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About or with teachers? A systematic review of learning analytics interventions to support teacher professional development

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Abstract

Learning analytics (LA) allows aggregate data about users to support decision making. Although teachers are recognised as important stakeholders, little is yet explored about the role that LA can play in teacher professional development (TPD). This paper aimed to conduct a systematic review of the use of LA in TPD context, focusing specifically on intervention studies, classifying purposes and methods as well as beneficiaries' engagement and lessons learned. Search terms identified 189 papers and 31 studies were selected based on the inclusion criteria. The results show that most studies adopted data-driven approaches to monitoring teacher behaviours, through automatic extraction of logs in technology-enhanced learning environments. The perspectives, benefits and limitations in the application of LA to TPD are finally presented.

Keywords: Learning Analytics, Teacher Professional Development, Big Data in Education, Data-Driven Approaches, Systematic Review

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Introduction

A change was already underway before the pandemic occurred: Automated big data processing systems had been meeting the education world for over 10 years. Learning Analytics (LA) has emerged as a significant area of technology-enhanced learning, due to its potential to assist educators by improving teaching and learning and institutions by facilitating decision-making processes (Ferguson, 2012). Moreover, education is the key site in which big data analysis techniques are spreading and gaining more credibility (Williamson, 2017). The rapid increase in the use of digital tools in classrooms due to the consequences of Covid-19 makes it urgent to question the role of teachers in this process.

In their reference model, Chatti et al. (2012) identified four critical dimensions of LA that need to be considered in its applications: Data gathered, managed and analysed (what), target audience (who), objectives (why) and methods (how). The use of LA can pursue several purposes, such as monitoring learning environments, predicting knowledge levels and behaviors, implementing intelligent web-based educational systems, giving automatic and personalized feedback, and (self-)reflecting on the efficacy of teaching practice. Moreover, according to Hoppe (2017), algorithms and methods of big data analysis can be configured in different computational approaches: Network, process, and content-oriented. Through network analytics, LA tools could present empirical findings related to social interactions in online forums and explored how to visualise students' learning networks. The process-oriented LA explores learner interactions on the system's logfiles to detect action patterns. Using content or discourse analytics LA investigates the relationships among topics or groups of themes, potentially providing teachers with insights into students' mental models and misconceptions.

Teachers have been considered important stakeholders since the beginning of the discipline, to "augment the effectiveness of their teaching practices or support them in adapting their teaching offerings to the needs of students" (Chatti et al., 2012, p. 8). Moreover, educators are responsible for reading, interpreting and using data, and the ethical use of data is a major concern (Selwyn, 2019). Although teachers are not specialists in comparative big data methods, they are crucial to LA development as experts in the complementary area of learning and education (Agasisti & Bowers, 2017). On one hand, a re-professionalisation effort is needed to equip teachers with data analysis skills in favour of pedagogical practices, allowing them to become active players in the LA community (Wyatt-Smith et al., 2019). Ferguson et al. (2016) attributed the central role to TPD in the preliminary actions for effective LA adoption: In the training of teachers and academics, both new and already in service, it is essential to integrate digital competence, data literacy, and specific expertise on LA to benefit students with these practices. On the other hand, LA does not always align with teachers' needs and match the most relevant information (Rosenheck, 2021). It's a key concern in LA the need to use the insights gathered from the data to give feedback on those aspects of learning that are valued by the learners (Clow, 2013). To overcome that limited approach, the human-centred perspective involves beneficiaries in the design of LA solutions (Buckingham Shum et al., 2019): It gives teachers an active role in the design of the systems that they are expected to use. If these issues are not addressed, the design and adoption of automatic monitoring and evaluation systems in education could remain limited to researchers and data analysis experts (Gunn et al., 2016).

To clarify how LA has been introduced into teacher professional development (TPD), the paper presents a systematic review to provide an overview of LA interventions to support teachers' professional competence development in both formal and informal learning settings. Indeed, teacher learning is a continuous process that cannot be limited to structured programmes, but it extends to a variety of actions and tools to foster professional growth (Opfer & Pedder, 2011). The review also focuses on beneficiary engagement and lessons learned to explore the challenges and the potential impact of LA on teachers' professionalism. To date, no systematic reviews on this topic are known in the literature. The review may be relevant for different types of stakeholders, such as researchers, educators, and institutions to explore the intersection between the two areas. Nevertheless, some previous reviews reported considerations on the relevance of the role of teachers for the application of LA. Ruiz-Calleja et al. (2017) found that a large part of LA applications in authentic work settings aims to analyse or support teacher learning. Mangaroska and Giannakos (2018) present an overview of LA use for learning design and highlights the need for teachers to provide explicit guidance on how to use the results of the analysis to redesign educational activities. Furthermore, Sergis and Sampson (2017) describe LA specifically in support of teacher inquiry, finding that the fragmented way in which data is returned to teachers through feedback doesn't allow for integration into a useful and comprehensive framework.

Method

This work was driven by investigating two research questions: (RQ1) "What LA purposes and computational approaches are used to promote TPD?" and (RQ2) "What are the perspectives and the challenges in applying LA in a TPD context?". The methodology adopted complies with the PRISMA guidelines (Moher et al., 2009). To carry out a general investigation of primary studies, this methodology involves the use of a replicable strategy of analysis and synthesis of the literature, minimising errors and bias to obtain more reliable results (Cooper et al., 2019). To conduct a systematic literature review, a protocol has been defined, consisting of five discrete stages: a) formulating the problem and the research questions, b) searching for the literature, c) reviewing and assessing the search results, d) analysing, coding and summarising the results, and e) reporting the review.

Eligibility Criteria

The paper collection stage was conducted to identify relevant studies. To reduce the number of relevant sources not identified through the protocol, the search was expanded to include all related terms (Cooper et al., 2019), especially taking into account the lexical diversity and fragmentation of the interdisciplinary sector under examination (Ruiz-Calleja et al., 2017). Once key search terms from the three thematic domains were defined, the same search was used for each database:

- Target: "Teacher*" OR "Educator*"
- Contexts of LA application: "Professional Development" OR "Workplace" OR "Professional Learning"
- Intervention: "Learning Analytics" OR "Educational Data Mining" OR "Educational Big Data" OR "Intelligent Tutoring System*" OR "Adaptive Learning System*"

In the formalisation of the query, the three domains of key search terms are joined by the Boolean operator AND to include all the studies at the convergence of these areas.

As a standard for the quality of the studies selected, only empirical peer-reviewed works were included. Specifically, studies were selected based on the following inclusion/exclusion criteria:

1. Publication characteristics: Peer-reviewed articles and conference papers
2. Language: English
3. Participants: In-service teachers of all educational levels and academics
4. Intervention: Application of LA techniques, as monitoring, analysis or evaluation tools to TPD
5. Research design: Quantitative, qualitative, mixed, multi-method and data-driven studies.

Data-driven is an inductive research approach, common in LA field, that analyses big data through data mining techniques to identify insights without a stated hypothesis (Romero & Ventura, 2020). By the above criteria, the following studies were excluded: Studies that do not offer empirical data (e.g., theoretical articles, tools' design papers without empirical results, secondary studies), posters, workshops, and papers from grey literature.

Search Procedure, Selection Process and Data Collection

Four academic electronic databases were consulted and not restricted by year of publication: Scopus, ERIC, Web of Science, and

EBSCO*host*. A second cycle included an independent search in journals and conference proceedings: *Journal of Learning Analytics, International Journal of Learning Analytics and Artificial Intelligence for Education, Journal of Educational Data Mining*, *Learning Analytics & Knowledge Conference*. The search was conducted in April 2020 and repeated in December 2021. Concerning the selection process, the title and abstract of the studies potentially eligible for inclusion were analysed, determining through this screening the subset of papers selected for the next stage. The full texts of all eligible references were then examined in detail. The authors of not available publications were contacted and two of them provided the full text for the eligibility screening. Moreover, updated versions of the same study were considered only once after screening the full text for comparison. To verify the assignment of inclusion and eligibility criteria, the rigorous procedure of a systematic review provides for double screening with a plurality of coders (Cooper et al., 2019). However, evidence has recently emerged in the literature on the use of a reiterated individual screening (Waffenschmidt et al., 2019). To this end, the screening and coding stages were fully repeated by the same author.

Consistent with the descriptive research question (Cooper et al., 2019), a narrative approach was followed for the extraction of data from the 31 publications selected. The results offer a topical survey of findings (Sandelowski & Barroso, 2003), organized around categories established both deductively and inductively from the reviewed studies. Firstly, the basic study features were coded to accurately describe the selected searches. To answer RQ1, the description categories were then classified to TPD, in particular concerning school order of teachers, level of training (Formal, Non-Formal, Informal), educational technology used, duration and period of training. In addition, each paper was coded deductively using relevant LA references: The classification of LA objectives (Chatti et al., 2012), computational approaches (Hoppe, 2017), and data sources from the literature review of Ruiz-Calleja et al. (2017). Definitions of the deductive categories and their coding labels can be found in Figure 1. Furthermore, to answer RQ2, the perspectives, considering the level of teacher involvement, and the challenges, classified as risks and benefits, were inductively coded.

Figure 1.
Definition of the LA Application Categories

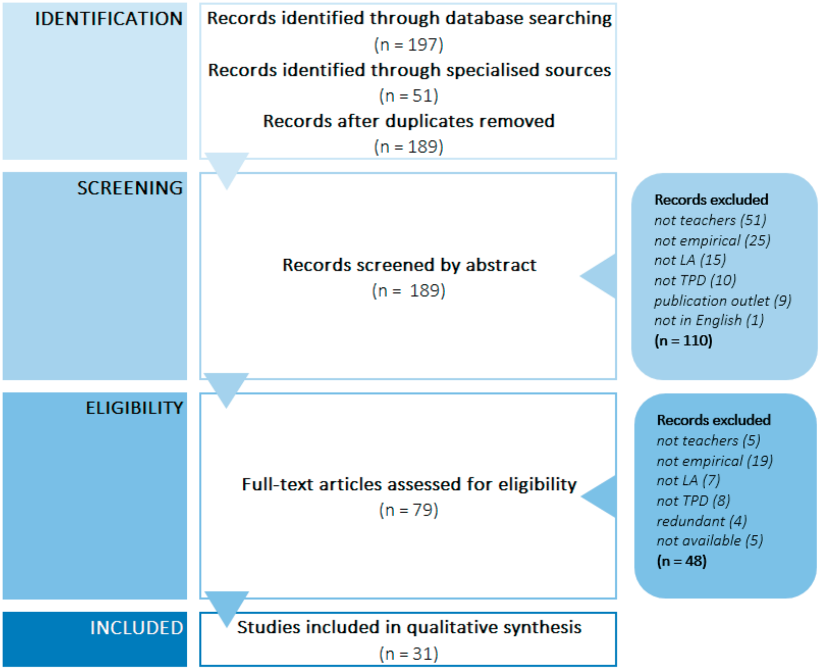
Categories	Explanation	Coding Labels
LA Purposes	Possible objectives of LA, with reference to the model developed by Chatti et al. (2012)	*Intelligent Tutoring and Adaptation* *Prediction and Intervention* *Assessment and Feedback* *Monitoring and Analysis* *Personalisation and Recommendation* *Reflection*
LA Computational Approach	Orientation of use of the analysis techniques with reference to the three approaches, not mutually exclusive, identified by Hoppe (2017)	*Content-oriented Analysis (CA)* *Process-oriented Analysis (PA)* *Network Analysis (NA)*
Data Sources	Methods of collecting data from teachers, as participants in the study (Ruiz-Calleja et al., 2017). In addition, the digital data sources and the offline physical information are classified	*Interview (I)* *Questionnaire (Q)* *Observation (O)* *Physical-world Data (PWD)* *System Logs (SL)* *User-generated Documents (UGD)* *User Profiles (UP)*

Results

Characteristics of Selected Studies

At the identification stage, the systematic search yielded 197 results extracted from bibliographic databases and 51 publications selected from specialised editorial resources. After the removal of 59 duplicates using the Zotero software, 189 references remained, whose titles and abstracts were scrutinised for inclusion criteria. The full text was analysed in 79 studies; 31 met the inclusion criteria. The process is illustrated in the flowchart in Figure 2, also listing the reasons for the exclusion in the two steps of analysing the abstracts and full texts. Full references of selected studies are in the Appendix.

Figure 2.
PRISMA diagram of the study selection process



The 31 studies selected are shown in Table 1.

Table 1.
Overview of the Studies Included

Authors	Year	Country	LA Purposes	LA Computational Approach	Teacher Data Sources
Ahn, Weng, & Butler	2013	USA	Monitoring/ Analysis	PA	SL
Alhadad & Thompson	2017	Australia	Reflection	PA	I
Bai	2011	China	Monitoring/ Analysis	NA	SL
Cambridge & Perez-Lopez	2012	USA	Monitoring/ Analysis	NA	SL

Authors	Year	Country	LA Purposes	LA Computational Approach	Teacher Data Sources
Chen, Fan, Zhang, & Wang	2017	China	Monitoring/ Analysis	PA	SL
Chen	2020	China	Reflection	CA	Q - UGD
Cinganotto & Cuccurullo	2019	Italy	Monitoring/ Analysis	PA/CA	SL - UGD
Fischer, Fishman, & Schoenebeck	2019	USA	Monitoring/ Analysis	CA	UGD
Herder, Swiecki, Skov Fougt, Lindenskov Tamborg, Brink Allsopp, Williamson Shaffer, & Misfeldt	2018	USA	Assessment/ Feedback	NA	I
Humble	2021	Sweden	Monitoring/ Analysis	CA	UGD
Hunt, Leijen & van der Schaaf	2021	Estonia	Assessment/ Feedback	CA	I - Q
Karunaratne & Byungura	2017	Rwanda	Monitoring/ Analysis	PA	SL
Khulbe & Tammets	2021	Estonia	Assessment/ Feedback	CA	Q
Liu, Zhang, Wang, & Chen	2018	China	Reflection	CA	UGD
Michos, Hernández-Leo, & Albó	2018	Spain	Reflection	CA	I - Q - UGD
Miller, Baker, Labrum, Petsche, Liu, & Wagner	2015	USA	Assessment/ Feedback	PA	
Prieto, Sharma, Kidzinski, Rodríguez-Triana, & Dillenbourg	2018	Estonia	Assessment/ Feedback	PA	PWD
Rice & Hung	2015	USA	Prediction/ Intervention	PA/CA	Q - SL
Riel, Lawless & Brown	2018	USA	Monitoring/ Analysis	PA	SL
Rienties, Herodotou, Olney, Schencks, & Boroowa	2018	UK	Monitoring/ Analysis	PA	Q
Rodríguez-Triana, Prieto, Martínez-Monés, Asensio-Pérez, & Dimitriadis	2018	Spain	Personalisation/ Recommendation	PA	I - O

Authors	Year	Country	LA Purposes	LA Computational Approach	Teacher Data Sources
Ruiz-Calleja, Dennerlein, Ley, & Lex	2016	Estonia	Assessment/ Feedback	PA/CA/NA	I - SL - UGD
Saar, Prieto, Rodríguez-Triana, & Kusmin	2018	Estonia	Personalisation/ Recommendation	PA	Q
Song, Petrushyna, Cao, & Klamma	2011	Germany	Assessment/ Feedback	NA	Q - SL
Sui, Spector, Ren, Lin, Zhang, Zhan, & Peng	2017	China	Personalisation/ Recommendation	PA/CA	Q - SL - UGD
Van Leeuwen	2015	Netherlands	Assessment/ Feedback	PA/NA	SL
van Leeuwen, Knoop-van Campen, Molenaar, & Rummel	2021	Netherlands	Personalisation/ Recommendation	CA	O
Vuorikari & Scimeca	2013	Belgium	Monitoring/ Analysis	PA	SL
Wen & Song	2021	Singapore	Reflection	PA	I
Xing & Gao	2018	USA	Prediction/ Intervention	CA	UGD
Zhang, Gao, Wen, Li, & Wang	2021	China	Monitoring/ Analysis	CA	UGD

Most are scientific articles (n = 17), among which the most represented journals are *Computers and Education* and *Journal of Learning Analytics*, followed by conference contributions (n = 14), mainly concerning the *International Conference on Learning Analytics and Knowledge*. The papers temporally follow the evolution of the discipline which had an increasing number of publications (Romero & Ventura, 2020). Indeed, five studies were published before 2013, eight refer to 2014-2017, while the majority (n = 18) refers to the period from 2018 to 2021. It is also possible to highlight that the empirical studies found are geographically located in countries of all continents: Europe (n = 14), America (n = 8), Asia (n = 7), Oceania (n = 1), and Africa (n = 1).

As regards the research design, the majority of contributions (n = 14) adopt the data-driven approach, while 10 studies use qualitative methods, such as the case study. Four publications combine qualitative and quantitative methods, including design-based research (Khulbe & Tammets, 2021; Saar et al., 2018). Otherwise, in two cases the experimental method is used (Chen, 2020; Hunt et al., 2021) and one is an action research project.

Relative to the target group, in most publications (n = 13) teachers of different school levels are involved at the same time. Other studies refer in particular to primary school (n = 2), secondary school (n = 6), and higher education (n = 5), including academics. The information related to the school level was not present in five studies. Regarding TPD characteristics, most papers (n = 20) described non-formal interventions (e.g., training courses structured by educational institutions) and eleven studies were conducted in an informal learning context (e.g., workshops, voluntary training, and professional online communities). No interventions in formal learning contexts (e.g., Degree course) were found, consistently with the eligibility criterion that excluded pre-service teachers. The duration of TPD interventions was coded in 14 studies: The duration varies from 1 to 6 months (n = 8), but there are also programmes up to one year (n = 4), while in two cases the TPD reaches 2 years. Examining the technology used for TPD, the applications of LA have been mainly studied through the use of a virtual learning environment (n = 20), among which the most frequent is Moodle. Four studies examined social network activities (e.g., Twitter), the other three focused on MOOCs and the remaining include mobile applications (n = 2), blogs (n = 2), and online groups (n = 1).

Synthesis of Results

In the following section, we discuss the summary of the results of the systematic literature review based on the research questions. An aggregative summary was used to illustrate the synthesis of results extracted after the coding step and classified by type of findings (Sandelowski & Barroso, 2003).

LA Purposes and Computational Approaches in the Context of TPD (RQ1)
Classifying the LA purposes by referring to the Chatti et al. (2012) model, it was possible to interpret and codify the results of the 31 selected papers to address the first research question. The most frequent LA purpose is related to *monitoring and analysis* (n = 12). In several studies, the LA tools were used to study the teachers' characteristics in online training activities. The elements analysed are participation, cognitive presence, and involvement (Ahn et al., 2013; Cinganotto & Cuccurullo, 2019; Karunaratne & Byungura, 2017; Zhang et al., 2021), development of professional competencies (Humble, 2021). The studies focused also on subgroups profiling, regarding the density of communication between teachers as community members (Bai, 2011), the behaviour of the most influential participants in online communities of practice (Cambridge & Perez-Lopez, 2012) and self-regulated learning strategies of returning learners, a special subpopulation in a TPD MOOC (Chen et al., 2017). Furthermore, teachers were optimistic about monitoring relevant student information through LA dashboards, while recognising the need for further training (Rienties et al., 2018). Finally, LA techniques also open up new research possibilities, particularly to the time variables. Riel et al. (2018), to describe participants' activities, introduced a measurement model of two new time variables, linked to the ranking in the progress of the trainees' activities and the frequency of access and stay in the digital environment. Time series measurements have also been used to analyse the permanence within both generalist and thematic social networks (Fischer et al., 2019; Vuorikari & Scimeca, 2013).

Supporting assessment and receiving feedback (n = 8) is another LA purpose frequently used for TPD. Teachers could visualise the interactions and performance of students in a complex digital environment such as virtual internships (Herder et al., 2018), but also diagnose student progress and intervene in real-time for supporting computer-supported collaborative learning (Khulbe & Tammets, 2021; Van Leeuwen, 2015). Moreover, the introduction of LA in TPD contexts allows for feedback on teaching strategies, distinguishing the proactive intervention of the teacher from other actions through the analysis of student information (Miller et al., 2015), receiving peer feedback through a LA enhanced e-portfolio (Hunt et al., 2021) and using an evaluation algorithm of classroom orchestration through teacher's wearable sensors (Prieto et al., 2018). LA can also support teachers to self-assess in complex and informal learning situations. In Estonia, a prototype dashboard for knowledge creation was designed and tested with encouraging results in an informal teacher training context (Ruiz-Calleja et al., 2016). In eTwinning, the European community for teachers, another prototype was built to allow participants to self-monitor their performance, comparing with other users and suggesting possible training gaps to be filled (Song et al., 2011).

A further LA purpose concerns the support to *reflexivity* regarding teaching and learning practices, highlighted in five studies. LA can support the teacher inquiry process to make insightful use of data. In particular, collecting and examining student information through visualisation systems allowed the development of knowledge useful for professional practice (Alhadadad & Thompson, 2017; Michos et al., 2018; Wen & Song, 2021). Moreover, visual LA to support teachers' reflection not only had significant effects on their self-efficacy but also influenced their actual teaching practice (Chen, 2020). Finally, examining the teachers' artefacts within a Chinese TDP programme, the composition and characteristics of the text examined through a classification algorithm allowed to distinguish the reflective approach in writing activities in different levels, such as descriptive, analytical and critical (Liu et al., 2018).

LA can facilitate and enrich the learning journey through *personalisation and resource recommendation*. Four studies focused on them, selecting students' information to add value to professional practice in the classroom. For teachers adapting LA tools to specific students' needs represents an indispensable standard for the design, along with usability and an adequate level of data detail (Saar et al., 2018) and variations in LA dashboard use by teacher characteristics (e.g., years of teaching experience, technological self-efficacy) were investigated (van Leeuwen et al., 2021). Furthermore, the use of a customized multimodal LA produced a positive impact on the teacher responsiveness in a blended training context for collaborative activity, increasing the awareness of real-time dynamics (Rodríguez-Triana et al., 2018). Finally, teachers themselves can benefit from customized LA as lifelong learners: Sui et al.'s adaptive model (2017), tested on 150,000 teachers in Shanghai, accurately anticipated their learning interests based on individual differences and preferences, making recommendations for continuing education and automatically adapting to their feedback.

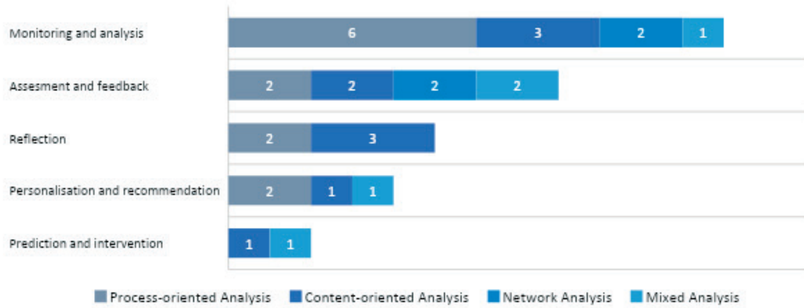
The LA purpose of *prediction and intervention* in TPD is present in two studies. The first study (Rice & Hung, 2015) used data mining in combination with traditional evaluation tools to build a predictive model. The study reported a relationship between time and frequency of access in the TPD learning environment and the teachers' performance. Xing and Gao (2018) studied the participation in a professional learning community on Twitter using text mining. The predictive model revealed that teachers exposed to more tweets on the cognitive and interactive, rather than social, dimensions are at a lower risk of dropping out.

Finally, no studies were found concerning the LA purpose for *tutoring and mentoring*, consistent with the target group of the review.

Describing LA computational approaches is useful to learn more about the different analysis used in the TDP contexts. Analysis of logs, activity sequences, and temporal variables are associated with the process-oriented approach (n = 12), to describe the participation and use of educational resources. In content-oriented-approach studies (n = 10), the participants' artifacts are analysed, often through textual data mining techniques. To illustrate the quality of relationships and communities' density and cohesion, instead, the studies applied a network-analysis approach (n = 4). Mixing different approaches, recommended by Hoppe (2017), is reported in five studies, where the techniques aimed to capture many points of view: Collaboration identified through system log data and chat interventions (Van Leeuwen, 2015), convergence between automated and self-report evaluation methods (Rice & Hung, 2015), trainee satisfaction from a comparison of log data and forum content (Cinganotto & Cuccurullo, 2019), educational interest from previous activities and preferences given (Sui et al., 2017) and combination of semantic and network analysis in a dashboard for the self-evaluation of the learning process at work

(Ruiz-Calleja et al., 2016). Regarding LA purposes, the computational approaches are distributed with a prevalence of process-oriented analysis for the monitoring purpose, where teachers' behaviours are relevant (Figure 3). Otherwise, content-oriented analysis is also related to reflection: Artifacts are analysed to explore teachers' professional attitudes and practices. The network-analysis approach is associated with LA for assessment and monitoring, regarding participation in communities of practice or feedback on student interactions.

Figure 3.
Selected Papers by Computational Approach per LA Purposes



Concerning the sources of data collection, 30 studies collected data directly from teachers. System logs are the most common data source (n = 13), followed by user-generated contents (n = 10; e.g., videos, texts, forum posts). Data on teachers were also obtained by instruments of traditional research methods: Questionnaires (n = 9), interviews (n = 7) and observation (n = 2). In 10 studies students' data were also considered, while only in one study data was obtained only from students (Miller et al., 2015). The main sources for student data are system logs, occasionally combined with user-generated documents and profile information.

Perspectives and Challenges in the Application of LA to TPD (RQ2)
To take the narrative synthesis of the systematic review findings a step further, LA applications for TPD were outlined from three perspectives about the level of teacher involvement and awareness in the stud-

ies. A *top-down* perspective (n = 16) describes the use of LA for the supervision and analysis of relevant characteristics in TPD courses, applying the techniques to teachers' behaviour as lifelong learners. In this perspective, teachers are not directly engaged in the analysis process and there is no feedback on the results, especially in data-driven studies. The TPD concerns professional skills not related to LA and the creation of learners' models and monitoring elements – such as participation, collaboration, involvement, and performance – within the training paths are the main objectives of this perspective. Furthermore, the second *horizontal* perspective (n = 8) is adopted by the researchers considering LA methods and approaches used by teachers. In these studies, the teachers actively participated in the TPD intervention on the co-design and potential use of automated computational techniques. Qualitative methods, such as interviews and observations, are also used to test and evaluate LA in action, as a form of self-evaluation or analysis of students' information. In the second perspective, LA practice, tool design and data visualisation are elements introduced to increase TPD. In the third perspective (n = 7), LA is already implemented in learning contexts and its impact on teaching is evaluated. In this *bottom-up* approach, TPD is the result of the LA application in work practice and for teaching effectiveness. The focus shifts to the pedagogical variables to be examined through big data techniques: Management of collaborative interactions, diagnosis and intervention, planning and management of teaching activities and self-efficacy and awareness of teachers' educational style.

The challenges of convergence of LA and TPD, in terms of benefits and limitations, have been analysed in the 31 papers selected in the review. However, not all studies make explicit the difficulties of application, nor the potential opportunities. The benefits of the application of LA for the TPD were coded to four fundamental elements: (1) *Use of a greater amount of information*, LA allow to explore data in new directions, overcoming the limitations of manual analysis and using digital data previously discarded to enrich the overall scenario of the learning context analysed; (2) *Usability and data access*, the use of analysis in concise and often visual form can provide access to information not otherwise usable and assist teachers' interpretation, simplifying and speeding up the process of reading data; (3) *Helpfulness to different stakeholders*, given their composite and complex nature, LA results can be used at different levels to generate interventions for beneficiaries: From instructional design, to orientation, monitoring and support of decision-making processes, both by teachers and institutions; (4) *Combination of different data sources and flexibility*, the technical possibility of analysing together data of different types can link elements that could only have been analysed separately and obtain a customisable configuration, to support teachers' needs for autonomy and versatility. Four main limitations of the LA use also emerged from the review of the research: (1) *Cost and development time*, the most advanced solutions in terms of personalised and pedagogically relevant results require a high expenditure of resources, which cannot be immediately converted into evident results; (2) *Connection with the theoretical dimension*, the operational definition and analysis of indicators can oversimplify complex and situated educational phenomena, a well-known risk in the LA community (Wise & Shaffer, 2015); (3) *Technical limits due to the high level of sophistication*, some techniques are conditioned by the digital learning infrastructure in which they are applied, while others depend on text analysis and are therefore linked to the original language of the data; (4) *Data literacy and critical issue of adoption by teachers*, the possibility of making use of insights from the LA is mediated by teachers' data literacy and motivation. This highlights the need for a commitment from teachers to reach the level necessary to benefit from LA tools, which should be recognised and solicited by educational institutions.

Discussion

It is noted that most LA research in TPD used data-driven approaches and automated log extraction in technology-enhanced learning environments, without the teachers being aware of it. Indeed, a greater involvement is advocated in the LA scientific community (Knight et al., 2014) and is desirable both in terms of a shared definition of the constructs to be explored and feedback on the results of the analysis (Clow, 2013). However, there are also signs of an increased focus on human-centred approaches in those TPD courses that carry out co-design interventions and evaluation of LA solutions, while supporting teaching practice and deriving possible student benefits from these prototypes (Buckingham Shum et al., 2019). Three different perspectives on adopting LA in TPD contexts are described in the review. While the *top-down* perspective analyses data “about teachers” and transposes approaches already in use for students (Ferguson, 2012), in the *horizontal* and the *bottom-up* perspectives research is conducted “with teachers”, representing progressive steps toward recognizing their central role in the process of automatic analysis of learning data (Gunn et al., 2016).

The examination of the benefits reported in the papers highlights that applying LA could amplify awareness of processes that cannot be directly observed, both because of the number of participants and the level of detail of the analysis, as claimed in Chatti et al. (2013). Moreover, the limits are detected mainly at the design level that should guide the measure of the learning process (Mangaroska & Giannakos, 2018) and tend to seek evidence that justifies data use (Ferguson et al., 2016). There is the risk of oversimplification and standardisation due to the technical challenge (Wise & Shaffer, 2015) and the consequent shift away from the need for customisation and participation in the design of such solutions (Buckingham Shum et al., 2019). However, the involvement of teachers as end-users requires adequate support to develop not only the necessary prerequisites for reading and understanding data but also the skills to interpret and critically reflect on the data and their collection and extraction process (Wyatt-Smith et al., 2019).

As the transformations of the digital world also directly affect educational practices, it becomes clear how teacher training can become a powerful lever for innovation. The LA discipline itself can benefit from teacher involvement. Data mining techniques should adapt to the needs and expectations of their users in real educational contexts (Rosenheck, 2021). However, teachers’ skills related to the interpretation of data can also be useful for constant feedback between the information functional to the teaching process and the possibilities offered by LA tools (Agasisti & Bowers, 2017). To benefit from the use of LA in a pedagogically relevant way, it is necessary to adopt a systemic approach (Opfer & Pedder, 2011) in which TPD is an element that is integrated into institutional policies and actions and is supported by appropriate and flexible methods of engagement (Ferguson et al., 2016; Wyatt-Smith et al., 2019). Indeed, soliciting the autonomy, awareness and reflexivity of potential users – at the same time also examined subjects – towards the responsible application of the LA is an indispensable step for the future of education (Selwyn, 2019), increasingly permeated by automatic data extraction (Williamson, 2017).

The current review is a first attempt to assess the state of art of the applications of LA for the TPD and some limitations should be acknowledged: 1) Including only peer-review publications, the review may have missed relevant information from grey literature; 2) The process was conducted by a single researcher, carrying a risk of author bias. Moreover, since both LA and TPD are complex and extensive fields, there is a need to explore more deeply how specific professional practices are studied through the analysis of educational big data.

Conclusions

To understand the contribution of LA to support TPD and the role played by teachers in the research, this systematic review shows that LA has already been used for TPD since an early stage of the discipline. Concerning TPD contexts, LA is mainly used to monitor and analyse data from learning environments, where teachers participate in non-formal or informal professional development interventions, to track participants' activities, and produce reports to support decision-making and instructional design. To this end, LA was conducted mainly with a computational process-oriented approach, also through the simultaneous use of different techniques, such as statistics, educational data mining, and information visualisation. A different path is outlined in the studies that focused on the teachers' attitudes, skills, and opinions with early adoption of LA: Identifying appropriate LA generated data, and discussing results produced actionable knowledge, mostly in the context of a co-design framework. Nevertheless, when LA is applied to assess and give feedback to teachers on their professional practice, they might be better able to decide whether intervention is necessary and modify their actual classroom behaviour for the benefit of students.

The systematic review also reported the main benefits and limitations considered in the application of LA to TPD. LA makes it possible to gather information previously unavailable and explore new perspectives of integration between different types of variables. This is relevant to match the needs expressed by teachers with the design of flexible technological solutions. Conversely, there are obstacles related to initial investment costs and technological complexity, but also due to difficulties in connecting theory and LA design and due to teachers' data literacy.

If the near future will bring a greater diffusion of educational technologies associated with big data processing techniques (Williamson, 2017), it is time to ask how teachers, and the whole field of education, can help define the direction of these transformations.

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