastrecht, M., Brinkhuis, M. J. S., Peichl, J., Remmele, B., & Spruit, M. (2023). Embracing Trustworthiness and Authenticity in the Validation of Learning Analytics Systems
- Motz, B. A., Bergner, Y., Brooks, C. A., Gladden, A., Gray, G., Lang, C., Li, W., Marmolejo-Ramos, F., & Quick, J. D. (2023). LAK of Direction.
- Grimm, A., Steegh, A., Kubsch, M., & Neumann, K. (2023). Learning Analytics in Physics Education.
- Knobbout, J., van der Stappen, E., Versendaal, J., & van de Wetering, R. (2023). Supporting Learning Analytics Adoption: Evaluating the Learning Analytics Capability Model in a Real-World Setting.
- Divjak, B., Svetec, B., & Horvat, D. (2023). Learning analytics dashboards: What do students actually ask for?
- Aghaei, K., Hatala, M., & Mogharrab, A. (2023). How Students' Emotion and Motivation Changes After Viewing Dashboards with Varied Social Comparison Group: A Qualitative Study.
- Heiser, R. E., Dello Stritto, M. E., Brown, A., & Croft, B. (2023). Amplifying Student and Administrator Perspectives on Equity and Bias in Learning Analytics.
- Poellhuber, L. V., Poellhuber, B., Desmarais, M., Léger, C., Roy, N., & Vu, M. M. C. (2023). Cluster-Based Performance of Student Dropout Prediction as a Solution for Large Scale Models in a Moodle LMS.
- Enodien, B., Taha-Mehlitz, S., Saad, B., Nasser, M., Frey, D., & Taha, A. (2023). The development of machine learning in bariatric surgery.
- Gadekar, B. P., & Hiwarkar, D. T. (2023). From Business Objectives to Analytics and Machine Learning Solutions: A Framework for Conceptual Modeling.
- Zhao, J. R., Chang, X., Feng, Y., Liu, C., & Liu, N. (2023). Participant Selection for Federated Learning with Heterogeneous Data in Intelligent Transport System.
- Dawson, S., Pardo, A., Salehian Kia, F., & Panadero, E. (2023). An Integrated Model of Feedback and Assessment: From fine grained to holistic programmatic review.
- Lin, J., Dai, W., Lim, L. A., Tsai, Y. S., Mello, R. F., Khosravi, H., Gašević, D., & Chen, G. (2023). Learner-centred Analytics of Feedback Content in Higher Education.
- Carney, P., Sebok-Syer, S., Pusic, M., Gillespie, C., Westervelt, M., & Goldhamer, M. E. J. (2023). Using learning analytics in clinical competency committees: Increasing the impact of competency-based medical education.