Learning Analytics Frameworks: A Review of Challenges and Practices in Higher Education

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Abstract. *Despite substantial attention, adoption of learning analytics by higher education institutions remained limited. The goal of this reseach was to analyze common challenges and practices for development and adoption of learning analytics in higher education present in learning analytics frameworks. In this context, framework is defined as a structured conceptualization that can help describe, understand, and/or implement learning analytics. The study combines systematic literature review with inductive content analysis. Categories of challenges were related to Stakeholders, Data, Infrastructure, and Ethics. The most common practice categories were Assessment and feedback; LA tools & deployment; Curriculum development & learning design.*

Keywords. learning analytics, framework, higher education, challenges and practices

1 Introduction

Learning analytics is an interdisciplinary research field that draws upon various disciplines and utilizes exponentially growing data pools generated by a variety of platforms and devices (Ferguson, 2012). Over the past decade, there has been a growing interest in learning analytics among researchers and practitioners in higher education, supported by the trend of mining and analyzing educational data provided by stakeholders to enhance teaching and learning processes in interactive environments (Chatti et al., 2012). These environments encompass different learning platforms, such as learning management systems (LMS), intelligent tutoring systems (ITS), and personal learning environments (PLE), all of which generate vast quantities of educational data (Greller & Drachsler, 2012). While there is an expectation that learning analytics will have exclusively positive effects on higher education, many institutional policy frameworks fail to adequately address the potential ethical implications and practices associated with tracking, collecting, and analyzing personal data (Slade & Prinsloo, 2013). Additionally, numerous studies tend to prioritize the implementation of various predictive analytics models, for example, to identify potential student performance (Azcona et al., 2018; Mussida & Lanzi, 2022; L. N. Singelmann & Ewert, 2022), giving limited attention to the educational and ethical principles of the research field. In other words, while learning analytics undoubtedly offers technical opportunities for higher education, there are also various challenges and issues regarding different perspectives on learning analytics adoption in higher education (Clark et al., 2020). This diversity in practices represents a significant challenge in the field, making it complex to create adequate models and frameworks in an attempt to aid learning analytics adoption in higher education (Dawson et al., 2018).

In recent review, Khalil et al. (2022) provided an overview of learning analytics frameworks focusing on development or application focus, ethics/privacy, representation, evidence of application, data types and sources, focus, and context. In contrast, the goal of this study was to investigate and highlight the established practices and challenges associated with the development and adoption of learning analytics frameworks in higher education. To achieve this goal, this study aimed to answer the following research questions:

RQ1. What are the main challenges in developing learning analytics frameworks in higher education institutions?

RQ2: What are the existing practices in implementing a framework for learning analytics adoption in higher education institutions?

In order to achieve the described goal, a systematic review was conducted using the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) framework (Page et al., 2021). Over the last few years, PRISMA has been widely recognized and used within the field of learning analytics in general, thus it is used in this review to answer research questions. The full procedure and its steps are described later in section 3 below. The contribution of this review lies not only in its analysis of non-experimental and experimental studies related to the topic but also in its focus on addressing and analyzing specific issues within the context of learning analytics adoption. In other words, this approach enables a comprehensive examination of the challenges and practices associated with the adoption of learning analytics in diverse higher educational contexts.

2 Theoretical Basis

During the initial stages of learning analytics development phases, the pioneers of learning analytics discussed the importance of designing guidelines that would support the adoption of learning analytics in higher education. Specifically, they emphasized that the implementation of learning analytics requires a carefully crafted design to ensure positive outcomes, such as enhancing the teaching and learning processes in higher education (Chatti et al., 2012; Greller & Drachsler, 2012). For that matter, Greller & Drachsler (2012) proposed a generic framework consisting of six critical dimensions: (1) Stakeholders; (2) Objectives; (3) Data; (4) Instruments; (5) External limitations – privacy and ethics related issues, institutional norms; (6) Internal limitations – required competencies. Similarly, Chatti et al. (2012) reviewed existing publications on the subject and mapped them into a four-dimensional reference model: (1) Data and Environment (What?); (2) Stakeholders (Who?); (3) Objectives (Why?); (4) Methods (How?). A resource-based capability model presented by Knobbout & Van der Stappen (2020) placed a greater emphasis on data and business analytics, aiming to provide specific operational steps for developing the capabilities required to adopt learning analytics. The model encompassed five capability categories: (1) Data, (2) Management, (3) People, (4) Technology, and (5) Privacy and Ethics. Slade & Prinsloo (2013) put greater emphasis on ethics and privacy guidelines that would serve as an ethical framework that higher education institutions can utilize to develop context-appropriate solutions aimed toward enhancing the quality and effectiveness of teaching and learning. It is not surprising that there is overlap among discussed frameworks, as they share similar objectives and views in achieving learning analytics goals. These frameworks, as well as process areas of the Higher Education Reference Model (*Higher Education Reference Model*, 2022) were the theoretical basis for classification of challenges and practices.

3 Methodology

3.1 Selection of papers for review

This paper adopted the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) framework for its structure. While PRISMA was primarily developed for review papers in healthcare, its applicability extends to other fields such as higher education, offering new perspectives to the research field (Khalil et al., 2023; Page et al., 2021). The search was performed in May 2023. The research process is illustrated in **Figure 1.** and described in detail below.

The databases included were Web of Science (WoS Core Collection), Scopus, and IEEE Explore Digital Library. The search terms were "learning analytics," "framework," and "higher education" structured as follows: 1) Web of Science Core Collection: TS=(learning analytics) AND TS=(framework OR maturity model OR MM) AND TS=(high* education*); 2) Scopus: TITLE-ABS-KEY ("learning analytics") AND (TITLE-ABS-KEY ("high* education*") AND (TITLE-ABS-KEY ("framework")) OR (TITLE-ABS-KEY ("maturity model")) OR (TITLE-ABS-KEY ("MM")))); 3) IEEE Explore: "Abstract": learning analytics AND ("Abstract": framework OR "Abstract": maturity model) AND "Abstract": high* education*. A total of 646 papers were identified from the three databases and filtered in each database according to the following inclusion/exclusion criteria: (1) Paper types – IN: Journal articles and conference papers; OUT: Books, book chapters, editorial materials, dissertations,

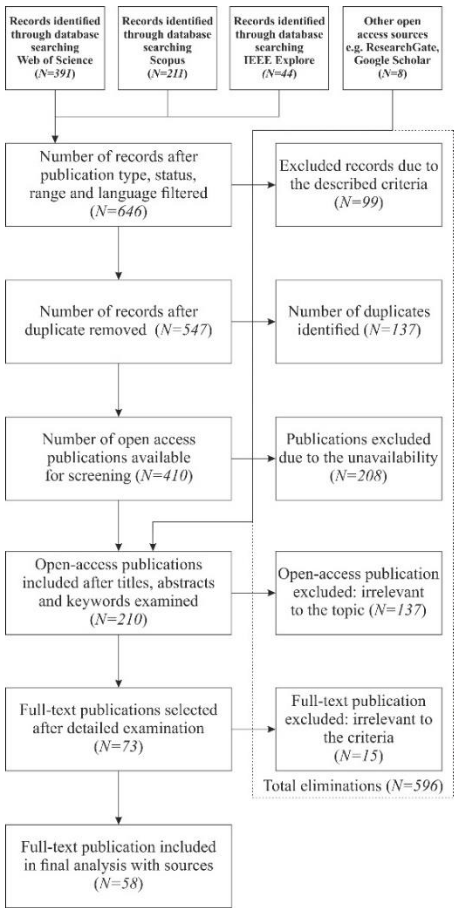

Figure 1. PRISMA flow diagram (Page et al. 2021)

workshop papers; (2) Paper status – IN: Peer-reviewed journal articles and conference papers, published papers; OUT: Non-peer-reviewed journal articles and conference papers, early access articles; (3) Publication date range – IN: 2011/01/01–2023/05/15 (yyyy/mm/dd); OUT: Outside of the proposed time interval; (4) Paper language: IN: English; OUT: Other languages. After applying the inclusion/exclusion criteria, 99 records were excluded, resulting in a total of 547 records. Among the resulting papers, 137 were identified as duplicates, and 208 were unavailable due to closed access. The final number of open-access papers available for further screening was 202.

Figure 2 presents the break-down of these papers by data source.

Title, abstract and authors' keywords of the remaining 202 papers were screened to include only papers that reported on: (1) the development of learning analytics frameworks in higher education; or (2) practices of learning analytics adoption in higher education. The first group of papers referred to an evaluation of existing frameworks and challenges related to the adoption of learning analytics in higher education. The second group addressed issues and approaches concerning learning analytics practices in higher education. Both experimental and non-experimental approaches were included. The experimental approach included case studies, action research in classrooms, model testing, etc. The non-experimental approach involved an analysis of known conceptual learning analytics frameworks, proposed guidelines and principles, evaluation of learning analytics dimensions, critical factors, and so on. Systematic reviews were excluded from further observation. By following the described process, a total of 137 papers were discarded as they were not relevant to the research questions. Additionally, 8 papers that met the criteria, but were not available in open access directly from the searched databases, were found in other repositories (Google Scholar, ResearchGate, publisher) and included in the analysis, resulting in a final number of 73 papers, after screening the titles, abstracts, and keywords.

After conducting a final full-text review, 15 of the remaining papers were excluded due to their lack of relevance or importance to the topic. As a result, the final analysis included 58 papers, 25 were in the first group, and 33 in the second group, based on the dominant characteristics of the papers. The final distribution of the data sources for the analysed papers is depicted in **Figure 3**.

3.2 Content analysis

An inductive content analysis was performed in each group of papers separately (Vears & Gillam, 2022). The unit of analysis was the whole paper. In the first group of papers the focus was on coding different types of challenges.

The second group of papers were classified according to the types of challenges identified in the first group of papers. Next, the papers were classified according to their focus on pedagogical or technological practices. Pedagogical practices referred to the processes by which stakeholders approach teaching and learning. They also dealt with ethical considerations and student privacy by developing policies for the ethical use of student data in pedagogical contexts. Likewise, pedagogical practices involved motivating and educating stakeholders to utilize learning analytics tools effectively. Furthermore, they encouraged discussions on learning analytics practices to enhance institutional policies and decision-making and promote the use of data-driven insights to improve the teaching and learning experience. On the other hand, technological practices included implementing tools and defining measures to effectively collect, analyze, and protect data in compliance with privacy regulations. They included selecting and integrating appropriate solutions for learning analytics, establishing data collection and analysis processes, ensuring data security, and guarding student privacy. Technological practices also involved using visualization tools to present analytics insights in a user-friendly manner for stakeholders and leveraging technology for iterative improvement of the learning analytics performance. These papers were also classified regarding the research design into 5 groups: 1) Pilot testing, 2) Focus groups, interviews, open discussions, 3) Case studies, 4) Reports, evidence-based recommendations, empirical analysis, 5) EDM, data collection, data analysis, predictive modeling and ML, ETL, etc. Finally, inductive coding was used to extract keywords from research questions, hypotheses,

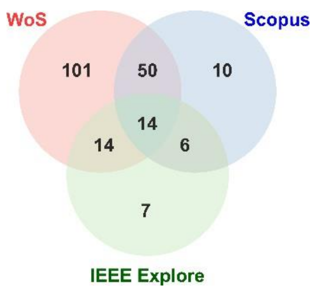

Figure 2 Number of open access papers satisfying inclusion/exclusion criteria, after deduplication, by source.

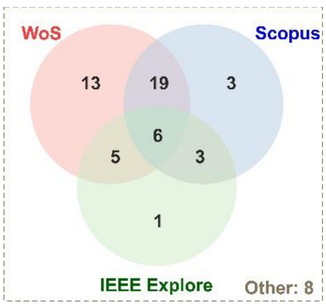

Figure 3 Number of papers included in the final analysis by source

Table 1. Patterns of challenges addressed by the first group of papers, indicating the challenge addressed by a star, and the number of papers for each combination of challenges.

Number of papers (#)	Challenges			
	(1)	(2)	(3)	(4)
5	*	*	*	*
5	*	*		*
1	*	*	*	
12	*	*		
2	*			*
25	25	23	6	12

and conclusions, indicating the type of practice or its area of application. These keywords were finally grouped into broader categories.

Excel table with references and results of content analysis is available as an open research data set (Kekez & Šimić, 2023).

4 Results

RQ1. What are the main challenges in developing learning analytics frameworks in higher education institutions?

Content analysis of the first group of papers identified four broad categories of challenges.

(1) *Stakeholder engagement in adopting learning analytics* - developing a learning analytics framework requires collaboration from various stakeholders in the process, including teachers, students, faculty administrators, decision-makers, IT staff, etc (Greller & Drachsler, 2012; Knobbout & Van der Stappen, 2020). Engaging teachers and students in learning analytics training and addressing their concerns, such as data analysis, privacy, and security, can be overwhelming and concerning, creating resistance among them and hindering learning analytics adoption (Gray et al., 2021) or can include different perspectives regarding the exploitation and use of learning analytics in higher education (Alenezi et al., 2018). In the teaching process, teachers are involved in designing learning activities, motivating students, and encouraging active participation (Joshi et al., 2020), often based on their subjective perceptions. Therefore, teachers may find it challenging to transition from diagnostic to practical data-driven interventions (Van Leeuwen, 2019) as, on average, they lack the technical knowledge to push the boundaries toward new approaches to teaching and learning (Scheffel et al., 2019; Schmitz et al., 2017). Furthermore, Sahni (2023) acknowledges that there are still challenges related to technology adoption and institutional support in effectively utilizing learning analytics tools, while highlighting the value and support that learning analytics tools have on students' learning experience resulting in higher levels of engagement, better results, and overall satisfaction.

(2) *Data availability, integration, and interoperability* - higher education institutions generate vast amounts of data, but it is scattered across different systems and platforms and in various formats. These data can provide a richness of information capable of improving the learning process and formal education in general (Clark et al., 2020). Enabling data consistency, accuracy, and availability is a significant challenge for higher education institutions when developing a comprehensive learning analytics framework. Different data formats, incompatible systems, and data privacy concerns can limit data integration efforts (Freitas et al., 2020). Establishing interoperability standards and ensuring data flow between systems and stakeholders present critical challenges in developing a framework (Chatti et al., 2012). Using educational data mining techniques can help the development of a learning analytics framework as it allows researchers to keep data consistency and allows complex methods for data analysis (L. Singelmann et al., 2021). Although educational data mining focuses more on extracting insights and value from data, it is complementary to learning analytics strategies to enhance educational processes based on valuable knowledge gained from students' data (Soltanpoor & Yavari, 2017).

(3) *Building an adequate infrastructure* - developing an effective learning analytics framework requires technological infrastructure and resources (Sanagustín, et al., 2019; Tsai et al., 2018). The LALA framework (Sanagustín, et al., 2019) defines the technological dimension as a set of manuals and steps that offer an overview of the technological needs and capacities that institutions must evaluate for the adoption of learning analytics. Institutions may face challenges by acquiring, implementing, and maintaining the necessary tools, platforms, and analytics capabilities. Furthermore, implementing new technologies and their integration into the existing systems and infrastructure is a follow-up challenge for higher educational institutions (Tsai et al., 2018) as many technologies and business models are commercial and do not directly apply to the educational processes (Alenezi et al., 2018).

(4) *Ethical and privacy concerns* - learning analytics involves the collection and analysis of sensitive student data. It is crucial to ensure compliance with privacy regulations and ethical guidelines when utilizing data for analytics. Balancing the need for data-driven insights with privacy protection is essential for building trust and maintaining ethical practices. By prioritizing privacy, institutions can establish a foundation of trust and transparency in using student data for learning analytics (Chatti et al., 2012; Greller & Drachsler, 2012; Slade & Prinsloo, 2013). Slade & Prinsloo (2013) discussed in detail ethical issues and dilemmas regarding data management, privacy, and security but also about potentially negative aspects of

learning analytics implementation in higher education institutions that could lead to a problem of viewing students primarily as data "producers" neglecting the importance of students' educational experiences. Greller & Drachsler (2012) stated that ethics extend beyond data gathering and integration, therefore ethical and privacy concerns overlap with other learning analytics categories. For example, ensuring transparency regarding data use may involve implementing protection measures, establishing clear communication channels with data 'producers' (e.g., students), and complying with relevant privacy regulations. These actions are part of different categories, as they require building a technological infrastructure, various operations on data, and stakeholder engagement.

As shown in **Table 1**, all papers address the Challenge (1) (stakeholder engagement), and only two papers do not address the Challenge (2) (data integration). Half of the papers address Challenge (4) (ethics), and only a quarter address Challenge (3) (infrastructure). The first mention of the technology infrastructure challenges appears in 2018.

RQ2: What are the existing practices in implementing a framework for learning analytics adoption in higher education institutions?

The second group of papers comprised 33 papers. Breakdown by the addressed challenges, practice type and category is presented in **Table 2**. Practice themes were grouped in eight broad practice categories. The most frequent category was *Assessment and feedback* (11 papers), followed by *LA tools & deployment* (8), *Curriculum development & learning design* (7), *Learning experience* (5), *Stakeholders* (4), *Ethics, privacy, security* (4), *Learning innovation* (4), and *Learning process* (2).

Similar to the papers on challenges, all papers on practices address the challenges of *Stakeholder engagement* and *Data availability, integration, and interoperability*. Papers usually address both *Building an adequate infrastructure* and *Ethical and privacy concerns* challenges.

Practice categories appearing most frequently together are *Assessment & feedback* and *Learning experience*. *Learning experience* category also appears frequently with the *Stakeholders* category. *LA tools & deployment* practices are often connected to *Learning process*. *Learning innovation* appears by itself, or in combination with *Assessment & feedback* or *Curriculum development & learning design*. Finally, *Ethics, privacy, security* category was not combined with other practice categories in the analysed papers.

Analysis of research designs showed that *Pilot testing* and *EDM, data collection, data analysis, predictive modeling and ML, ETL, etc*. were used in papers on Technological practices, while papers on Pedagogical practices employed various research designs, including both qualitative (*Focus groups, interviews, open discussions* and *Case studies*), and quantitative research (*Reports, evidence-based recommendations, empirical analysis*).

Even though these papers analyse a wide selection of LA practices and propose or discuss implementation of an LA framework, most of them do not provide evidence of fully successful framework implementation.

Table 2. Breakdown of the number of papers on LA practices by the challenge addressed, type and categories of practices.

Challenges					**Practice type**		
Stakeholders	**Data**	**Infrastructure**	**Ethics**	**Practice categories**	**Pedagogical**	**Technological**	**Total**
*	*	*	*	Ethics, privacy, security	2		2
*	*	*	*	Learning innovation	1		1
*	*	*	*	LA tools & deployment	1		1
*	*	*	*	LA tools & deployment Stakeholders Learning process	1		1
*	*		*	Ethics, privacy, security	2		2
*	*			LA tools & deployment	5		5
*	*			Assessment & feedback Learning experience	3		3
*	*			Learning experience Stakeholders	2		2
*	*			LA tools & deployment Learning process	1		1
*	*			Assessment & feedback Curr. dev. & learning design	1		1
*	*			Curr. dev. & learning design Learning innovation	1		1
*	*			Assessment & feedback	3	3	6
*	*			Curr. dev. & learning design	3	1	4
*	*			Assessment & feedback Learning innovation		1	1
*	*			Learning innovation		1	1
*	*	*		Curr. dev. & learning design		1	1
				Total	**26**	**7**	**33**

5 Discussion

Lee, Cheung & Kwok (2020) maintain that identification of practices provides helpful indicators for educational stakeholders to adopt learning analytics and can also motivate stakeholders to seek practical solutions or for researchers to find valuable research directions. Investigation of practical approaches offers insights and guidance to overcome challenges and maximize the benefits of learning analytics adoption in higher education institutions (Leitner et al., 2019). We hope that results of this study will be a valuable addition to previous research on challenges and practices in LA adoption.

This synthesis revealed that most of the analysed studies discuss approaches for learning analytics adoption, but do not provide specific procedures and steps for achieving successful implementation. Although higher education institutions are mostly aware of the benefits of learning analytics adoption, many struggle to implement theoretical concepts into practice. Higher education institutions recognize the issues, but lack the specific practices that would serve as a solution.

There are several limitations to this research. First, we limited the review to open access publications and publications available through public repositories. Still, even the limited scope of these papers offered a rich overview of different challenges addressed through LA frameworks and approaches to their implementation. Second, classification of the papers on practices into those on pedagogical or technological approaches may have introduces a degree of uncertainty. There were papers that used both approaches in different measure. The authors' decision on the prevalent approach may lack objectivity. Finally, inductive content analysis is always to some degree subjective, thus this research should be extended with reliability analysis, that could not fit the extent of this paper.

6 Conclusion

This study highlights the interdisciplinary nature of learning analytics and its potential to enhance the learning process through data collection and analysis. Despite its growing attention, the adoption of learning analytics in higher education institutions remains quite limited. The study analyzed papers focused on learning analytics frameworks and practices in higher education and revealed several findings. Papers on LA framework development focused on four types of challenges: 1) Stakeholder engagement in adopting LA, 2) Data availability, integration, and interoperability, 3) Building an adequate infrastructure, and 4) Ethical and privacy concerns. The first two challenges were addressed by almost all the papers, and a quarter of the papers address the fourth challenge. The third challenge appears only in the most recent papers (since 2018), and is addressed by the least number of papers.

Papers on implementing LA frameworks followed the similar distribution of challenges, all papers addressed challenges 1) and 2). The third and the fourth challenge were only addressed in papers focusing on pedagogical aspects of LA adoption. Eight broad categories of LA practices were identified. These were, in decreasing frequency of appearance, *Assessment and feedback; LA tools & deployment; Curriculum development & learning design; Learning experience; Stakeholders; Ethics, privacy, security; Learning innovation;* and *Learning process.*

Taking into account study limitations, we may conclude that it provides a first glimpse into challenges of developing and implementing LA frameworks, and approaches used to overcome these challenges. By managing these challenges, higher education institutions can harness the full potential of learning analytics to enhance teaching and learning outcomes. Further research is needed to paint a more complete picture of the ever-changing landscape of LA adoption.

Acknowledgments

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References

Alenezi, A., Emmanouilidis, C., & Al-Ashaab, A. (2018). Knowledge Management to Support Learning Analytics in Higher Eduction. *2018 IEEE 5th International Congress on Information Science and Technology (CiSt)*, 362–367. https://doi.org/10.1109/CIST.2018.8596653

Azcona, D., Hsiao, I.-H., & Smeaton, A. F. (2018). Personalizing Computer Science Education by Leveraging Multimodal Learning Analytics. *2018 IEEE Frontiers in Education Conference (FIE)*, 1–9. https://doi.org/10.1109/FIE.2018.8658596

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning*, *4*(5/6), 318. https://doi.org/10.1504/IJTEL.2012.051815

Clark, J.-A., Liu, Y., & Isaias, P. (2020). Critical success factors for implementing learning analytics in higher education: A mixed-method inquiry. *Australasian Journal of Educational Technology*, *36*(6), 89–106. https://doi.org/10.14742/ajet.6164

Dawson, S., Poquet, O., Colvin, C., Rogers, T., Pardo, A., & Gasevic, D. (2018). Rethinking learning analytics adoption through complexity leadership theory. *Proceedings of the 8th International Conference on Learning Analytics and Knowledge LAK'18*, 236–244. https://doi.org/10.1145/3170358.3170375

Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, *4*(5/6), 304. https://doi.org/10.1504/IJTEL.2012.051816

Freitas, E., Fonseca, F., Garcia, V., Ferreira, R., & Gasevic, D. (2020). Towards a Maturity Model for Learning Analytics Adoption An Overview of its Levels and Areas. *2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT)*, 122–126. https://doi.org/10.1109/ICALT49669.2020.00059

Gray, G., Schalk, A., Rooney, P., & Lang, C. (2021). A Stakeholder Informed Professional Development Framework to Support Engagement with Learning Analytics. *LAK21: 11th International Learning Analytics and Knowledge Conference*, 237–247. https://doi.org/10.1145/3448139.3448162

Greller, W., & Drachsler, H. (2012). Translating Learning into Numbers: A Generic Framework for Learning Analytics. *Educational Technology & Society*, *15*(3), 42–57.

Higher Education Reference Model (2.6.1). (2022). CAUDIT.

Joshi, A., Desai, P., & Tewari, P. (2020). Learning Analytics framework for measuring students' performance and teachers' involvement through problem based learning in engineering education. *Procedia Computer Science*, *172*, 954–959. https://doi.org/10.1016/j.procs.2020.05.138

Kekez, I., & Šimić, D. (2023). *Learning Analytics Frameworks: A Review of Challenges and Practices in Higher Education / Data* [dataset]. Harvard Dataverse. https://doi.org/10.7910/DVN/OITRGE

Khalil, M., Prinsloo, P., & Slade, S. (2022). A Comparison of Learning Analytics Frameworks: A Systematic Review. *LAK22: 12th International Learning Analytics and Knowledge Conference*, 152–163. https://doi.org/10.1145/3506860.3506878

Khalil, M., Slade, S., & Prinsloo, P. (2023). Learning analytics in support of inclusiveness and disabled students: A systematic review. *Journal of Computing in Higher Education*. https://doi.org/10.1007/s12528-023-09363-4

Knobbout, J., & Van der Stappen, E. (2020). A Capability Model for Learning Analytics Adoption: Identifying Organizational Capabilities from Literature on Learning Analytics, Big Data Analytics, and Business Analytics. *International Journal of Learning Analytics and Artificial Intelligence for Education (IJAI)*, *2*(1), 47. https://doi.org/10.3991/ijai.v2i1.12793

Lee, L.-K., Cheung, S. K. S., & Kwok, L.-F. (2020). Learning analytics: Current trends and innovative practices. *Journal of Computers in Education*, *7*(1), 1–6. https://doi.org/10.1007/s40692-020-00155-8

Leitner, P., Ebner, M., & Ebner, M. (2019). Learning Analytics Challenges to Overcome in Higher Education Institutions. In D. Ifenthaler, D.-K. Mah, & J. Y.-K. Yau (Eds.), *Utilizing Learning Analytics to Support Study Success* (pp. 91–104). Springer International Publishing. https://doi.org/10.1007/978-3-319-64792-0_6

Mussida, P., & Lanzi, P. L. (2022). A computational tool for engineer dropout prediction. *2022 IEEE Global Engineering Education Conference (EDUCON)*, 1571–1576. https://doi.org/10.1109/EDUCON52537.2022.9766632

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Systematic Reviews*, *10*(1), 89. https://doi.org/10.1186/s13643-021-01626-4

Sahni, J. (2023). Is Learning Analytics the Future of Online Education?: Assessing Student Engagement and Academic Performance in the Online Learning Environment. *International Journal of Emerging Technologies in Learning (IJET)*, *18*(02), 33–49. https://doi.org/10.3991/ijet.v18i02.32167

Sanagustín, M. P., Hilliger, I., Maldonado, J., Pérez, R., Ramírez, L., Muñoz-Merino, P. J., Tsai, Y.-S., Ortiz, M., Broos, T., Zúñiga-Prieto, M., Sheihing, E., & Whitelock-Wainright, A. (2019). *LALA Framework (Technical Report): Building Capacity to Use Learning Analytics to Improve Higher Education in Latin America* (p. 138). https://researchmgt.monash.edu/ws/portalfiles/portal/324504028/324503712_oa.pdf

Scheffel, M., Tsai, Y.-S., Gašević, D., & Drachsler, H. (2019). Policy Matters: Expert Recommendations for Learning Analytics Policy. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, & J. Schneider (Eds.), *Transforming Learning with Meaningful Technologies* (Vol. 11722, pp. 510–524). Springer International Publishing. https://doi.org/10.1007/978-3-030-29736-7_38

Schmitz, M., Van Limbeek, E., Greller, W., Sloep, P., & Drachsler, H. (2017). Opportunities and Challenges in Using Learning Analytics in Learning Design. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Data Driven Approaches in Digital Education* (Vol. 10474, pp. 209–223). Springer International Publishing. https://doi.org/10.1007/978-3-319-66610-5_16

Singelmann, L. N., & Ewert, D. L. (2022). Leveraging the Innovation-Based Learning Framework to Predict and Understand Student Success in Innovation. *IEEE Access*, *10*, 36123–36139. https://doi.org/10.1109/ACCESS.2022.3163744

Singelmann, L., Striker, R., Vazquez, E. A., Swartz, E., Pearson, M., Ng, S. S., & Ewert, D. (2021). Creation of a Framework that Integrates Technical Innovation and Learning in Engineering. *2021 IEEE Frontiers in Education Conference (FIE)*, 1–9. https://doi.org/10.1109/FIE49875.2021.9637179

Slade, S., & Prinsloo, P. (2013). Learning Analytics: Ethical Issues and Dilemmas. *American Behavioral Scientist*, *57*(10), 1510–1529. https://doi.org/10.1177/0002764213479366

Soltanpoor, R., & Yavari, A. (2017). CoALA: Contextualization Framework for Smart Learning Analytics. *2017 IEEE 37th International Conference on Distributed Computing Systems Workshops (ICDCSW)*, 226–231. https://doi.org/10.1109/ICDCSW.2017.58

Tsai, Y.-S., Moreno-Marcos, P. M., Jivet, I., Scheffel, M., Tammets, K., Kollom, K., & Gašević, D. (2018). The SHEILA Framework: Informing Institutional Strategies and Policy Processes of Learning Analytics. *Journal of Learning Analytics*, *5*(3). https://doi.org/10.18608/jla.2018.53.2

Van Leeuwen, A. (2019). Teachers' perceptions of the usability of learning analytics reports in a flipped university course: When and how does information become actionable knowledge? *Educational Technology Research and Development*, *67*(5), 1043–1064. https://doi.org/10.1007/s11423-018-09639-y

Vears, D. F., & Gillam, L. (2022). Inductive content analysis: A guide for beginning qualitative researchers. *Focus on Health Professional Education - A Multidisciplinary Journal*, *23*(1), 111–127.