

A Structured Literature Review on No / Low code Plat-forms

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Abstract: This paper provides an in-depth analysis of learning dashboards, particularly focusing on Low Code. It explores the growing popularity of dashboards due to their widespread use in educational technologies such as e-training sys-tems and online courses. Low/No-code development is highlighted as a sig-nificant system, allowing individuals to perform operations without exten-sive coding knowledge. The paper discusses the benefits for companies and associations seeking software solutions in the technology-driven era. It ana-lyzes the advantages and disadvantages of Low/No-code development and examines the latest industry platforms. Additionally, it discusses potential enhancements to this development methodology and offers insights into its future impact on society and related industries. By assessing the trajectory of this trend, the paper predicts significant changes in software development practices and the dynamics of digital transformation. In summary, it sug-gests that Low/No-code development is a promising trend with the potential to significantly influence the broader technological landscape.

Keywords: Software engineering, Digital evolution, Development with minimal coding, Development without coding.

I. INTRODUCTION

The volume and complex data amassed through educational technologies like e-training System and Online Courses are fleetly raising. The rise of Learning Analyt-ics is a direct outgrowth of the expanding number of online educational platforms and the imperative to comprehend the dynamics of technology- intermediated litera-cy [1]. Post data collection, there is a needful for processing, analysis, and visualiza-tion [2]. Shemwell [3] asserts that visual displays are vital for sense- making, recog-nizing that humans can competently reuse expansive data when presented meaning-fully. Learning dashboards are necessary in this aspect, flaunting data through dif-ferent visualizations similar as graphs, needles, dials, and charts [4]. Amid rapid digital transformation, companies seek platforms to expedite development and de-livery of essential operations without compromising quality. Low-code development platforms (LCDPs) have emerged to meet this demand, automating the development lifecycle through graphical interfaces and visual abstraction. Approximately 84% of enterprises have adopted low-code platforms, citing benefits such as reduced costs and improved stakeholder engagement. These platforms address the shortage of skilled developers by enabling non-programmers to contribute effectively. The low-code development market has experienced significant growth, with projections indi-cating a further increase by 2024. Oracle APEX is a leading platform offering robust web development capabilities and data management. Reports show a substantial increase in profits from low-code development platforms and a growing adoption of low/no-code approaches in software development.

Year	2019-20	2020-21	2021-22
Low/No-Code development website	\$3,420.60	\$4,348.10	\$5,651.70
Process Management and Intelligent Business Suites	\$2,529.60	\$2,684.80	\$2,791.70
Development Platforms with multi-Experience	\$1,573.40	\$1921.00	\$2,316.90
Automation and Robotics Process	\$1,183.50	\$1,676.00	\$2,177.40
Development			
Platform and Citizen Automation	\$342.8	\$428.7	\$549.5
Any other Low/no-Code Development			
Technologies	\$58.6	\$74.4	\$86.3
Revenue (overall)	\$9,142.6	\$11,262.2	\$13,834.2

TABLE 1. MARKET ANALYSIS





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II. PRIOR RESEARCH

Many similar terms are being used for knowledge grasping dashboards, consisting' learning dashboard," dashboards for analytical learnings," understanding analytical dashboards," dashboards for data,' and' dashboards for web.' Different definitions for dashboards have also been proposed. An examination of many types of low-code platforms and an analysis was done by Apurv anand Sahay and colleagues in their work [5]. The authors dived into the overall structure of low-code platforms and proposed another method for automating the business processes through the imple-mentation of the Aurea BPM low/no-code platform in [6]. The adoption of such platforms has significantly diminished the likelihood of errors and has streamlined the process of developing business applications, resulting in a decreased time con-sumption. While low- code development platforms (LCDPs) like Oracle APEX are crucial in the business and IT industry, they have also opened new openings in ad-vanced education, simplifying basic operation creation, as discussed by Alenka Bag-gia etal. In [7]. The increase in automation of business processes and the significantly increased workforce in companies undervalued the importance of an automat-ed user access inspection system. In reference [8], the paper explores and focus on how important the user access review is and effective steps for ever changing risk scenarios. Chanyuan (Abigail) Zhang, in [9], investigates the joining of AI and ro-botics in inspection. However, these practices pose significant cost challenges relat-ed to training of employee, acquisition of software, and product maintenance. This research proposes a methodology to create an operational system for user access review and inspection control utilising Oracle's low-code/no-code APEX platform in order to address these issues and recognise the critical role that automation of in-spection plays. The device promises to provide a cost-effective solution, decrease the frequency of unauthorised access events, and reduce auditing time as compared to manual operations.

III. KEY INQUIRIES FOR INVESTIGATION

The following paper systematically reviews the literature to evaluate the present state of research conducted in relation of the dashboards related to learning and ana-lytics. Paper emphasizes on dashboards over general visualizations. Following are the study's research topics that were addressed:

RQ1: In what educational environments, for which user groups, and during what types of learning endeavors and work are dashboards currently employed?

RQ2: How has the evolution of dashboards in educational technology been shaped by the specific purposes they serve, the indicators they incorporate, and the technologies employed in their development?

RQ3: How thoroughly have learning dashboards been assessed in terms of their efficacy and maturity, considering aspects such as user satisfaction, influence on learning outcomes, and adaptability across diverse educational settings?

RQ4: What current obstacles, unresolved matters, and prospective directions re-quire consideration in the continuous advancement and implementation of in terms of educational technology?

IV. APPROACH AND PROCEDURE

To explore the research questions mentioned earlier, we undertook a detailed and exhaustive overview of published research which follow the guidelines advocated by Charters and Kitchenham [10]. This review spanned across five pivotal academic databases within the Technology Augmented Learning domain, namely Spring-erLink, Science Direct, IEEE Xplore, ACM Digital Library, and Wiley. Additionally, Google Scholar was integrated to uncover potential "grey literature," including re-ports of technicality and other resources for research which are not typically cata-loged in mainstream databases but deemed essential for comprehensively evaluating the state of the research field [10]. For the search process, we deconstructed the query to focus on studying the dashboard and the primary fields for conducting research where dashboards have recently found applications, namely Grasping Analyt-ics or Educational Data Mining. This strategic approach, centering around the term 'dashboard' and the related emerging fields, aimed to provide a comprehensive in-quiry that consolidates and summarizes existing knowledge rather than introducing entirely new insights [21]. To cover various dashboard proposals for educational applications in detail, our search strategy concentrated on the term 'dashboard' with-in the domains of Grasping the Analytics. However, it is essential to recognize a limitation: we were not have identified papers which did not specially used the 'dashboard' term or were not associated with these specific fields. Importantly, sig-nificant work on visualizations for educational applications, not explicitly designat-ed as 'dashboards' at the time, may have been inadvertently excluded. After explor-ing alternative spellings, we were searching the string "learning analytics" and "dashboard" (e-training system). After the search, each potential study underwent several stages of evaluation.



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Fig. 1. Steps of Analysis

Originally, we assessed titles and abstracts, seeking papers describing dashboards, their indicators, or architectural models for constructing dashboards. Researches that are unconnected to study related dashboards uses within the terms of Grasping the Analytics or Mining the data related to education which is not included. Subsequent-ly, every study was retrieved, thoroughly understood, and praised based on prede-termined set way. Papers falling outside the scope, which are low in quality and credibility are discarded. To meet the review goals, extracts of data were also com-pleted for every selected research study. Finally, false papers or primary parts of analyzed works were removed, if they differ in aspects. In order to ensure that each manuscript is reviewed by a minimum of two reviewers, the papers were divided up at random among the six reviewers throughout the first two review stages. The re-view crew as a whole discussed any disagreements or ambiguities in the papers.

V. PLATFORMS UTILIZING LOW-CODE TECHNOLOGY

Low/no-code platforms comprise three core components: server-side functionality, system integration, and application modeling. The application modeller plays a pivotal role, offering various features like graphical interfaces, drag-and-drop capability, and authentication systems. In Oracle APEX, users can customize pages using PL/SQL queries or dropdown menus. The platform supports agile and scrum methodologies, allowing for flexibility in handling changes and visualizing the development process. Additionally, it includes compilers, code generators, and optimizers that streamline code generation and model management, considering collaborative tools, database systems, and API connector services. Oracle APEX also provides SQL workshops for database management, supporting both SQL and NoSQL databases. Table 2 provides a relative analysis of these low- code platforms based on different features.



Fig. 2. Oracle APEX Page Designer

	Kissflow	PowerApps(Microsoft)	OutSystems	Mendix	Appian	Oracle APEX
Visual Modelling tools and user interface	Visual modelling tools like templates. Drop and Drag interface	Pre-built templates and UI components Model-driven or component-focused design	Visual model that produces results quickly Design drag and drop	Tools for visual development Parts can be reused. Facility drag and drop	No-code visual designer Facility drag and drop	Interface that is easy to use for developing visual codes
Open source	No	No	No	Yes	No	Yes
Built in workflows	Present	Absent	Absent	Absent	Absent	Absent
Learning curve	Easy to learn	Quite a high learning curve	Business analysts and developers will find it easy to learn	Require seasoned developers and programmers	Not simple to understand Training manuals	Easy to learn

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253

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Supported Databases	SQL	Azure, SQL server, OneDrive, Salesforce	Database SQL server, SQL Azure, IBM, Oracle MySQL, , SAP	Absence of direct technical support SQL, Oracle Database, IBM, MySQL ,MariaDB	could be improved. IBM, Amazon, SQL Server,	Oracle database
Cost and free trial	Starting from \$9/user/month Depending on the subscription Free trial available	\$7-\$40/user/month No free trial available	Begins at \$4000 per month. Expensive for a single use A free trial is offered.	Starts from \$1875/month Free trial available	Begins at \$90 per month. A free trial is offered.	There are no application or user fees, Required licence for peripheral components A free trial is offered.
Deployment	Cloud	Cloud	Cloud, SaaS, Web	On-site, public and private clouds	On premise, SaaS	On-site Oracle database cloud solution available in both private and public clouds

VI. RESULT

Here, we give a summary of the contributions found in the reviewed papers. also, we outline the crucial findings of the review, categorized based on four research questions the educational context targeted by the proposed solutions, the features of the dashboards in question, the level of development and refinement of the proposals, and the unresolved challenges identified by the studies.

A. Categories of Contributions

In the analysis, two distinct types of contributions were identified. Firstly, there were papers presenting theoretical proposals or frameworks (constituting three pa-pers, equivalent to 5 percent of the total). For example, Richards [11] introduced an architectural concept for a personalized adaptive dashboard, Mottus etal. [12] put forth methods for measuring and visualizing student engagement, and Vozniuk etal. [13] outlined an architecture designed for constructing and deploying learning dash-boards across various learning environments using widgets. Secondly, the predomi-nant portion of papers (39 papers, accounting for 71 percent) detailed implementa-tion of a particular learning dashboard was practically demonstrated in this study. Furthermore, a combination of a theoretical framework and its practical application was provided by 13 studies (5 percent). Notably, the term 'dashboard' lacked a clear description in most papers, with 93 percent not offering a distinct definition. Only a small fraction (7 percent), represented by four papers, explicitly defined 'dashboard,' each presenting a unique interpretation.

B. Learning Context

To address RQ1(' In what educational environments, for which user groups, and dur-ing what types of learning endeavors and work are dashboards currently em-ployed?'), we present a synopsis of the contexts learnt which are discussed in the papers that have been reviewed.

Target Users: Administrators, researchers, students, and teachers were the four categories of users that the review found. Teachers (75 percent) and Students (51 percent) emerged as the dashboards' main users. As Figure 3 illustrates, administrators and researchers were present in the experiments, though not completely.



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Learning Scenarios: Three categories of learning scenarios formal, non-formal, and informal were used to categorise the papers.

Educational Level: Thirteen percent of the articles (15 out of 40) did not indicate the learning environment, which is concerning given the level of education that the dashboards are intended for. In particular, review shows that 50% of the papers (20 out of 40) focused on academic settings.



Fig. 3. User analysis of the dashboard

Pedagogical Approach: The extraction of explicitly mentioned pedagogical approaches from the learning activities in the papers revealed that 56 percent (31 papers) didn't include specific references. Noteworthy pedagogical approaches included cooperative learning (CSCL, 13 percent, seven papers), blended learning (9 percent, five papers), and online learning (7 percent, four papers). Based on the descriptions, it was possible to determine the quality of the activities. 18 papers, 46% used dashboards to analyse individual sessions, 2% (three papers) used dashboards to visualise the results of several sessions, and 46% (18 papers) utilised dashboards over the duration of complete courses. It's essential to note potential imprecision in this analysis due to insufficient detail in the descriptions of learning activities in multiple papers.

C. Learning Dashboard Solutions

To address RQ2(' How has the evolution of dashboards in educational technology been shaped by the specific purposes they serve, the indicators they incorporate, and the technologies employed in their development?'), a comprehensive analysis was conducted, encompassing the stated purpose, indicators, data sources, platforms, visualizations, and technologies employed in various dashboards.

Purpose

Based on their intended use, learning dashboards were divided into three categories: (1) administrative monitoring (2 percent), (2) monitoring others (71 percent), and (1) self-monitoring (51 percent). Furthermore, 5% of the papers didn't clearly define the goal of their dashboard.

Types of Data Sources

There are six primary categories of sources from which dashboard data can be gath-ered. (1) Computer-mediated user activity logs; (2) user-produced or used learning artefacts (e.g., content analysis); (3) user-provided data (e.g., questionnaires and interviews) for analytics; (4) institutional database records; (5) sensor-tracked phys-ical user activity; and (6) external APIs for data collection from external platforms. Logs were cited as the primary data source in the majority of cases (85%, 34 pa-pers), followed by learning artefacts (29%, 11 papers), user data (12%, 4 papers), institutional databases (9%, 3 papers), physical user activity (7%, 2 papers), and external APIs (5%, 2 papers). Seven percent of the studies did not cite their data sources. In contrast, 24% (9 studies) used two data sources, 16% (6 papers) com-bined three, and 49% (19 papers) depended on only one. Three percent (one re-search) explored five different types of data sources for its dashboard, compared to only four percent (two publications) that included four data sources.

Platforms

The solutions from 51 different platforms were used in the examined publications, with Moodle being the most widely used (18%, 7 papers). Unidentified LMS (13 percent, 5 studies), Twitter (9 percent, 3 papers), Wikis (8 percent, 3 papers), and blogging platforms (5 percent, 2 papers) were among the other platforms that were commonly encountered. Data from a MOOC platform (EdX) and a specific learning environment (PLE) named Graasp were used in two different articles. Two more studies used data from tools created as part of the NEXT-TELL project. Thirty per-cent of the studies (12) combined data from two platforms, three platforms, four platforms, or even six platforms (one publication), whereas sixty percent of the pa-pers (24) used data from a single platform.

Platforms versus Data Sources

Readers can consult Fig. 4 for a clearer understanding of the relationship between the platforms and data sources used; the size of the bubbles indicates the number of publications employing that combination of platforms and data sources. Generally speaking, the bulk of the publications (23) only used one platform, and most of those only collected one kind of data (17 papers). Still, a sizable portion of the studies used integrated data, either by merging different kinds of sources (38 percent, 15 publications) or numerous platforms (25 percent, 10 papers).



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Fig. 4. Bubbles show papers, axis compare platforms and data types (zero unspecified).

Indicator Types

More than 100 distinct indications were found in the investigation, and they were grouped into six major categories based on the questions each indicator was meant to address. These categories comprised indicators that were related to learners, ac-tions, content, results, context, and social affiliation. Notably, most articles lacked an exhaustive inventory of the indicators utilised on the dashboard, which poses a challenge when attempting to draw valid conclusions regarding the distribution of indicators. Dashboard screenshots provided in the articles were frequently used to identify the different types of indicators.

Indicator Targets

Individual indicators were offered in the majority of publications (85%, or 34 pa-pers), while indications related to entire classes were included in 45% of the papers (18 papers). Nine percent (3 studies) contained indicators about big groups, as in the case of MOOCs, and fifteen percent (6 papers) had indicators about groups or pairs.

Visualization Types

29 different kinds of visualisations incorporated into learning dashboards were men-tioned in the examined studies. The top 15 visualisations used are shown in Fig. 5. Bar charts (84 percent, 33 publications), line graphs (60 percent, 24 papers), tables (54 percent, 21 papers), pie charts (38 percent, 15 papers) and network graphs (24 percent, 10 studies) are the most commonly used visualisations. Similarities be-tween target users and visualisation kinds were found using co-occurring analysis across all user groups. In a similar vein, there was little difference in visualisation types between other educational settings (university, secondary).



Fig. 5. Visualization Types

Technology

Of the 29 publications, the technology used to generate the dashboards was not mentioned in 53% of them. In 36% of the studies (a total of 14), it was possible to determine that the dashboard was a web application. A few articles addressed specific technologies (frameworks and libraries) that were used in the dashboard's creation. For instance, Google Charts was used in three studies, D3.js was cited in two, and the Next-TELL toolbox was mentioned in two. Other technologies that were at least cited once in the articles included QlikView, Google App Engine, Google Maps, Learning Log Dashboard (L2D), LARAe, GLASS tool, iGoogle widgets, JsCharts, Highcharts, Navi Badgeboard, Navi Surface, R, and Java.

D. Evaluations

To address RQ3(' How thoroughly have learning dashboards been assessed in terms of their efficacy and maturity, taking into account aspects such as user satisfaction, influence on learning outcomes, and adaptability across diverse educational settings?'), The procedures and scope of the assessments included in the learning dashboard papers were examined. The studies show that the evaluation maturity of existing learning dashboard solutions varies greatly; most of the publications (58 percent) included no evaluation at all. Positively, it can be estimated that 24 publications, or 60% of the examined studies, used data from real educational environments, such as past or current courses, to create dashboard analyses and visualisations. This emphasises how important it is to understand the usefulness of data visualisations through the use of actual educational data. Only 29% (11 papers) of the dashboard proposals evaluated the suggestions factually in real-world classroom settings, indicating a generally poor quality of evaluation.



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In these cases, stakeholders were shown dashboards, and information was gathered regarding their practical application in classes or meetings Only one study discussed evaluation techniques using expert panels or simulation, and four of the evaluations were controlled lab investigations. Furthermore, four publications acknowledged informal evaluations but did not elaborate on them.

Mixed methods—which combine qualitative and quantitative techniques—were the most often used assessment approaches (26 studies, or 65% of the papers with evaluations). Evaluation approaches that were exclusively qualitative (four studies) or entirely quantitative (two papers) were used in smaller papers. The most often utilised data sources in these assessments, which highlighted the various sources for evaluating learning dashboards, were questionnaires and interviews. Just six assess-ments gathered information from educators and learners, indicating a variation in the targeted stakeholders among the evaluations. Ten studies utilised teachers as primary informants, and nineteen publications used students as the primary inform-ants. The evaluation scale typically comprised 35-80 students and/or 2- 5 teachers; however, articles (27) and (30), which collected data from hundreds of teachers and students respectively, were exceptions to this rule. Specifically, out of the 23 publi-cations that had assessments, was to gather helpful criticism for enhancing the dashboards. A subset of assessments (seven papers) fo-cused on determining whether dashboards improved teachers' or students' awareness, whereas five papers assessed how dashboards affected motivation and behaviour. The impact of these technologies on learning has only been partially demonstrated by research; one study attempted to evaluate learning benefits experimentally in a controlled setting but was unable to establish statistically significant impacts.

Lastly, it's noteworthy to note that while only eight publications include this in-formation, several reviews mentioned the device used to access the dashboard. Six of them reported using a desktop, two cited tabletops, and one suggested using both a desktop and shared screens. This remark can point to a lack of thought given to how information is presented and visualised in relation to the device and environ-ment.

E. Ongoing Challenges

To address RQ4(' What current obstacles, unresolved matters, and prospective directions require consideration in the continuous advancement and implementation of dashboards in the field of educational technology?), The sections of the papers pertaining to future work and open issues were examined. A number of papers emphasised that an important part of their future work will be to extend their recommendations through evaluations with larger or other user groups. Five studies (9 percent) that examined open topics in the learning dashboard sector focused on ethical and data privacy issues. In particular, it was realised that students needed to be made aware of the fact that their learning traces are being recorded and analysed, together with information about who is participating in the process and why the data is being used. Two articles (7 percent) have identified user experiences and usability as major implementation problems for learning dashboards. This problem involves figuring out what information should be displayed on the dashboard at the right level of granularity, investigating special needs for different user groups (teachers, students, etc.), and putting effective visualisation techniques into practice. It is acknowledged that the sheer amount of information displayed or the variety of visualisations utilised may cause people to feel perplexed. While high-level indicators are simpler to understand, some research, such as [33], have indicated that their usefulness depends on consumers' confidence in their accuracy and completeness. In addition, users could find it difficult to understand the information displayed on the dashboard. One publications (4%), in response to these problems, suggested integrating techniques for automatic information analysis that would give educators and students feedback or alerts. With an emphasis on the importance of addressing user experience, usability, and ethical issues in the continuous implementation and development of learning dashboards, this review emphasises the identified future directions and problems in the field of learning dashboards.

VII. KEY DISCOVERIES AND INSIGHTS

Results from our study shed light on key insights regarding learning dashboards. While most proposals cater to teachers monitoring students in traditional education-al settings, there's a growing focus on providing dashboards directly to students, particularly in secondary and lifelong learning contexts. Some proposals lack speci-ficity regarding educational levels or pedagogical approaches, potentially hindering adoption due to a disregard for user requirements, including data literacy.

Current dashboard solutions mainly rely on single platforms and log analysis, but there's a shift towards utilizing multiple data sources and platforms to offer a com-prehensive view of learning processes. This emphasizes the need for data integration standards like xAPI and Calliper. Despite the variety of indicators used, there's a lack of research on the acceptability of indicators and visualizations for users with varying levels of data literacy.

Assessment plans are in the exploratory phase, with a slow transition to real-world testing. Long-term evaluations are lacking, which is crucial for users consid-ering similar solutions. Furthermore, there's limited research on the impact of dash-boards on student learning, highlighting a significant gap that needs further investi-gation.





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REFERENCES

- [1]. Elias, T. (2011). Learning analytics: Definitions, processes and potential Retrieved fromhttp://learninganalytics.net/Learning Analytics Definitions Processes Potential.pdf
- [2]. Bo€rner, K., & Polley, D. E. (2014). Visual Insights: A Practical Guide to Making Sense of Data. Cambridge, MA, USA: MIT Press.
- [3]. Shemwell, S. (2005, January). Futuristic decision-making. Retrieved from http://www.scribd.com/doc/12873609/Dr-Scott-M-Shemwell-Publications-and-Interviews
- [4]. Baker, B. M. (2007). A conceptual framework for making knowledge actionable through capital formation (Doctoral dissertation). Univ. Maryland Univ. College, College Park, MD, USA.
- [5]. Sahay, A., Indamutsa, A., Di Rusico, D., & Pierantonoi, A. (2020). Supporting the understanding and comparison of low-code development platforms. In 46th Euromicro Conference on Software Engineering and Advanced Applications (SEAA). Retrieved from virtual event.
- [6]. Waszkowski, R. (2019). Low-code platform for automating business processes in manufacturing. IFACPapersOnLine, 52(10).
- [7]. Baggia, A., Leskovar, R., & Rodič, B. (2019). Low code programming with Oracle APEX offers new opportunities in higher education. In Third International Scientific Conference ITEMA Recent Advances in Information Technology, Tourism, Economics, Management and Agriculture.
- [8]. Ramaseshan, S. (2019). Effective User Access Reviews. ISACA Journal, 4.
- [9]. Zhang, C. (2019). Intelligent Process Automation in Audit. Journal of Emerging Technologies in Accounting, 16(2).
- [10]. Kitchenham, B., & Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering (Tech. Rep. EBSE-2007–01). Keele Univ., Keele, U.K.
- [11]. Richards, G. (2011). Measuring engagement: Learning analytics in online learning. Electron. Kazan. Retrieved from https://cowboy.ksu.ru/conf/ek2011/sbornik/002.doc
- [12]. Mottus, A., Kinshuk, Graf, S., & Chen, N.-S. (2014). Use of dashboards and visualization techniques to support teacher decision making. In Ubiquitous Learning Environments and Technologies, Kinshuk.
- [13]. Vozniuk, A., Govaerts, S., & Gillet, D. (2013). Towards portable learning analytics dashboards. In Proc. IEEE 13th Int. Conf. Adv. Learn. Technol., 412–416. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6601968
- [14]. European Commission. (2001). Making a European area of lifelong learning a reality. Commission Eur. Communities, Brussels,
- USA.Retrievedfromhttp://eurlex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2001:0678:FIN:EN:PDF [15]. Sutherland, R., Eagle, S., & Joubert, M. (2012). A vision and strategy for Technology Enhanced Learning: Report from the STELLAR Network of Excellence. Retrieved from http://www.stellarnet.eu/kmi/deliverables/20120810_d1.8_final.pdf
- [16]. Soller, A., Martinez-Mones, A., Jermann, P., & Muehlenbrock, M. (2005). From mirroring to guiding: A review of the state of the art in interaction analysis. Int. J. Artificial Intell. Educ., 15, 261–290.
- [17]. Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. Int. J. Technol. Enhanced Learn., 4(5/6), 304-317. Retrieved from http://www.slideshare.net/R3beccaF/solar-learning-analytics-the-state-of-the-art
- [18]. Romero, C., & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. Expert Syst. Appl., 33(1), 135–146.
- [19]. Few, S. (2006). Information Dashboard Design. Sebastopol, CA, USA: O'Reilly.
- [20]. Brouns, F., et al. (2015). D2.5 learning analytics requirements and metrics report. Retrieved from http://lnx-hrl-075v.web.pwo.ou.nl/handle/1820/6031
- [21]. Ji, M., Michel, C., Lavou, E., & George, S. (2014). DDART, a dynamic dashboard for collection, analysis and visualization of activity and reporting traces. In Proc. 9th Eur. Conf. Open Learn. Teaching Educ. Communities, 440–445. Retrieved from http://dx.doi.org/10.1007/978–3-319-11200-8_39
- [22]. Park, Y., & Jo, I.-H. (2015). Development of the learning analytics dashboard to support students' learning performance. J. Universal Comput. Sci., 21(1), 110–133. Retrieved from http://www.jucs.org/jucs_21_1/development_of_the_learning/jucs_21_01_0110_0133_park.pdf
- [23]. Yoo, Y., Lee, H., Jo, I.-H., & Park, Y. (2015). Educational dashboards for smart learning: Review of case studies. In Emerging Issues in Smart Learning. New York, NY, USA: Springer. Retrieved from http://link.springer.com/chapter/10. 1007/978–3-662-44188-6_21
- [24]. Steiner, C. M., Kickmeier-Rust, M. D., & Albert, D. (2014). Learning analytics and educational data mining: An overview of recent techniques. Retrieved from http://csskmi.tugraz.at/ mkrwww/leasbox/downloads/ectel14_booklet.pdf#page=8
- [25]. Few, S. (2007). Dashboard Confusion Revisited. El Dorado Hills, CA, USA: Perceptual Edge.



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DOI: 10.17148/IARJSET.2025.12231

- [26]. Duval, E., et al. (2012). Learning dashboards & learnscapes. Retrieved from https://lirias.kuleuven.be/handle/123456789/ 344525
- [27]. Duval, E. (2011). Attention please! Learning analytics for visualization and recommendation. In Proc. 1st Int. Conf. Learn. Analytics Knowl., 9–17. Retrieved from http://dl.acm.org/citation.cfm?id=2090118
- [28]. Moissa, B., Gasparini, I., & Kemczinski, A. (2015). A systematic mapping on the learning analytics field and its analysis in the massive open online courses context. International Journal of Distance Education and Technology, 13(3), 1–24. http://dx.doi.org/10.4018/IJDET.2015070101
- [29]. Verbert, K., et al. (2014). Learning dashboards: An overview and future research opportunities. Personal and Ubiquitous Computing,18(6), 14991514.http://link.springer.com/article/10.1007/s00779–013-0751-2
- [30]. Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. American Behavioral Scientist, 57, 1500–1509.
- [31]. Boyer, E. L. (1990). Scholarship Reconsidered: Priorities of the Professoriate. Princeton, NJ, USA: Princeton University Press.
- [32]. Kitchenham, B., & Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering (Tech. Rep. EBSE-2007–01). Keele University.
- [33]. Richards, G. (2011). Measuring engagement: Learning analytics in online learning. Electronic Kazan. https://cowboy.ksu.ru/conf/ek2011/sbornik/002.doc
- [34]. Mottus, A., Kinshuk, Graf, S., & Chen, N.-S. (2015). Use of dashboards and visualization techniques to support teacher decision making. In Ubiquitous Learning Environments and Technologies, eds. Kinshuk and R. Huang. Berlin, Germany: Springer. http://link.springer.com/chapter/10.1007/978–3-662-44659-1_10
- [35]. Vozniuk, A., Govaerts, S., & Gillet, D. (2013). Towards portable learning analytics dashboards. In Proceedings of IEEE 13th International Conference on Advanced Learning Technologies, pp.412416.http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6601968
- [36]. European Commission. (2001). Making a European area of lifelong learning a reality. Commission European Communities, Brussels,
- USA.http://eurlex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2001:0678:FIN:EN:PDF
- [37]. Creswell, J. W. (2013). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. Newbury Park, CA, USA: Sage.
- [38]. Bull, S., Johnson, M. D., Alotaibi, M., Byrne, W., & Cierniak, G. (2013). Visualising multiple data sources in an independent open learner model. In Artificial Intelligence in Education, eds. H. C. Lane, K. Yacef, J. Mostow, and P. Pavlik. Berlin, Germany: Springer. http://link.springer.com/chapter/10.1007/978–3-642-39112-5_21
- [39]. Monroy, C., Rangel, V. S., & Whitaker, R. (2013). STEMscopes: Contextualizing learning analytics in a K-12 science curriculum. In Proceedings of the 3rd International Conference on Learning Analytics and Knowledge, pp. 210–219. http://doi.acm.org/10.1145/2460296.2460339
- [40]. Santos, J. L., Verbert, K., Govaerts, S., & Duval, E. (2013). Addressing learner issues with StepUp!: An evaluation. In Proceedings of the 3rd International Conference on Learning Analytics and Knowledge, pp.1422.http://dl.acm.org/citation.cfm?id=2460301