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# LEARNING ANALYTICS SYSTEMS TO IMPROVE THE QUALITY OF STUDENTS' OUTCOMES

***Abstract**: Learning analytics (LA) is a rapidly growing area of research that focuses on using data from learning technologies to improve the quality of students' outcomes. This paper aims to provide a comprehensive understanding of the current state of research on learning analytics technologies and how they can positively impact student outcomes. To achieve this, a systematic review using a PRISMA methodology was conducted. Inclusion and exclusion criteria were applied to select relevant papers, resulting in a final set of 31 papers for analysis. The identified papers were then organised and analysed. The findings show that the use of learning analytics has many benefits for both learners and instructors. However, its adoption by higher educational institutions has been slow and limited due to a lack of resources, funding, and skills. Four systematic reviews on the topic have been conducted, but they do not reveal any significant changes in the status of research and practice over the years. The analysed papers highlight the use of learning analytics for predicting student learning behaviours and identifying at-risk students who may benefit from targeted interventions. These interventions have been shown to improve students' academic performance and retention rates. Furthermore, learning analytics has also been used for technology enhanced learning and to improve overall academic outcomes for students. Moving forward, it is crucial to focus on overcoming the barriers to adoption that hinder the widespread use of learning analytics in higher education. Additionally, exploring alternative options beyond the traditional dashboard-based approach could offer new insights and improve the overall effectiveness of learning analytics systems. This research has implications for universities, learning staff and students.*

***Keywords:** Learning analytics, student performance, technology enhanced learning, student outcomes, online learning, Moodle Learning Management System*

## 1. Introduction

As per Theodotou (2023), learning analytics (LA) is an integration of learning technologies and data analytics. These systems help educators understand student behaviour, performance, and engagement, which can be used to improve student outcomes. These systems analyse data from various sources, like Learning Management Systems (LMS), to provide insights into

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learners' behaviours, preferences, strengths, weaknesses, progress, and outcomes. This information can be utilised by educators to make well-informed choices when it comes to designing curriculum, implementing teaching strategies, and providing personalised support for students. Thus, a learning analytics system empowers educational institutions to make data-driven decisions and improve resource allocation. Seven types of learning analytics have been recognised: predictive, adaptive, engagement, social network, competency-based, big data, and learning experience. Predictive analytics uses historical data to predict future events, especially student academic outcomes.

Adaptive learning analytics leverages data to customise the learning experience for each student. Engagement analytics analyses student interactions with course materials, discussions, and other learning activities to identify the elements of maximum engagement. Social network analytics analyses connections, communication patterns, and group dynamics, institutions can foster collaboration and build supportive learning communities. Competency-based analytics tracks individual progress and skill acquisition, ensuring that learners are well-prepared for the workforce. Big data analytics handles large volumes of structured and unstructured data on various aspects of learning for data-driven decisions. Learning experience analytics focuses on the overall quality of the learning experience to determine areas for improvement (Theodotou, 2023).

Advantages of utilising learning analytics systems encompass specific course options, creation of curricula, assessment of student learning accomplishments, understanding of behaviour and processes, individualised instruction, elevated educator effectiveness, access to post-education job possibilities, and progress in educational research (Theodotou, 2023).

The above background provides an overview of learning analytics, its components, types and their outcomes. This paper aims to systematically review research works on the topic.

The research question to be answered through this review is: How do learning analytics systems improve the quality of student outcomes?

## 2. Methodology

Google Scholar was used as the search engine to identify research papers on the review topic using different search terms and their combinations covering the different aspects of learning systems, analytics, and student outcomes. The identified papers were screened and selected repeatedly using inclusion and exclusion criteria (table 1) on the PRISMA flow diagram (Fig 1).

**Table 1.** Criteria

| Inclusion criteria | Exclusion criteria |
|---|---|
| English only | Other languages |
| Full texts only | Abstracts |
| Journal papers and reports | Books, book chapters, dissertations |
| Contain at least some relevant information | No relevant information |
| Above average quality rating | Below-average quality rating |

An MS Excel worksheet was used to tabulate all relevant information on each paper. At the end of the whole process, 31 papers were available for this review. These are described and discussed in the following sections. Some quantitative trends of the reviewed papers are also discussed.

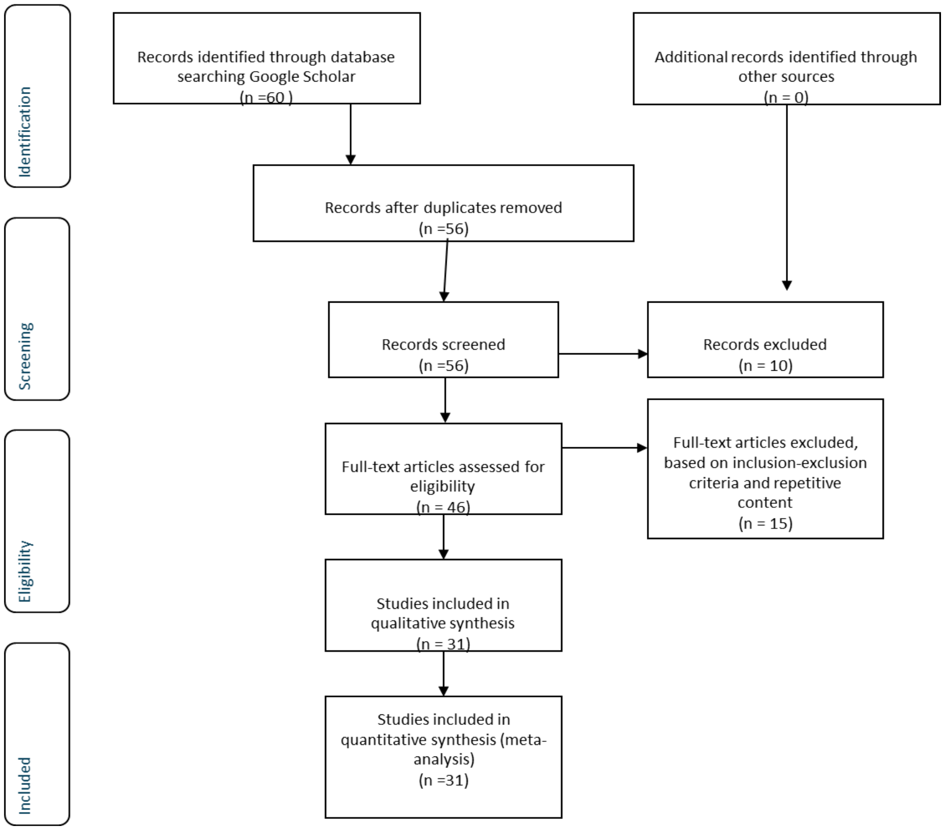


**Figure 1.** PRISMA Framework

## 3. Result

In a systematic review, a decade of research (2010-2020) on learning systems analytics used to predict student outcomes was evaluated by Namoun and Alshanqiti (2020). The review used 62 papers dealing with the forms of predicting learning outcomes, the predictive analytics models developed to forecast student learning, and the dominant factors influencing student outcomes. PICO (People/Problem, Intervention, Comparison and Outcome and PRISMA were used to synthesise the findings.

Learning outcomes were measured in terms of class standing or ranks and achievement scores or grades. Reviewed papers that used regression and supervised machine learning methods most frequently. The predictors most frequently identified were online learning activities, term assessment grades, and student academic emotions, which were the most evident predictors of learning outcomes. The authors categorised the papers in many ways through charts and tables. PICO used for synthesis were:

- People/Problem- Studies predicting student performance using the learning outcomes.
- Interventions- Intelligent models and techniques.
- Comparison- Comparison of identified models and techniques.
- Outcome- Quality and accuracy of the approaches, Set of performance predictors of learning outcomes.

The quality parameters used to assess the papers were: Verification of the predictive model with a second dataset, threats to validity reported, research implications and recommendations, well-defined research questions, use of separate datasets for training and testing, research limitations and challenges, results in sufficient detail, clear description of predictor variables, data collection instruments clearly described, sound research methodology, and clear research contributions.

In another systematic review by Blumenstein (2020), the results of the 38 papers selected were presented under the topics of collaboration, independent learning, and personalisation as tabulated statements and forest plots. Effect sizes were measured for cognitive, meta-cognitive, socio-communicative, and affective learning gains for course outcomes, learning performance and online presence. A Learning Analytics Learning Gains Design model was presented based on 13 papers, as given in Fig 2.

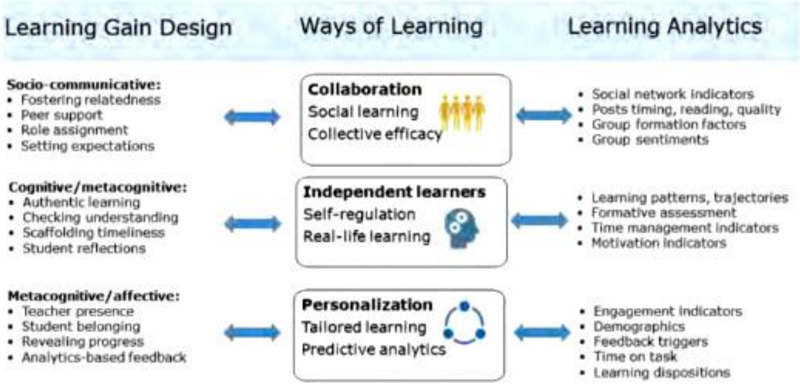

**Figure 2**. LALGD model (Blumenstein, 2020)

The three LGDs lead to three ways of learning. Learning analytics methods used for each LGD are different, as shown in Fig 2.

There is a lack of integrated LA tools to evaluate learning outcomes and predict student performance and achievement against specific outcomes. Yassine et al. (2016) proposed a new framework for developing a learning analytics tool to assess these outcomes in Moodle. The framework was constructed around a straightforward evaluation of the objectives of the course, achieved by integrating an in-depth assessment of each objective and its corresponding activities on the learning management system. Then, it analyses the result to evaluate the achievement of program outcomes and propose any improvement necessary for the course. Moodle has many analytics tools. GISMO is a visualisation tool for Moodle that is used to analyse the general learning process of all students in all subjects. MOCLog, based on GISMO, is a sum of tools that are used to analyse and present data within Moodle.

Learning Analytics Enhanced Rubric (LAe-R) is a plugin tool created for Moodle to assess rubrics techniques. SmartKlass is a multi-platform, open-source learning analytics that enables data tracking through a simple and easy-to-use dashboard. The Mindmaps Course is a recently introduced feature in Moodle that permits instructors and students to develop interactive concept maps on the Internet. This feature enables users to input course components, such as sections, modules, lessons, and pages, directly onto the map. Additionally, it displays activity dependencies based on specified conditions. The plug-in Engagement Analytics tool provides information about student progress against a range of indicators. It also provides feedback on the level of "engagement" of a student. The analytical processes considered in the proposed model are defining LMS as an online learning activities involving outcome measurement, designing a course map, analysing student activities and learning outcomes, and information visualisation. The challenges to the model include aligning learning outcomes with different learning activities, identifying the required type of data from the massive data available, and the scalability and reliability of the analytical tool.

To evaluate the impact of LA on our understanding of learning and produce insights translated to mainstream practice or contributed to theory, Dawson et al. (2019) used a review of 522 research papers published in LAK conferences and the Journal of Learning Analytics from 2011--2018. The reviewed studies were coded for five dimensions: study focus, data types, purpose, institutional setting, and scale of research and implementation. The coding and subsequent epistemic network analysis indicated that LA research has developed in the areas of focus and sophistication of analyses. However, its impact on practice, theory and frameworks has been limited. This could be due to a continuing predominance of small-scale techno-centric exploratory studies that have not fully accounted for the multi-disciplinarity of education. Hence, LA research should move from exploratory models to more holistic and integrative systems-level research.

A systematic review of 11 papers by Larrabee Sønderlund et al. (2019) evaluated the quality of assessment studies on the use of LA in higher education-focused intervention studies. The authors tabulated the main aspects of the selected 11 papers. The items tabulated were the country, study design, population, LA intervention, predictor variables, intervention design, results, and research quality. The quality of research in these papers was generally poor. Only three research articles were discovered by the authors that thoroughly evaluated the success and retention rates of LA interventions in higher education. Some recommendations for future research have been listed.

A study on the business course students at the University of New York (SUNY) was conducted by Strang (2016) to evaluate the relationship between online student activities and academic performance. The information was gathered from a course on Moodle, an online learning platform, and the performance of students on tests was evaluated against their level of engagement as measured by learning analytics indicators. This was done to determine the strength and predictive potential of the proposed connections. Five assignments in Moodle were used to test the hypotheses. Lessons read by the students were not related to grades. Students who read the lessons were not very likely to engage in more activity toward their assignments, as shown by a significant negative correlation between Lesson and Engage A. Although attendance was not graded, students who logged in more frequently did not spend time reading their lessons, as shown by the negative correlation between lessons and Engage C.

Overall, no significant relationships were obtained between student learning performance and online activity either through reading lessons or from the Moodle engagement analytics data. Learning analytics was unable to predict student learning performance based on Moodle engagement analytics used with the online AACSB-accredited business discipline course in this sample. Learning analytics was unrelated to grade. Thus, no reliable generalisation could be made from the results of this study.

A tool called Course Signals was created by Arnold and Pistilli (2012) from Purdue University to assist collegiate faculty in providing early intervention. This tool utilises LA to give students immediate feedback. CS utilises grades to forecast students' success and assesses factors such as demographics, previous academic record, and engagement with Blackboard Vista, the university's learning management system. The outcome is communicated to students through personalised emails from the faculty and a specific colour on a stoplight – traffic signal on the LMS to indicate how each student is doing. Soon after launching, a sizeable population of students and faculty started using CS due to the benefits of the intervention. Grades of students improved, which led to their increased retention, thus impacting the economics of the University. When CS predicts imminent poor performance of certain students, the faculty can intervene with effective solutions for the students to improve grades. Students also reported positive perceptions about the CS.

The relationships between student grades and key learning engagement factors were investigated by Strang (2017) in a mixed methods study using a sample of 228 online undergraduate business course students at an accredited American university. A general linear model showed that four online interaction variables predicted a 77.5% variance in the grades of undergraduate business courses at the university.

A sample of 53 students of a web programming course at an Indonesian university participated in a trial consisting of 1) Week 1, with tutorials for all participants on concept mapping in a traditional classroom; 2) Week 2, in which, a pre-test was conducted to determine the student’s initial abilities; and 3) Week 3-6, online learning process followed by a post-test to measure learning outcomes. To predict which student activities would improve the learning outcome of the students, linear regression of the online learning activities data in the LMS was used. The data generated were treated as LA. Working on exercises using concept mapping (n=2715) improved learning outcomes (16.1% variance in outcome explained by working on exercises in concept mapping) (Ulfa & Fatawi, 2021).

A report by Arroway et al. (2016) points out that business analytics and learning analytics share the same characteristics of interest, investment, and implementation. They differ only in purposes. Business analytics aims to improve business practices, and learning analytics aims to improve student outcomes. For both, data quality, technical infrastructure, stakeholder buy-in and senior leadership support are essential. The additional unique challenges of learning analytics are higher education history and culture, methodological difficulties in the measurement of learning, immature tools and processes, and a longer time lag for the evaluation of outcomes. For effective implementation of learning analytics, the authors suggest maximising stakeholders to maximise their buy-ins, ensure diverse support and funding for shared investment, and attract shared goals, motivations, scope, and outcome measures to create a unified understanding of the concept and its potential. There is also a need for a mature data governance system, IT system, infrastructure support and qualified staff to handle learning analytics. A pilot implementation for targeted easy-to-achieve early success can maximise stakeholder buy-ins. Those involved in the pilot implementation will become active supporters of LA in the institution. The EDUCAUSE analytics maturity index and the student success technologies maturity index can be used to assess the institutional strengths and weaknesses and to identify the investments.

Alves et al. (2017) utilised learning analytics to examine the patterns of usage of a virtual learning environment (VLE) and the academic performance of 2636 undergraduates in order to identify potential indicators for predicting student retention and dropout rates. The study primarily employed a quantitative approach, with a literature review serving as the primary data collection method. The findings revealed a correlation between reduced usage of the VLE and decreased attendance in on-site classes, resulting in a lower number of passing grades in course units. This suggests that absenteeism and failure to pass courses can predict the likelihood of college dropout or retention.

In their study, Nguyen and colleagues (2018) sought to address two main inquiries: (1) Can learner learning outcomes be predicted accurately using their interactive activities? (2) What is the most effective way to oversee and support learners in an online learning setting? Their proposed solution involved a model for predicting learning outcomes, which utilised a learning analytics dashboard for both learners and teachers to track progress, along with online guidance for learners based on various machine learning and data mining techniques. The model was tested by 290 second- and third-year students in information technology at a university. They were participating in three online courses in the Moodle LMS. The machine learning algorithms tested were K-means, Birch, and Agglomerated clustering. The experimental results showed that the predicted results applied to about 75% of the students with 50% accuracy. The difficulty of labelling new data without training was solved by clustering data. Linear regression was used for predictive modelling. Interactions between two weeks were inaccurate. Hence, only specific weeks were chosen for predictive modelling. The extent of interactions with the system and the learner performing the learning activities required by the instructor are two factors determining the success of implementing the model.

An effort was made by Daud et al. (2017) to investigate the effect of family income and students' personal information to predict the completion of the degree by students. Data on scholarship-holding students were collected from different universities of Pakistan. Learning analytics, and discriminative and generative classification models were applied for prediction. Discriminative models were Support Vector Machine (SVM), C4.5, Classification and Regression Tree (CART). The generative models were Bayes Network (BN) and Naïve Bayes (NB). Precision, recall, sensitivity and F1 score were estimated. Experimental results showed that the proposed method (hybrid model) significantly outperformed the existing methods due to using family expenditures and students' personal information feature sets. The current data showed 50% retention of students. Some recommendations have been given based on the results.

To solve some of the problems in using learning analytics, Ellis et al. (2017) tested the use of both observational and self-reported data. Two models were used for this purpose. Data were collected from 291 first-year engineering students at an Australian university. The learning context is a blended learning environment. The online component consisted of weekly interactions with digital material containing subject matter, visualising videos, interacting with formative assessment elements, and submitting summative assessments in Moodle. The system had a dashboard with feedback about the individual participation rates in online activities. The data consisted of survey data on the students and data on their online activities in Moodle. The survey covered surface and deep approaches to study. The online data covered the duration of student activities, dashboard engagements and students' views on it, students' views on any page and various sections of course notes, interactions with videos, interactions with multiple choice questions embedded in course notes and those with the videos, and students' answers to summative assessments. For each event and student, eight variables were used along with the accumulated whole semester data. Academic performance was measured using final marks by aggregating six types of tasks. Model 1 used only the self-reported surface approach to learning, and model 2 was obtained with the self-report variable and the five observational variables with significant correlations with the final score. The surface approach to study, the number of times an online resource was accessed and the number of multiple-choice questions answered predicted academic performance.

Using the socio-material concept, Wilson et al. (2017) tested their ideas on learning analytics in a case study. The authors created a series of analytics based on easily obtainable data by instructors from the Blackboard-based LMS. Data from a master's level module was used. This module was the first module in a professional learning programme for practising teachers. The objective of the module was to promote critical analysis of educational policies by utilising collaborative professional learning. This was achieved by tapping into the diverse perspectives of the 43 participants, including their disciplinary background, academic level, geographic location, social background, and previous experiences. This particular module was chosen as it exemplified the integration of online and social learning methods, which are crucial for fostering complex, higher-order learning in higher education.

After an initial face-to-face orientation, the entire module was offered online. It was not structured around lectures but on readings and participatory observations and in five phases. The authors used the written works and online activities of the students as their data for the study. Out of 43, four did not complete the module, and five had to re-write their final assessments to pass the module. They were categorised as at-risk participants. They were provided with feedback and improvements to learn better. Another group consisted of eight participants who did extremely well. They could be used as standards of comparison. The results showed obvious differences in patterns of interaction between students and resources. These differences were so pronounced that they could be marked and identified in an automated, machine-based process. However, these patterns were not necessarily correlated with performances. Thus, this case study showed learning analytics to be used for warning and guiding poor performers and those who want to drop out.

A group learning approach was implemented in a Computer systems course for first-year engineering students at a university in Australia. The course spanned 13 weeks and had around 300 enrolled students. Data was tracked for 290 of these students, with 81.5% being male and 18.5% female. Most of the students were not very familiar with the approach. The FL method required students to complete online activities beforehand, which would then be followed by an in-person session with the instructor (a lecture). The revised lecture format emphasised active learning, where students were expected to participate and work together on solving problems. This study was concerned with the lecture preparation activities: voice with multiple choice questions, documents with embedded multiple choice questions, and the sequence of problem-solving exercises. The dashboard provided real-time feedback to students on their scores and their comparison with the class average, facilitating social comparisons. According to the findings of Jovanović et al. (2017), the efficacy of the FL design in promoting student engagement and readiness for active participation in the classroom can be determined by the instructor. They also found that selective or adaptive scaffolding, in the form of feedback and guidelines, can aid students in improving their learning behaviour and increasing their awareness of their learning strategies compared to high-performing students. Clustering of students led to five student profiles, and of learning strategies led to four strategies.

To assess the influence of a pilot program aimed at retaining students, Dawson et al. (2017) contrasted the findings acquired through various techniques for examining the impact of the program on student retention rates. In this pilot study conducted from 2012 to 2014, 11,160 students participated. A predictive model was created to anticipate potential dropouts using information from student information systems, interactions on the learning management system, and assessment results. From this model, 1868 students were identified as academically at-risk. Early interventions, including learning support and remediation, were implemented. Traditional statistical methods indicated a positive correlation between the intervention and student retention but with negligible effect sizes. However, employing more advanced statistical techniques, specifically mixed-effect models, amplified the variability in the data by over 99% but did not demonstrate any significant impact of the intervention on student retention.

While globally, research on learning analytics in higher education is increasing, many methods have been used in these research works. These methods include classification, clustering, association rule, visual data mining, statistics, correlation, regression, sequential patterns, text mining, outlier detection, social network analysis, gamification, data distillation for human judgement, and the use of models for discoveries. Different techniques are used for each category of LA application. They include statistical and machine learning methods. Hooda and Rana (2020) used a review of the literature to answer five research questions. The status of LA and its growth in different countries are positive. The specific learning context and purpose of LA can lead to the correct choice of the methods. The nature of the problem determined the LA technique to be used. The purpose of LA/EDM techniques for HEIs is to improve assessments, feedback, and recommendations, predict learners' performance and their dropout rate, help in designing and improving curriculum for both learners and instructors, support pedagogy-related issues, and enhance learners' collaboration, and self-regulation in a social learning environment, increase students' engagement in learning course, and increase their retention rates and grades. MOOCs, VLE (Virtual Learning Environment), Wikis, LMS (Learning Management System), Online learning, E-learning, Social learning, YouTube videos, and classroom courses are the most common learning environments. The challenges are data quality, privacy, scalability, data ownership, and ethics of LA (Hooda & Rana, 2020).

The focus of the investigation conducted by Jo and colleagues (2015) was to propose more meaningful elements for learning analytics with the goal of helping students continuously enhance their academic performance through the use of educational technology. The study included 41 undergraduate students from a women's university in South Korea. The resulting model, comprised of seven predictors, accurately accounted for 99.3% of the variance in the final grades. Among these predictors, the total login frequency in the learning management system (LMS), the consistency or inconsistency of learning intervals within the LMS, and the cumulative scores of assignments and assessments were found to have a significant relationship with final grades. However, measures such as total studying time in the LMS, interactions with co

urse materials, interactions with peers, and interactions with the instructor were not found to be significantly correlated with final grades.

As a solution to the problem of student retention, new descriptive statistics for student attendance and modern machine-learning techniques were used by Gray and Perkin (2019) to create a predictive model. Tests showed that student failures at Bangor University can be identified at week 3 of the semester with an accuracy of about 97% for pass/fail and 88% for exact failure mode. The result was placed within the appropriate pedagogical context for its regular use as part of a comprehensive student support mechanism. The authors conducted some feature selection experiments to ascertain the point at which attendance becomes a reliable predictor of students' academic outcomes for the academic year using WEKA tools. The University has a policy of monitoring student attendance using smart ID cards. This facilitated data collection. The data set consisted of three biographic variables: the numeric codes for the student's program, the school, and the year of study, as well as the Academic Standing Code describing the completion status of that academic year. The codes contained PA (pass), FN (fail), FC (conditional fail requiring supplementary assessment), RY (repeat the year) and RS (repeat a single semester). Repetition of the experiment using 2016/17 data to train and using 2015/16 data to test produced slightly lower predictive accuracy. Using only attendance for the model may be a limitation of this study.

Hellings and Haelermans (2022) used a randomised experiment to study the effect of a learning analytics dashboard on half of 556 fresh Java programming students of courses with four specialisations and a weekly email with a link to their dashboard. The Java Programming course is a blended learning course with an online practice environment, which consists of both a Moodle course with quizzes and practical assignments and a Myprogramming lab (MPL) e-text environment. The dashboard informed the students about their online behaviour, progress, predicted chance of passing, predicted grade, online intermediate performance, and final exam performance in the learning management systems. In the experiment, three types of data were collected: student characteristics, student online practice behaviour and student performance. In the experiment, 276 students were allotted to the treatment group (email and dashboard), and 280 students were allotted to the control group, randomly stratified by specialisation. Ultimately, three groups of students were identified: students assigned to the treatment group (A = 1) and also opened the dashboard at least once (D = 1) (n = 205), students assigned to the control group (A = 0) and therefore could not use the dashboard (D = 0) (n = 280) and students assigned to the treatment group (A = 1) but did not open the dashboard at all (D = 0) (n = 71). To account for this variation, the authors used a two-stage least square instrumental variable. All the demographic and dashboard variables were compared with the total cohort. The email with dashboard access and dashboard use positively impacted student online behaviour. There was no effect on the students' final exam performance in the programming course. However, there were differential effects of specialisation and student characteristics.

In 2015, Park and Jo conducted a comprehensive examination and initial exploration of the necessity for learning analytics dashboards. As a result, an early version of a learning analytics dashboard (LAD) was developed. To enhance the LAD, a usability test was performed on 38 college students from two blended learning courses, utilising a stimulus recall interview format. Furthermore, the LAD was assessed in a controlled experiment with a comparison group, and supplementary surveys were given to solicit students' views on its usefulness, adherence, comprehension of graphs, and potential to induce behavioural changes. Although the LAD did not have a considerable impact on students' academic performance, findings from the usability and pilot tests revealed that the visual representation of the data did have an impact on students' comprehension. In addition, overall satisfaction with the dashboard was a determining factor in their level of understanding and perceived behavioral changes. These findings were used to enhance the LAD for universal implementation.

At present, there is limited empirical proof regarding the effects of scaled feedback on student academic progress and studying patterns. In a recent study, Lim et al. (2021) shared their findings on how a learning analytics (LA)-based feedback system affected self-regulated learning and academic performance among first-year undergraduate students in a large course. The researchers analysed log data from the LMS, e-book, and self-regulated learning indicators (such as performance on course assessments) over a period of three years, during which the latest course offering included an educational technology intervention for providing LA-based process feedback. To ensure comparability, they employed propensity score matching to create two equal-sized groups: one that received the feedback (the experimental group) and one that did not (the control group). Growth mixture modelling and mixed between-within ANOVA were used to identify differences in the patterns of online self-regulated learning operations over the semester.

Herodotou et al. (2019) presented an advanced predictive learning analytics system, OU Analyse (OUA), and evidence from its evaluation with online teachers at a distance-learning university. OUA uses machine learning methods for early identification of at-risk students who may not submit the next assignment and fail. Teachers can access OUA dashboards to provide weekly predictions on students' failure risks. OUA has been in use in the UK Open University since 2013. Predictive models use students' demographic data and course activities in virtual learning environments (VLE). In the study conducted by the authors, 15 courses with 14,128 undergraduate students and 559 teachers, presented in the academic year 2017/18 joined the study from a range of disciplines (9 Science; 4 Technology; 1 Health and social care;1 Law). Of 559, 189 teachers were given access to OUA dashboards, of which 65.6% had used OUA at least once. The rest served as control. The average to high use of OUA dashboards by teachers led to improvements in the performance of at-risk students. A comparison of these results was made with previous years' data when the same teachers did not use OUA.

In a study by Holmes and colleagues (2019), a unique learning analytics approach was employed to examine the integration of learning design (LD) in an online distance learning setting. One key aspect of this method was the exploration of LD patterns. By analysing information gathered from the virtual learning platform, student success data, and self-evaluations of 47,784 participants, the researchers investigated how these patterns influenced student behaviours, pass rates, and overall satisfaction. Additionally, the study incorporated social network analysis, which revealed connections between various LD patterns and variances in student behaviour. However, no significant correlations were found between LD patterns and pass rates or satisfaction levels.

According to Wiley and colleagues (2020), the success of incorporating learning analytics into learning design hinges on grounding and alignment. The researchers developed, experimented with, and assessed teacher-oriented learning analytics for a virtual middle school science unit about worldwide climate change. These tools offered teachers valuable information about their students' comprehension at key points in their educational journey. A total of three researchers, three system developers, and five local middle school science teachers and their 885 students participated in this study, which involved two academic years and two design cycles. The methods used were interviews and secondary data analysis. The study provided empirical evidence for the value and importance of grounding all aspects of developing and evaluating LA for learning design in theory.

In a model of pedagogical learning analytics, Wise (2014) included four principles of pedagogical learning analytics intervention design for teachers and course developers to support the productive use of learning analytics by students: Integration, Agency, Reference Frame and Dialogue. Three core processes in which to engage students were also described: Grounding, Goal-Setting and Reflection. The model was not validated.

In a study conducted by Hasan et al. (2020)

at an HEI in Oman, it was found that incorporating video-based learning and flipped teaching can have a positive impact on students' academic performance. This research focused on predicting students' success by utilising video-based learning analytics and data mining techniques, using a sample of 772 students from e-commerce and e-commerce technologies modules. Data from the student information system, learning management system, and mobile apps were collected and analysed using eight different classification algorithms. The Orange data mining tool was used for data preprocessing, and supervised learning was evaluated using confusion metrics. Techniques such as data transformation, feature reduction, and genetic search were applied to enhance the accuracy of the results. The study found that Random Forest algorithm was the most accurate in predicting student success, with 88.3% accuracy, using equal width and information gain ratio. This research highlights the potential of video-based learning and data mining for improving academic performance and providing insights for faculty to better understand student interactions.

The researchers in Colvin et al.'s (2015) study conducted two interconnected studies. The first study (Study 1) analysed interviews with top-level administrators to investigate the use of LA in their institutions, as well as the benefits and limitations perceived. The goal was to gain knowledge about current implementations and the factors that influence them. By coding the interview data, the researchers were able to conduct cluster analysis, which revealed the intricate and multi-faceted nature of LA projects and identified two distinct implementation approaches. Study 2 was built on Study 1 to investigate the factors required for establishing sustainable LA implementations to demonstrate a long-term impact. Considering that LA is still a relatively new development in higher education, an exercise was conducted to map out the perspectives and insights of international experts, practitioners, researchers, and stakeholders on future requirements. The study, titled "Student Retention and Learning Analytics: A Snapshot of Australian Practices and a Framework for Advancement," revealed two distinct approaches to implementing LA in institutions. Universities in the first cluster viewed LA primarily as a means to address student retention, resulting in a solutions-based approach. This approach focused on a technical solution and using data to prompt teacher action, with a hierarchical project management structure and limited cross-organisational collaboration. On the other hand, the second trajectory (cluster 2) saw LA as a tool to understand and improve learning and teaching practices. The implementation models in this cluster were more intricate and involved a wider range of stakeholders. For cluster 2, LA was considered as a site for potential disruptive innovation to improve the quality of the student learning experience. In the first study, the two clusters related to leadership, strategy, readiness, conceptualisation, and technology collectively informed how senior leaders responded to institutional challenges, enabled leadership, and defined learning analytics. Thus, the way an organisation initiates its implementation, project management, and scope of its learning analytics endeavours is crucial to its overall strategic capability. The findings of Study 2, based on feedback from an international panel of experts, highlighted the factors that contribute to the long-term sustainability of learning analytics. The importance of developing capacity and promoting innovation, as well as ensuring that the technical and data aspects of learning analytics are robust, transparent, reliable, and practical, were also emphasised. Sustainable adoption of learning analytics involves a complex system of interconnected resources and assets. The two key capabilities within this system are the strategic capability that guides the implementation of learning analytics and the implementation capability that integrates actionable data and tools into educational practices. Apart from these two drivers, two more identified were the need for appropriate analytical tools for LA and an organisational learning capacity for later improvements if required. The authors listed a few recommendations for further research and practice.

The study by Tempelaar et al. (2018) focussed on how learning disposition data can help to translate learning feedback from a learning analytics application into actionable learning interventions. The previous study dealt with deriving timely prediction models in a data-rich context involving trace data from LMS, formative assessment data, e-tutorial trace data and learning dispositions. Using the same context, the authors applied cluster analysis based on e-tutorial trace data for student profiling into different at-risk groups and characterising them with learning disposition data. Course performance data, LMS trace data, MLS mastery data, Blackboard logs, Hofstede cultural dimensions, self-regulated learning, meta-cognitive strategies, dispositional attitude, learning and epistemic emotions, goal-setting, help-seeking, motivation, and engagement data were collected. Linear, multivariate models, hierarchical regression analysis and k-means cluster analysis were done. Altogether, the study revealed a strong potential for learning dispositions in combination with learning analytics trace data for better predictions and interventions on at-risk students' failure in both the short and long term. Thus, an organisation's ability to strategically plan and execute its learning analytics (LA) initiatives is essential for its success. A study involving input from global experts identified key factors for the long-term viability of LA, such as developing capacity, promoting innovation, and maintaining technical and data integrity. Sustainable adoption of LA is a multifaceted process that involves various interconnected resources and assets. Within this system, two critical capabilities are the strategic planning ability that shapes the LA framework and the implementation capability that integrates data and tools into educator strategies.

The study surveyed 84 undergraduate students from a South Korean women's university and used multiple linear regression to identify the factors that influence academic achievement. The results showed that the six independent factors could explain 33.5% of the variation in final grades. The study found that four factors, including total time spent studying in LMS, peer interaction, regularity of learning intervals in LMS, and number of downloads, significantly impacted students' academic success in the online learning setting (Yu & Jo, 2014).

## 4. Discussion

Learning Analytics (LA) is an integration of learning technologies and data analytics. Although many benefits of using LA have been recognised, their uptake by higher educational institutions is low. Resources, funding and skills are important barriers to low levels of adoption. Mostly, LA is used to predict student learning behaviours, especially when students are at the risk of losing the year due to poor performance. LA can help to improve their performance through timely interventions.

The reviewed papers tested various interventions for identifying at-risk students, their retention, online learning behaviours and academic outcomes. A few reviews informed the status of LA research and implementation in higher education settings. Not much difference was seen in the reviews published in different years. In many papers, LMSs like Moodle have been used.

In this review, an MS Excel file was prepared using certain points discussed in some reviews as they were found to be good for categorisation of different papers and assessment of quality. Some quantitative trends based on these analyses are presented below.

### 4.1 Years of publication

The frequency of papers published in different years is presented in Fig 3.

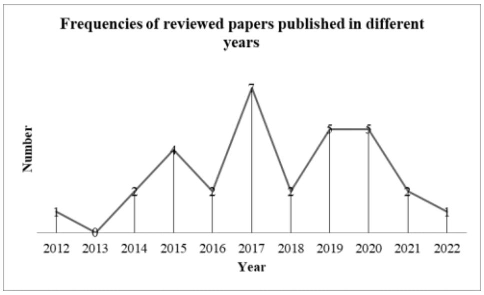


**Figure 3.** Frequencies of papers published in different years

More papers (23 out of 31) were published from 2017 to 2022 than before 2017. This trend indicates the increasing interest in LA over the years.

There were four review papers and 24 intervention studies among the 31 papers reviewed. No information about this was available for the remaining three papers. Among the intervention studies, nine used research methods like randomised controlled trials, quasi-experiments, case studies and simple comparison studies. Some model testing was done in five papers.

### 4.2 Quality of papers

Based on the available details tabulated, quality scoring was done on the reviewed papers. The values ranged from 1 (poor quality) to 5 (the highest quality- usually for RCT). The distribution of papers according to their quality rankings is presented in Fig 4. No paper was so bad as to get a score below 2. There were five papers ranking 2. Fairly moderate quality (3.5 to 4) was reflected by 15 out of 31 papers getting 3.5 or 4. One each, both randomised controlled trials, were ranked 4.5 and 5.

These trends show that the researchers have been paying considerable attention to publishing good-quality papers. This has enabled a large number of papers on LA to be accepted by both scientists and practitioners.

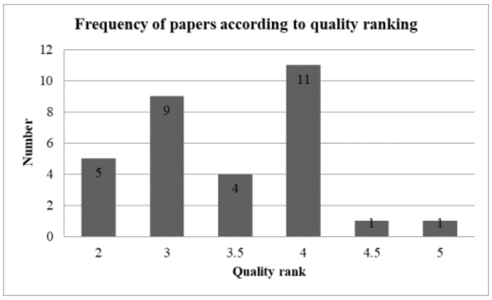


**Figure 4.** Frequency of papers according to quality ranks

## 5. Conclusion

Learning Analytics (LA) is defined as an integration of learning technologies and data analytics. LA bestows many benefits to both students and teachers. Yet its uptake by higher educational institutions has been slow and low. The main barriers are resources, funding and skills.

Four systematic reviews were made about the status of research and practice in LA. However, in reporting the status, no difference was observed between reviews of different years.

The reviewed papers showed that, mostly, LA is used for the prediction of student learning behaviours, especially when they are at the risk of losing the year due to poor performance. LA can help to improve their performance through timely interventions.

The reviewed papers tested various interventions for identifying at-risk students, their retention, online learning behaviours and academic outcomes.

Future research should focus on methods to cross barriers of adoption so that more universities adopt LA in their academic systems. An interesting disruptive approach will be to explore a better option for the current dashboard-based LA.

### 5.1 Limitation

Not many recent papers were obtained for this review. Although some quantitative trends were presented, meta-analysis of data across papers was difficult due to the incompatibility problems.

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