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Collaborative Learning Analytics: Centring the Ethical Implications Around Teacher and Student Empowerment. A Systematic Review

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Abstract

This article systematically reviews the role of learning analytics (LA) in collaborative learning, particularly exploring how it can empower both teachers and students. Based on the analysis of 87 articles, selected by adopting the PRISMA workflow, the study discusses the intersection of LA with collaborative learning (CL), emphasizing the potential benefits of such integration in enhancing educational processes and outcomes. The review highlights that though the research in collaborative LA (cLA) is mature and the need to liaise technology with pedagogical theory is clear, the research practices mapped in the literature still show critical gaps in empowering teachers and students in the use of cLA systems. Indeed, our study spots the problems of informed consent and data privacy issues in cLA research but makes a step forward in the direction of analyzing participant appropriation of LA technologies from their design and deployment. On these bases, we contend that user empowerment through cLA usage is not only relevant for learning, but it is also part of an overall ethical approach to LA. Overall, the article makes a compelling case for the careful and thoughtful integration of LA into collaborative learning environments, both from the research and the educational practice sides.

Notes for Practice

- Broaden the application of learning analytics (LA) beyond higher education to encompass K–12, adult education, and vocational training. Develop specific LA methodologies adapted to the unique needs of these diverse educational contexts.
- Integrate robust theoretical frameworks in LA studies to provide deep insights and avoid simplistic interpretations. Prioritize transparency in ethical practices, ensuring data privacy, informed consent, and bias mitigation to maintain trust and respect for participant rights.
- Engage educators and students in the participatory design of LA tools to enhance their relevance and effectiveness. Strengthen pedagogical data literacy among all stakeholders to empower them to understand and use LA data for improved learning and teaching outcomes.

Keywords: Systematic literature review, learning analytics, collaborative learning, data ethics, educational contexts

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1. Introduction

Research in LA has evolved through the exploration of approaches to pedagogical models such as collaborative learning (Kaliisa et al., 2022). Collaborative learning has been studied long since the 1980s with attention paid to social learning, later transferred to digital learning, in an area of studies called “computer-supported collaborative learning” or CSCL (Dillenbourg et al., 2009; Rubia & Guitert, 2014). The interest was initially put on understanding how collaboration in digital environments might be effective. Several forms of notation and coding interactions were developed (Amarasinghe et al., 2017; Nor et al., 2010). Later on, the huge amount of data generated by students throughout their interactions was considered the base for establishing research efforts around collaborative learning and LA. Several researchers have argued that by analyzing student interaction data, LA can identify patterns of participation, communication, and contribution (Viberg et al., 2018). Such analysis might allow teachers and students to understand individual participation as well as the group's collaborative process, supporting decision-making and, hence, quality collaboration (Cerro Martínez et al., 2020).

However, more recently, ethical and privacy considerations when implementing learning analytics in the context of LA research overall and of collaborative learning specifically have been considered. This strand of research considers the crucial problem of using data responsibly to improve learning and collaborative processes (Hernández-Leo et al., 2023). Producing predictions and categorizing student behaviour could be problematic not only in technological or statistical terms (Buckingham Shum & Luckin, 2019). There are several conundrums linked to what is being represented through data selection (Perrotta & Williamson, 2018; Prinsloo, 2017). Also, teacher and student agency in making their own decisions in the process of teaching and learning could be disrupted by algorithms that display "visual concepts" of good learning (Selwyn, 2019). Surveillance and "de-skilling" might be part of a dystopic scenario. If the LA system is just taken "off the shelf" — with vendors only interested in introducing an LA-based product that promises good personalization and self-regulation instead of collaboration — then the ability of students to address their own learning pathways might be interfered with. This issue has also been connected to the lack of strategies contextualizing approaches to LA deployment at an institutional level (Tsai & Gašević, 2017).

The LA mediation of collaborative learning is also part of the landscape described above. In fact, in a recent review of the literature on collaboration and social learning with LA, Laliisa et al. (2022) observed several gaps. They pointed out that the teachers participate very little in developing SLA tools that should support their work, there is a lack of pedagogical theory and analytical models supporting the several LA developments, and there is little integration of technological and methodological innovations (such as epistemic networks or longitudinal studies). Nonetheless, our initial screening of the literature could not find a synthesis of evidence considering the ethical considerations empowering teachers and learners along a collaborative process mediated by LA. Therefore, the aim of this review is to highlight such a gap, focusing on the emerging recommendations for a research agenda supporting responsible and ethical development and testing of collaborative LA.

2. Background

As in other areas of LA research, that connected to collaborative learning has encountered several challenges relating to data ethics. Though ethics is an extremely complex concept, in the following, we will characterize it through the lenses, theoretical definitions, and empirical operationalizations of several studies.

Collecting and analyzing data on collaborative learning may raise privacy and ethical issues such as biases in the classification of students, or inappropriate labelling of elements in the learning processes and activities (Griffiths, 2020; Cerratto Pargman & McGrath, 2021). The technical issues initially related to the scalability of collaborative learning environments working with large numbers of participants, such as MOOCs or large-size lectures (Viberg et al., 2018). The data collected in terms of text, interactions, logs, and so on required huge computational power. Therefore, good pedagogical definitions were needed to capture processes and results (Chejara et al., 2023). Data quality and interoperability were hence considered as key for an ethical approach, focusing the integration of various sources and platforms on important pedagogical concepts. This exercise was deemed challenging due to differences in data formats and the quality required to produce a plausible dashboard.

For example, the case study about the Norwegian system by Hoel and Chen (2016) clearly emphasized the problematic selection of stable concepts by several stakeholders representing different interests around education and educational practices, accountability, and measurement. But data quality was thought to be more connected to quantity and feasible access, above the consideration of whether such data should or could be collected in the first place (Ferguson, 2012). The topic garnered attention with advocacy from non-profit institutions, such as the Data Quality Campaign's (2021) four policy principles: 1) measure what matters, 2) be honest and build confidence, 3) make data usage practicable, and 4) provide access while protecting privacy. The EU-funded project DELICATE (Determination, Explain, Legitimate, Involve, Consent, Anonymise, External), also built a list of indicators for higher education institutions to implement trusted learning analytics (Drachsler & Greller, 2016). The DELICATE principles indeed raised concerns about pedagogical conceptualization prior to measurement and data extraction highlighting the dilemma of whether relevant information damaged data ethics. Issues of student awareness about the data captured without their consent, their interest in their own data, and their right to learn without surveillance gained prominence in the literature (Prinsloo et al., 2022). Researchers also pointed out that students possess only a surface-level understanding of privacy and their rights connected to it (Francis et al., 2023). Indeed, another relevant area of literature emphasized how user agency and empowerment through LA depended on teacher and student engagement with dashboards and clear data understanding and literacy (Wasson et al., 2016). Participatory forms of LA configuration from the inception of LA systems, namely by design, gained consensus (Buckingham Shum & Luckin, 2019). For example, questions regarding the actual need to tell a struggling student that they might be at risk; or that an elective course is not appropriate for their level of prior knowledge; or that nudging systems towards desirable micro-behaviours (such as consuming videos or accessing the virtual classroom) — allegedly aimed at improving student self-regulation — might well be limiting their autonomy (Selwyn, 2019). In this regard, both teachers and students should be aware of what the LA system is signalling — that the student is about to drop out from a certain educational approach or pedagogical model — since certain data collection methods might not be fair at covering the full range of student activity. The literature in this area highlights the social obligation to prevent harm and suffering to both present and future populations, emphasizing the duty to vulnerable and diverse students, more than finding new technological solutions to anonymize data or to improve their quality (Cerratto Pargman & McGrath, 2021; Slade & Tait, 2019).

Overall, the studies connected to developing LA are frequently enthusiastic about the user experience, or impact on educational processes, even though the literature also reports little mainstreaming in LA usage (Ferguson et al., 2016). Therefore, whether the system's configuration (according to prior conceptualizations by researchers) goes in the direction of teacher and learner expectations in open scenarios is still a huge concern. In tight connection with this, developing accurate predictive models for collaborative learning outcomes is challenging due to the diverse and dynamic nature of interactions among learners in their situated, local educational contexts (Cerro Martínez et al., 2020; Hu et al., 2022).

In the field of collaborative LA, the editorial by Wise et al. (2023) listed nine elements for robust collaborative LA throughout critical lenses. They advocate for collaborative LA as a space that delves into complex pedagogical concepts and their connected learning processes; collaborative LA is therefore ethically configured from its inception. The nine elements are as follows:

1. Overall orientation to mobilize data traces to inform learning
2. Careful clicks-to-constructs mappings that attend to the learning task
3. Theorization about group and/or individual level
4. Theorization and modelling of learning as a temporal process
5. Multi-channel and/or physical space data
6. Careful attention to what information to provide to whom and how
7. Human-centred approach to LA design
8. Examination of how LA are used in the world
9. Attention to systems level and ethical concerns

This last element is based on the eight prior items and is not distinctively about the prior frameworks cited here; it includes elements dealing with the expectation of privacy, the need for a strong technical infrastructure, the underlying power structures, and "most explicitly, an anticipatory consideration of how LA will interface with these to cement and/or change the situation" (Wise et al., 2023, p. 4). Nonetheless, this last, ninth principle is only enunciated.

Going a step further, Rets et al. (2021) build on Floridi's approach, pointing out that his five principles for the ethics of AI (beneficence, non-maleficence, autonomy, justice, and explicability) should be considered. "How does it work?" and "Who is responsible for the way this system works?" are two key questions. We might add a third: "For whom does this system work?" The answers to such questions illuminate the issues of learner ability to control their own learning process; to adopt the technologies whenever they want; and to develop skills to become aware and to express themselves along their learning journeys.

As learning analytics evolves, addressing the challenges and leveraging the advances will be critical to unlocking the full potential of collaborative learning and optimizing educational outcomes. As we noticed above, two relevant questions are at the forefront of data collection and analysis: 1) to what extent are data ethics in LA met as a requirement? and 2) does a collaborative LA system encompass learner empowerment to trigger "learning to learn about collaboration" while interacting with the system? With this in mind, we designed the current study using a systematic review of the literature. We look at some recent literature on collaborative LA (cLA) to show how far research has come in three areas: 1) collaborative learning in relation to LA in a variety of technological settings and mediums; 2) the existence of practices that focus on ethics in cLA; and 3) the focus on learner empowerment in cLA.

3. Methods

Three main research questions emerged:

RQ1: How is collaborative LA research developing in terms of methodology?

RQ2: Do the studies consider an ethical perspective in data extraction?

RQ3: Are the studies designed to empower teachers and students in their participation in collaborative learning, as a key dimension of research ethics?

The first RQ was aimed at understanding the development of LA systems, considering automation, visualization, and direct interaction by users to inform their actions at an advanced level. Particularly, we wanted to explore the characterization of LA type, based on levels of automation (descriptive, diagnostic, predictive, and prescriptive), considering the levels of human intervention to make an LA system "work" (Alfredo et al., 2024).

The second RQ explored data ethics according to the presence of approaches in terms of privacy, data usage, and engagement of students in the definition of the analytics system (Hernández-Leo et al., 2023; Slade & Tait, 2019). The articles were coded according to the completeness of their references to ethical issues noted in our Background section. A complete approach would include clear paragraphs (within the paper included in our review) considering relevant dimensions of LA ethics, from research to design and testing. Incomplete references to LA ethics would consider one or two dimensions of ethics or would be superficial (e.g., the users signed informed consent). Studies with no reference to LA ethics would be excluded.

The third RQ focused on the way data was extracted and to what extent this operation aimed to engage learners in interactions with the LA system. If the study reflected only a mere operation of data extraction to investigate learning processes with no final engagement of learners and teachers, it was excluded.

3.1. Data Collection

Based on the PRISMA methodology (Moher et al., 2009), this article provides a comprehensive review of the relevant literature. Systematic reviews involve a specific procedure for evaluating, summarizing, and communicating the literature while dealing with otherwise unmanageable document volumes. In addition, the process aims to eliminate researcher bias in data acquisition and analysis (Petticrew & Roberts, 2006). Following this methodology, five scientific databases that index peer-reviewed research were examined (Figure 1). These databases were chosen due to their coverage of 1) peer-reviewed empirical research, 2) social research, and 3) educational research. We selected articles published in a timeframe of five years (2018–2022) exploring either learning analytics or collaborative learning.[1]

This search returned 471 articles on SCOPUS, which came to 1,006 records after adding the articles extracted from WOS, ERIC, and DOAJ. Following the elimination of duplicates (542), 464 manuscripts were considered for the screening phase. In this phase, four researchers read the abstracts of the papers and eliminated those that were irrelevant to the intended analysis. The group organized several sessions connected to the discussion of exclusion criteria, inclusion of studies, and the construction of several variables through which the literature would be classified. Therefore, four sessions were used for screening, extracting articles, and agreement on inclusion criteria; two sessions were used to define the codebook (presented in the Annex); and three sessions were for training on the work of classification and article coding.

The exclusion criteria were as follows:

1. Conceptual papers, methodological studies, and literature reviews since they did not expose participants to a given LA system
2. Articles pertaining to non-educational studies such as those dealing with analytics for citizen participation or health care quality evaluation
3. Articles dealing with only one specific dimension of the collaborative process, such as psychosocial studies, analysis of the neural basis for collaboration, etc.
4. Articles developing or analyzing the accuracy of algorithms supported by AI and the Internet of Things (IoT), or those aimed at mathematical or computer science conceptualizations with no empirical analysis
5. Articles that considered learning processes other than collaborative learning

According to the above scheme, 377 papers were excluded, leaving 104 for the final analysis. Throughout the process of codification, 17 other papers were excluded because of incomplete information such as: mentioning courses but not the number of participants (2); conceptual or methodological focus not detected during screening (9); and papers in which the procedures and engagement of participants were too general and could not be classified appropriately (4). Two articles were excluded after requesting author copies (not accessible online or via the university's SSO to databases and journal collections). In total, 394 papers were eliminated, and 87 were considered in the final analysis. Figure 1 depicts PRISMA's workflow.

[1] We utilized the query TITLE-ABS-KEY ((learning AND analytics) AND (collabor* AND learn*)) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018)).

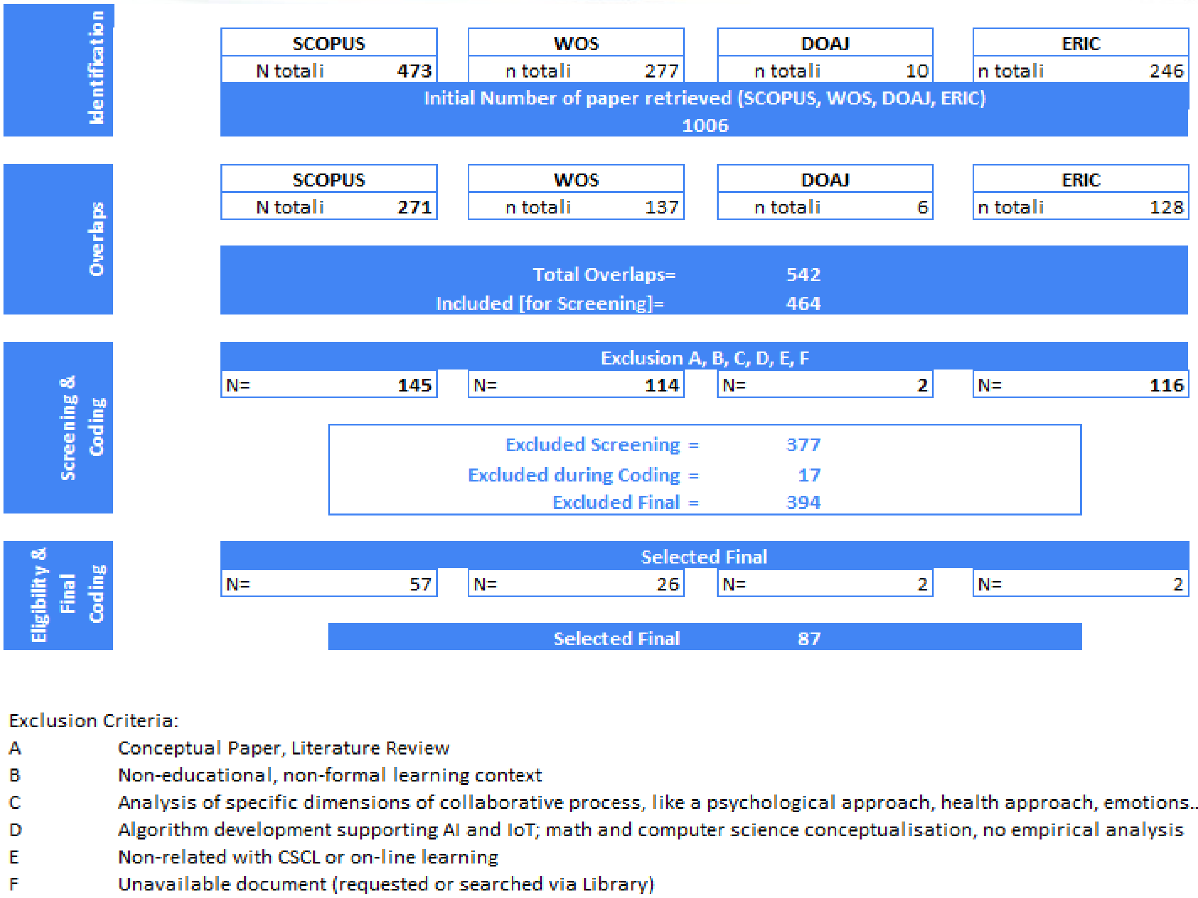


Figure 1. PRISMA workflow — article selection.

The comprehensive list of authors and selected papers is presented in the Annex (Table 4)

3.2. Data Analysis

The papers were coded according to the categories defined through the three sessions referred to above. The codebook is introduced in the Annex (Table 2). Two further sessions were used to discuss the coding and adjust the observations. The identified codes attempted to capture the relevant elements in this study. First, we characterized the context of the research study by coding the Educational Level and the Technology Enhanced Learning (TEL) approach. Second, we observed whether the studies adopted pedagogical constructs associated with data points (how data was extracted, analyzed, and represented). Third, some specific codes were used to answer the three research questions. To answer RQ1, we considered the TEL approach at the crossover with the Types of LA and the Prevalence of Data Extraction. For RQ2, we considered the variable of ethics perspectives, studying that in combination with the TEL approach and level of education. We represented its incidence not only using the number of studies, but also the number of participants according to the ethics perspective. Finally, to answer RQ3, we explored the variable Access to the LA system. We considered access as the way teachers and learners engaged with LA data and its representations as means of empowerment. A situation where the researchers extract data for their analysis highlights the prevalence of preliminary studies with little or no impact on learner empowerment.

After defining the coding system, the authors each analyzed the same ten-paper sample (approximately 11% of the total dataset of 87 papers) and calculated the inter-rater agreement adopting Cohen's kappa, a quantitative measure of reliability that highlights how often the raters may agree by chance. Cohen's kappa was 0.59, which indicates moderate agreement (0.4–0.6). The percentage of agreement was excellent in any case (95.4%). Consequently, three researchers proceeded to code the remaining 77 papers divided into three groups (25+26+26) using the criteria discussed by the research group. The classification was made using a shared Google spreadsheet, where the researchers kept commenting about the codes given. In this final phase of codification, 23 specific labels were adjusted to gain full consensus.

The database-collected data was analyzed using descriptive univariate and bivariate statistics, followed by inferential testing. This analysis centred on the characterization of the sample and the investigation of the relationships between the dimensions under consideration in response to the three research questions.

4. Results

4.1. Typical Characteristics of the Studies Sampled

From the 87 papers, we observed that the main research focus was on higher education (63.22%), followed by primary and secondary education (21.84%), and then continuing education (6.9%). Vocational training was also represented, although to a lesser extent. Higher education employs a greater diversity of technological approaches, whereas continuing education and vocational training primarily rely on online methods. Table 1 displays the levels of education according to the TEL approach. In this regard, we considered the required technological mediation (distance, face-to-face, or blended).

Table 1. Educational Level x TEL Approach: Sampled Studies and Number of Participants

Educational Level x TEL Approach	Number of Studies (%)		Number of Participants (%)	
K–12	19	21.84%	1,585	4.82%
Blended	8	9.20%	567	1.72%
FTF	9	10.34%	546	1.66%
Online	2	2.30%	472	1.43%
Higher Ed	55	63.22%	12,274	37.31%
Blended	12	13.79%	1,190	3.62%
FTF	14	16.09%	951	2.89%
More than one	2	2.30%	449	1.36%
Online	27	31.03%	9,684	29.44%
Continuing Education	6	6.90%	11,839	35.99%
Blended	1	1.15%	13	0.04%
Online	5	5.75%	11,826	35.95%
Professional Learning	3	3.45%	57	0.17%
FTF	2	2.30%	53	0.16%
Online	1	1.15%	4	0.01%
More than one level	4	4.60%	7,140	21.71%
FTF	3	3.45%	140	0.43%
Online	1	1.15%	7,000	21.28%
Grand Total	87	100%	32,895	100%
TEL Approach Total	Number of Studies (%)		Number of Participants (%)	
Blended	21	24.14%	1,770	5.38%
FTF	28	32.18%	1,690	5.14%
More than one	2	2.30%	449	1.36%
Online	36	41.38%	28,986	88.12%
Grand Total	87	100%	32,895	100%

Most studies analyzed dealt with an online model (41.38%), which was followed by the face-to-face model (32.18%), indicating significant interest in online education compared to other options. On the other hand, online education also displayed the largest number of participants, representing 88.12% of the total participants. This suggests that online education may be more accessible for conducting collaborative LA studies. However, although online education is dominant in terms of the number of papers and participants, there is a significant representation of other approaches, such as blended and face-to-face learning.

In the following, we considered the pedagogical constructs adopted and the data points supporting them, making them a relevant base for building an ethical approach. Table 2 displays this information.

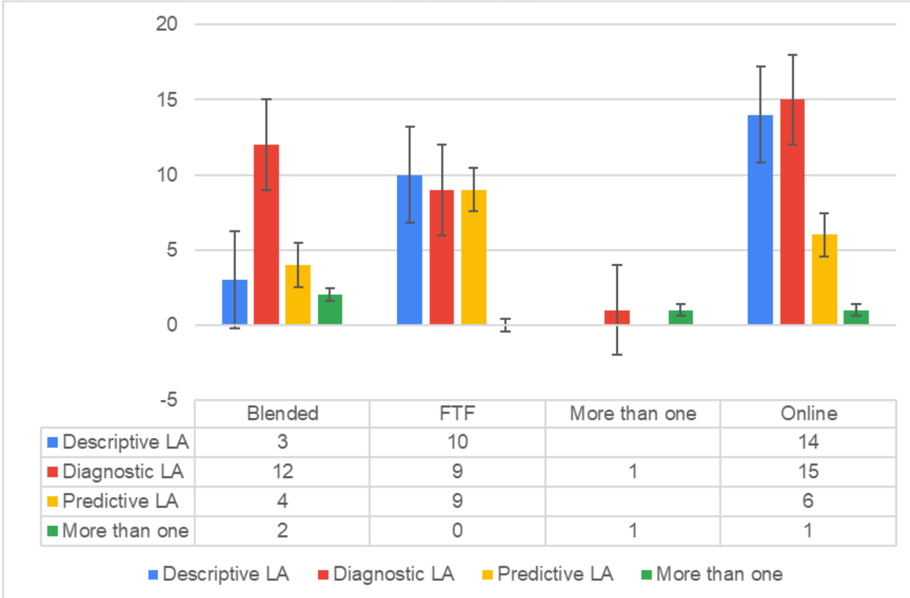
Table 2. Focus of Pedagogical Constructs and Data Points Adopted to Support Tracking and Representation

Data Points	Focus of Constructs				
	Learning Centred	Teaching Centred	Research Methodology Centred	Grand Total	%
Logs	9	7	10	26	29.89%
Multimodal	1	1	4	6	6.90%
Other psychometrics	2	1	0	3	3.45%
Social networks	1	0	10	11	12.64%
Text	11	2	7	20	23.00%
Visualizations	5	7	3	15	17.24%
Facial recognition	1	0	0	1	1.15%
Focus group	0	0	1	1	1.15%
Learning Outcomes	1	0	1	2	2.30%
Survey	0	0	1	1	1.15%
Eye-tracking	0	0	1	1	1.15%
Total	31	18	38	87	100%
Total x Focus	35.63%	20.69%	43.68%	100%	

In terms of the focus of the constructs, most studies considered the research methodology, with 43.7% (n=38) dedicated to this area. This suggests a strong emphasis on the research and development of analytical methods in collaborative LA rather than their application. This dimension is followed by studies focused on learning, which represent 35.6% (n=31) of the research analyzed, indicating a high interest in understanding and improving the learning process through data analysis. Considering the most used data types, logs (30%, n=26) stand out above the rest, followed by text analysis (23%, n=20) and visualizations (17.24%, n=15). This aligns with the overall literature on LA system development, where logs and visualizations are critical. Nonetheless, text collection becomes central when analyzing the quality of contributions, and the relevance of this element confirms the concern of collaborative LA research in capturing this side of the process.

4.2. RQ1: How is collaborative LA developing in terms of research methodology?

Types of data extraction and types of LA were the concepts adopted to analyze the levels of automation. We built over the phenomenon of the “Mechanical Turk,” where there is human labour required to process data that appears to be automated. We observed the intersection of the TEL approach with the four types of LA widely considered in the literature (descriptive, diagnostic, predictive, and prescriptive; Du et al., 2021). These four types indicate the levels of increasing automation, from simple extractions of logs and data collection (descriptive LA) to systems that extract, organize, represent, and trigger actions based on the relevant data (prescriptive LA). Figure 2 represents this element.

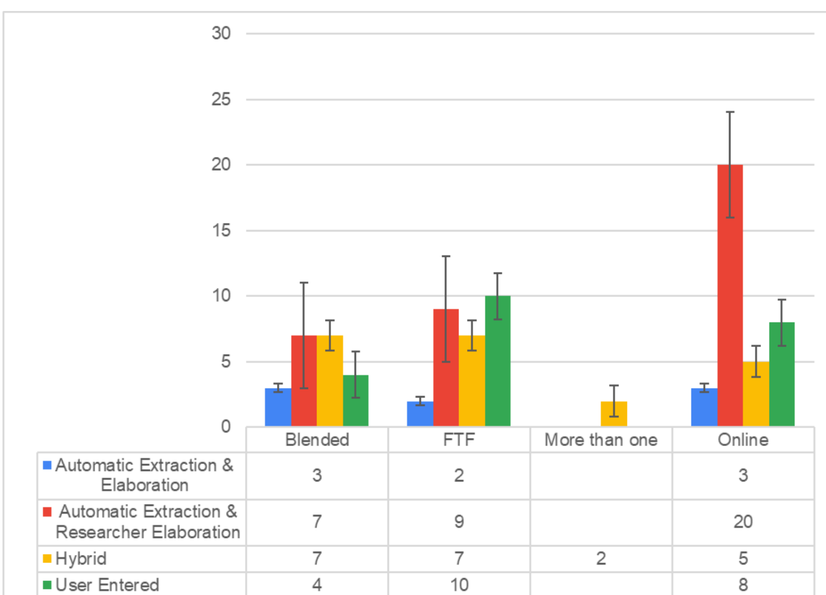


	Blended	FTF	More than one	Online
Descriptive LA	3	10		14
Diagnostic LA	12	9	1	15
Predictive LA	4	9		6
More than one	2	0	1	1

Figure 2. TEL approach x types of LA.

Most papers related to descriptive and diagnostic analytics focus on online education (14 and 15 studies, respectively). Noteworthy, face-to-face studies in school settings focused on the usage of all types of analytics. Specifically, they adopted predictive LA (n=9), highlighting more technologically advanced usages of data processing. Research on diagnostic analytics is more balanced between different training models, indicating a moderate level of automation in all contexts, with presumably several forms of human intervention to represent or trigger actions. An inferential analysis using the Chi-squared test highlighted a slight significance — X2 (df=9, N=87) = 19.165, $p < .05$ — indicating that online diagnostic and descriptive LA are more likely to be adopted. Though non-significant, predictive learning analytics is led by face-to-face education in terms of the number of studies, suggesting that this type of LA could be relatively more developed in classroom experiments, which include the use of devices or systems and multimodal analytics to support/increase collaborative processes.

Continuing with our exploration on the levels of automation (presumably supporting more advanced technological approaches but also more complicated forms of data extraction and elaboration), we observed the range of data extraction — from fully automatic extraction and elaboration, passing through the researcher elaboration, hybrid practices mixing data-driven and human-driven elaboration, to fully human-led data extraction and elaboration. We studied this dimension at the crossover with the TEL approach in Figure 3.



	Blended	FTF	More than one	Online
Automatic Extraction & Elaboration	3	2		3
Automatic Extraction & Researcher Elaboration	7	9		20
Hybrid	7	7	2	5
User Entered	4	10		8

Figure 3. Data extraction prevalence x TEL approach.

Generally, data can be extracted and manipulated for learning analytics in many ways. For the blended model, studies tend to mainly use automatic extraction methods with researcher elaboration and user input methods. In comparison, the face-to-face model shows a more equal distribution between automated extraction methods with researcher elaboration, hybrid methods, and user input methods. However, in the case of online education as a technological approach, automatic extraction methods with researcher elaboration prevail. This suggests that learning analytics is at a considerable level of development, with a combination of automatic and semi-automatic methods for data extraction and processing in different teaching and learning contexts.

We did not find any significant relationship between the types of data extraction at the intersection with the approaches to TEL. Nonetheless, a Chi-squared test for given probabilities on the whole data extraction prevalence yielded a significant difference between the approach of automatic extraction and the researcher's elaboration on other forms — X2 (3, N=87) = 18.057, p < .001.

4.3. RQ2: Do the studies consider an ethical perspective in data extraction?

To answer the second RQ, we delve into the ethics of data extraction, considering the reference to ethics within the papers to be at a minimal level. We considered as an optimal standard the reference to participant engagement since the design phase. Also, taking part in LA system improvement was considered a good standard. We also included in this last case the reference within the paper to participant autonomy and appropriation of the LA system along the process. Table 3 reports this analysis. The frequencies are referred to in the table, whereas the colour shows the relative percentages.

Table 3. TEL Approach, Number of Participants, and Ethics

TEL Approach	No Reference		Incomplete Reference		Complete Reference	
	N Stud	N Part	N Stud	N Part	N Stud	N Part
Blended	16	956	5	814	0	0
FTF	23	1465	3	128	2	97
Online	30	24911	6	4075	0	0
More than one	0	0	1	382	1	67
Total	**69**	**27332**	**15**	**5399**	**3**	**164**

< 2%	3-5%	6-10%	11-15%	16-20%	21-30%	31-40%	>40%

Most studies did not fully reference ethical considerations in data extraction. However, when considering the number of participants, there is a high figure (n=4,075) referring to studies with incomplete ethical references for the online model, followed closely by the mixed modality. The "incomplete reference" to ethics (five blended, three FTF, and six online) regards studies that mostly mention approval under an ethics committee and provide information to the participants about the procedures of data extraction and elaboration. Overall, only two studies considered participant agency and appropriation. This indicates a possible area for improvement in learning analytics research in terms of ethics and data privacy. Failure to provide details about how informed consent was obtained from participants, how personal data was protected, or how potential biases in data collection and analysis were addressed suggests that while the importance of ethics in research is recognized, not enough information is provided on how these ethical considerations are addressed in practice. This highlights the need for greater transparency and ethical rigour in learning analytics research. To underpin this relationship, we performed a Chi-squared test, which was significant: (df=6, N=87) = X2 = 19.826, p < .01.

4.4. RQ3: Are the studies designed to empower teachers and students in their participation in collaborative learning, as a key dimension of research ethics?

We tried to delve into the more advanced expression of an ethical approach based on empowering teachers and students in their participation in collaborative learning. Though the studies are all committed to improving teaching and learning, and express their intention to support effective learning, to us, empowerment means moving forward. We read through several papers about actual forms of LA usage, exploring to what extent the data extracted only supported the researcher's hypothesis or curiosity versus student and teacher engagement with the researchers to transform their collaborative practice. Table 4 represents these relationships. Having access to LA structure, discussing it, and understanding its usage was key to coding the papers.

Table 4. TEL Approach and Stakeholder Engagement

TEL Approach	Researchers		Students & Researchers		Teachers & Researchers		All the Participants	
	N stud	N part	N stud	N part	N stud	N part	N stud	N part
Blended	10	602	3	222	6	355	2	591
FTF	9	496	6	348	11	686	2	160
More than one	1	67	0	0	0	0	1	382
Online	21	23379	3	2523	11	2952	1	132
Grand Total	**41**	**24544**	**12**	**3093**	**28**	**3993**	**6**	**1265**

< 3% 3-5% 6-10% 11-15% 16-20% 21-30% 31-40% >40%

First, we note that most studies across technological approaches provide learning analytics primarily to researchers. As a result, researchers have greater control and ability to use the data generated by learning analytics in their projects. However, access for researchers does not necessarily translate into the empowerment of teachers and students in their participation in collaborative learning. Second, some studies also provide access to students in addition to researchers. This suggests an attempt to engage students in the process of data analysis and decision-making, utilizing insights from learning analytics. However, the number of studies that offer this type of access is relatively low compared to those that provide access only to researchers. Third, some studies also offer access to teachers as well as researchers. This is important because it allows teachers to use learning analytics data to inform and improve their teaching practices, potentially empowering them in their role as facilitators of collaborative learning. However, including all participants — researchers, teachers, and students — in loops of development and critical appraisal of collaborative LA systems and dashboards is a relatively rare practice. This inclusive approach is especially valuable as it promotes transparency and collaboration between all actors involved in the educational process, which can lead to greater empowerment of both teachers and students to encourage their active participation in the collaborative learning process.

To further our exploration, we performed a Chi-squared test comparing the TEL approach with the Access and Usage of LA. This relationship yielded no significant data (namely, most forms of Access and Usage of LA are similar across the blended, online, and FTF approaches). However, when analyzing the whole sample of papers, we observed a critical level of significance, indicating a very low presence of papers that fully embrace practices where all are empowered through the LA system: (df=3, N=87) = X2 = 34.609, $p < .0001$.

5. Discussion

We discovered in response to our first RQ that research primarily focuses on higher education, with continuing training and primary and secondary education following closely behind. This finding reflects a significant interest in the application of learning analytics in diverse educational contexts, although with a clear predominance in higher education. In this regard, the strong emphasis on leveraging digital platforms for collaborative learning analytics must be considered, particularly within higher education settings where written online activities facilitate data collection. Observations align with this effect, showing that online education is the most studied technological setting, both in terms of the number of investigations and the total

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number of participants. LA could not exist without the possibility of data tracing, implying that the research on LA is more opportunistic than connected to problems in less structured settings, such as blended or onsite activities.

We echo Selwyn's (2019) assertion that a limited comprehension of education poses a risk when implementing learning analytics, as it fosters "a broader suspicion of educational data inevitably being inaccurate, incomplete, poorly chosen, or simply a poor indicator of what it supposedly represents" (p. 12).

As we can observe here, LA will represent a public of adult students, mostly self-regulated, using an online learning environment for collaboration. However, we observed that the contexts where empirical evidence was generated also included relevant studies on the combination of formal classroom learning with non-school-related informal learning activities, though the same researchers considered problematic the high levels of data extracted and the uncertainty around the analysis (Chejara et al., 2023; Prieto et al., 2018). In this respect, the connections between conceptualization and pedagogical theorization become key to reading the extracted data. This issue continues to be discussed in the LA research field, though we must say, according to our analysis, that in the case of collaborative learning, theory does play a relevant role. Consistently with Wise et al. (2021), we found that a good conceptual base in online settings relating to collaborative learning has had a relevant role in shaping data collection methods and dashboard representations of collaboration. The researchers assert that "the rise of analytic approaches that attend only to quantitative representations of collaboration can be met with scepticism as a productive route to understanding" (p. 426), inviting us to pay careful attention to theory.

For our second research question about an ethical perspective to data extraction, we observed an increasing interest in the ethics of LA (Slade & Tait, 2019), which certainly refer to the ongoing debate about the ethics of data-driven research approaches in education (Hernández-Leo et al., 2023) and AI in education (Holmes et al., 2022). However, only a few studies pay careful attention to ethical issues in the research and the development of overall LA as part of an ethics debate. Our results show that most studies do not provide complete details on the research approach to data extraction. As Prinsloo (2022) pointed out, the answer is not only linked to the technological feasibility of extracting data but to the way this data is used to empower participants regarding their privacy. We also noticed a lack of detail on informed consent or approaches to data protection during the research activities in developing or applying LA tools. In no case did we observe debates or concerns relating to the mitigation of bias in data collection and analysis, though it is a pivotal point in the debate on LA-ethics (Cerratto Pargman & McGrath, 2021). This suggests a need for greater attention to and transparency in this aspect.

Relatedly, we investigated a third research question on techno-pedagogical design for empowerment and participation. This ethical concern pertains to enhancing the positive aspects of technology while mitigating any potential harm. We observed, in this regard, a predominance of access mainly for researchers, followed by student access to analyze user experience (UX) and/or discuss the impact on their learning. Teachers received access to the LA development process, either for usage or trial, to a significantly lesser degree. While some studies grant access to all participants — researchers, teachers, and students — most approaches focus on allowing participants to experience the LA tool after its design. And while this may lead to improvements, the practice of participatory design and appropriation in broader settings is not yet widespread.

In 2016, the EU Commission pointed out the problem of LA mainstreaming (Ferguson et al., 2016); after almost a decade, the problem is not completely solved. All actors involved in the educational process must understand the implications of collaborative learning in order to conceptualize dashboards that display the learner's level or quality of their collaboration as metrics. Particularly, developments that exclude teachers from the process cannot claim to support teaching improvements, though they are reported. Furthermore, if teachers have access to learning analytics but students do not, then an important opportunity to realize the full potential of these tools is lost. At a metacognitive level, student access to data allows them to actively participate in the process of reflecting on their own learning and make informed decisions about how to improve their academic performance, but only if they understand what is being conceptualized through such data (Du et al., 2021). Personalized support to learners also happens when their teachers have been at least trained on the collaborative LA system (Cerro Martínez et al., 2020), therefore understanding the LA affordances and their connection with what is relevant to strengthen collaboration.

6. Conclusion

In our systematic review of the literature, we focused on three crucial RQs influencing the evolution of collaborative learning analytics as a relevant area of research in the overall context of LA. Our analysis of 87 papers indicates a mature state of research in this field, with some areas showing greater development than others. The existence of advanced tools that can effectively capture and analyze complex data patterns is evidently considered essential for fostering meaningful insights into collaborative learning processes. However, digging deeper into the selected articles through the research questions led us to consider several issues that require attention. Evidently, further research is required to examine the use of LA in collaborative learning processes between formal and informal learning, not only in higher education but also in K–12, adult education, and vocational training. Moreover, the prevalence of online and blended learning environments underscores the need for tailored learning analytics approaches that accommodate diverse educational contexts. Above all, because the research community is already familiar with the risks of poor theorization in LA and the importance of fair and accurate data selection. However, ethical issues and participant engagement in the design of these data-driven systems are still problematic. Our analysis indicates that the current focus of research is primarily on developing models and exploring ex-post data extraction rather than focusing on participatory designs and discussions about the data available in various learning contexts. We must not forget that pedagogical data literacy is important not only for understanding and using LA in educational settings but also for allowing users to question and reset data-driven practices (Raffaghelli & Sangrà, 2023). The role of reflection (either theorized in relation to self-regulation and or as metacognition) has already been connected to LA research overall, and to the specific area of collaborative LA (Wise et al., 2021).

But as the research community acknowledges, theorization must lead to good forms of using data to represent learning processes, beyond reductionism. For example, Sangrà et al. (2019) embrace the concept of "learning ecologies" as a continuum between non-formal, informal, and formal settings and as a self-guided construction of relationships, pursuit of activities, and consuming resources. In connection with this approach, they point out that a prospective area of research could be associated with multimodal analytics based on learner activities in multiple learning contexts through the adoption of data and dashboards that help learners represent their learning ecologies. Relationships and collaboration are, of course, key to this approach. However, if research on LA does not advance in the consideration of participatory approaches where the same learners decide on the ideas they want to visualize and the data they want to understand their learning, any LA approach will fail. Indeed, the ethics of LA strongly emphasizes the need for transparency and data privacy, but also highlights that the positive usage of technology is a key component beyond only preventing harm. Our research has shown that this is still far from occurring.

Our study is limited in offering a perspective on what LA in collaborative learning is or could be, but we have tried to show the criticalities that prevent progress in research on this topic due to its fragmentation and lack of educational applications. Furthermore, while the topic has advanced discussions on a conceptual basis, as in the case of Gašević et al. (2019), our aim here was to show the problems of alignment between ideals and actual research. One may perceive this as a constraint on the study's scope, as it does not encompass the entirety of scholarly literature on LA for collaborative learning. However, it was a necessary step to achieve a systematic review. As interest in LA grows, researchers are obviously aware of the need to blur the lines between formal and informal learning, digital and physical, as well as pedagogical and technological approaches. While data ethics remain a concern in LA research, the reviewed literature fails to demonstrate the broader application of these concepts.

Future observations call for bridging LA research with the generative AI debate in education. AI's possibilities and uses for collaborative learning could become part of collaborative LA systems. At this point, clearly, collaborative LA research should face all the "beasts" of generative AI. And though there are evident overlaps relating to ethical issues and user agency and empowerment in both fields, this is something to be explored. For example, could a chatbot signal collaborative milestones based on the inputs of a collaborative LA system? Could the reports coming from the collaborative LA dashboards move beyond visual representations to provide interpretations? The field of possibility is immense, as is the need to keep on reflecting on research and development practices to support ethical approaches and the full empowerment of teachers and learners.

CRediT Authorship Contribution Statement

Montse Guitert: Resources, project administration, investigation, supervision, writing — review & editing.
Teresa Romeu: Validation, investigation, formal analysis, writing — review & editing.
Juliana E. Raffaghelli: Conceptualization, methodology, investigation, formal analysis, data curation, original draft, writing — review & editing.
Juan Pedro-Cerro: Validation, data curation, writing — review & editing.

Declaration of Conflicting Interest

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