Online-Journals.org

iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 19 No. 6 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijet.v19i06.50165

PAPER

Where Is the Teacher in Data Analytics in Education? Evaluating the Maturity of Analytics Solutions and Frameworks Supporting Teachers

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ABSTRACT

COVID-19 has changed the mindset of many teachers from traditional education to online education. The increased use of learning management systems is leveraging opportunities for increased use of learner data to draw insights about the learners and the learning environment. However, typically learners are the primary beneficiaries, while teachers are quite invisible in the research of data analytics in education, although both are equally important. Thus, this paper aims to position teachers in the spotlight by differentiating between these current two definitions of learning analytics (LA) and teaching analytics (TA) and evaluating the applicability and maturity of existing analytics solutions to support teachers in making decisions on teaching and learning. A systematic literature review was conducted in relevant scientific fields. The results showed clear evidence to distinguish TA from LA and that there are only a few TA solutions and frameworks that can be applied widely or in reality. Evaluating TA solutions and frameworks needs to be attentively considered. This paper also contributes a comprehensive TA process framework that encapsulates the missing elements in the previous models and adds the recent highlights raised in the fields. The implications for research and practice are also discussed.

KEYWORDS

teaching analytics, learning analytics, learning design, teachers, design research cycle

1 INTRODUCTION

During COVID-19, many teachers had to quickly transfer to online education [1]. This led to the growth of data creation by students and teachers on learning management systems, opening more chances for learning and teaching enhancement through data analytics. The tendency toward online or blended education and increased use of education technology systems in teaching and learning continues

Nguyen, N.B.C., Karunaratne, T. (2024). Where Is the Teacher in Data Analytics in Education? Evaluating the Maturity of Analytics Solutions and Frameworks Supporting Teachers. *International Journal of Emerging Technologies in Learning (iJET)*, 19(6), pp. 19–37. https://doi.org/10.3991/ijet.v19i06.50165

Article submitted 2024-05-17. Revision uploaded 2024-05-21. Final acceptance 2024-05-21.

after the pandemic, which increases the advantages of drawing implicit insights from data. This paper contributes to the theoretical perspective of supporting teachers in making decisions on teaching and learning through data analytics by differentiating between the current two popular terms in the fields: learning analytics (LA) and teaching analytics (TA), which is still a debate in the respective research fields. Concurrently, this paper also provides an evaluation of the applicability and maturity of the existing TA solutions and frameworks for supporting teachers and teaching.

LA emerged in tandem with the surge of data in education and with a focus on students and their learning experiences. This aligns well with the definition of LA by the Society for Learning Analytics Research "LA is the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimizing learning and the environments in which it occurs" [2]. Accordingly, the questions related to teachers and teaching are not directly included or addressed in the definition. The discourse of data-informed decision-making to support the quality of learning and teaching through pedagogical innovations, timely feedback, or enhanced learning design (LD) can be found in contemporary LA research. However, the substantial focus of this discourse turns toward students and addresses the questions of students rather than the dilemmas that teachers encounter. The language used in the LA field does not speak directly to the concerns and issues that teachers grapple with [3]. The results supporting teachers and teaching are not emphasized clearly and explicitly enough in the LA papers. Therefore, we argue that a direct and explicit focus on teachers is also of equal demand. Based on this fact, TA emerged to stress the issues and questions of teachers and teaching directly. However, the conceptualization of TA is still in its infancy [4] compared to the maturity of the LA research.

[4] defined TA as "a reconceptualization of LA for teachers to improve teaching performance and learning outcome." According to [5], TA focuses on "the design, development and evaluation of notations, representations, and visualizations of learning and teaching processes and products and the enculturation of a 'professional vision' for teachers to make the visual analytics notations, representations, and visualizations meaningful and actionable in pedagogical settings." Based on the definitions of LA and TA, the two key actors—students and teachers—are clearly stated and separated in each term. However, the related literature still describes the methodological approaches that have been implemented aiming at supporting teachers or improvements for LD as the ultimate goals under LA (ex. [6]). As a result, the controversy is still ongoing, which is, on one hand, that TA is viewed as a sub-field of LA since they see TA from the aspect of LA in connection with the teacher inquiry process [7]; on the other hand, LA and TA are considered as two separate research fields [4, 5].

In contemporary literature, there are two ways to find TA papers. In some publications, the term TA is explicitly used as a keyword. In other relevant publications, TA is implicit in the discourse of LA to improve LD. Additionally, a major challenge for LA and TA is to realize the promise of developing actionable interventions based on analytical results to improve learning and teaching, which is often alluded to as closing the loop [8]. Nevertheless, the loop has rarely been closed since many studies were apt to stay in the early stages [7, 9], resulting in a shortage of practical and successful evidence of TA and LA applications [8]. The first aim of this paper is to draw a clear line between the terms LA and TA and evaluate the maturity of TA solutions based on closing the loop, leading to the first research question:

RQ1: What are the differences between LA and TA? How mature are the TA solutions to be applied in practice?

In line with the discourse in RQ1, we also investigate the maturity of the frameworks for TA and LD supporting teachers (including teaching and environments) when designing courses integrated with data analytics due to the fact that it is still a question of how generalizable and applicable the frameworks work in authentic settings and in widespread practice [10]. Hence, the second purpose of this paper is to synthesize and evaluate the existing frameworks for TA and LD to provide a holistic perception of what the research community offers to support teachers with LD, leading to the second research question:

RQ2: How generalizable and applicable are the existing frameworks for TA and LD to come into use?

2 RESEARCH METHOD

We conducted a systematic literature review (SLR) as a methodology in the databases, covering the relevant, well-known outlets for identifying the differences between LA and TA and the applicability of the existing frameworks for TA and LD.

2.1 Article search strategy

[4] conducted an SLR to contextualize the notion of TA and develop various concepts around TA. This study, however, has not investigated the maturity of the TA solutions and their relevance for enhancing teaching practices in general and LD in particular. Additionally, [9] did SLR research to evaluate the development status of LA software concerning LA-driven LD improvements in higher education by using the software development life cycle as a reference model. To move forward from these two papers which have been done in a similar topic or direction, we clarify the TA field in this paper by conducting an extensive SLR to distinguish TA from LA, delving into the analysis of the development process of TA solutions that the studies have gone through, and evaluating the applicability and maturity of existing TA solutions to support teachers to enhance LD in various contexts (not limited to higher education), as well as the existing frameworks for TA and LD. This approach has not been used in previous literature. This review intends to offer various stakeholders, especially teachers, learning designers, and those working with LD, a landscape of TA-integrated LD, how applicable TA solutions are to improve LD and be applied in practice, and the perception of what has been explored, implemented, and validated in TA-integrated LD.

In the identification of relevant articles, the databases covering the publication venues in the subjects, including EBSCO, ACM, IEEE Explore, Science Direct, SpringerLink, Scopus, and the Journal of LA, were examined. The search queries primarily contained two key topics: “teaching analytics” and “learning design”. Due to the immaturity of the TA field, the term “learning analytics” was also searched together with “learning design” since this combination often leads to papers benefiting teachers and teaching. Moreover, the other keyword “instructional design” was included since it was interchanged with “learning design” in some papers. The inclusion criteria and the details of the SLR are depicted in Table 1. To find the right and relevant articles, the search scope in the databases was selected within keywords, subjects, or abstracts, depending on the available option of the advanced

search function in each database. Two databases, SpringerLink and the Journal of LA, did not have the advanced search function, so the search scope could not be considered.

Table 1. Details of the systematic literature review

Databases	Search Queries	Inclusion Criteria	Search Scope	Results
EBSCO	("learning analytics" OR "teaching analytics") AND ("learning design" OR "instructional design")	Peer reviewed, articles or conference papers, in English, not duplicated, searched in keywords, between 2010 to 2022	Subjects	81
ACM Digital Library			Abstract	17
IEEE Explore			Keywords	16
ScienceDirect			Keywords	9
SpringerLink			Not available	779
Scopus			Keywords	163
Journal of Learning Analytics			Not available	19
			Total	1084

2.2 Coding scheme and eligibility criteria

The selected corpus of articles was analyzed using the document analysis method. The coding scheme consisted of 19 aspects to record the relevant methodological and substantial features of the studies in table form. These aspects include stakeholders, theories, research questions, country, education level, subject, contribution/outcomes, differences between TA and LA, dataset size, data, implementation, technique/algorithms, current issues in analytics and pedagogy, evidence of analytics in LD, reach intervention, implications, limitations, future work, and kind of artifact. However, only relevant aspects that helped answer the research questions were considered.

According to the search strategy described above, the total number of papers was 1084 from the databases with the inclusion criteria. These papers went through the PRISMA diagram to select the final set of papers. The first step was to remove duplications using the Rayyan website for all the databases except SpringerLink. 149 duplicates were found. Regarding SpringerLink, this database did not support the function of filtering out incomplete papers such as lecture notes, in-progress work, workshop papers, and posters. Thus, the researcher examined the results from SpringerLink manually by skimming titles and abstracts to remove the incomplete papers. In the second step, the remaining results from SpringerLink and the other databases were combined and skimmed through titles and abstracts to eliminate papers irrelevant to teachers, LD, and LA or TA. In the third step, the 189 remaining articles were full-text read, coded, and analyzed. Among the 189 articles, the researcher continued to exclude the irrelevant papers that were not found by skimming titles and abstracts. In the set of irrelevant papers, although the papers regarding learning spaces, teacher professional developments, or tool evaluation aimed at teachers, they were not counted due to beyond the research focus of this paper. Some papers explored teacher education, which was pertinent to LA, TA, and LD, yet the key target was students in teacher education, so these papers were disregarded. As a result, the articles using LA/TA to improve LD, implementing teacher-facing dashboards or tools for teachers to create LDs, or developing

a framework of analytics and LD were taken into account. After all, 104 hits were relevant for the in-depth reading and analysis of the content. In the last step, the researcher included 21 papers with TA solutions which came to the stage of evaluation or intervention and 11 papers with evaluated frameworks for LA/TA and LD to present in the result section since these papers help answer the RQs. To clarify why the researcher divided into two sets of final results for two RQs, for RQ1, the researcher considered the studies using TA methods to generate solutions for the identified problems, thereby measuring the maturity of TA solutions. RQ2 stressed the frameworks for TA/LA and LD; accordingly, it was not necessary to use TA methods to develop the frameworks, but the frameworks can be developed based on theories, previous literature, or qualitative methods. In spite of this reason, there were five common papers in both final sets of articles. As explained, for each RQ, the papers were analyzed following different aspects; thus, there was no conflict for these common papers. Figure 1 summarizes the bibliographic information for the selection process.

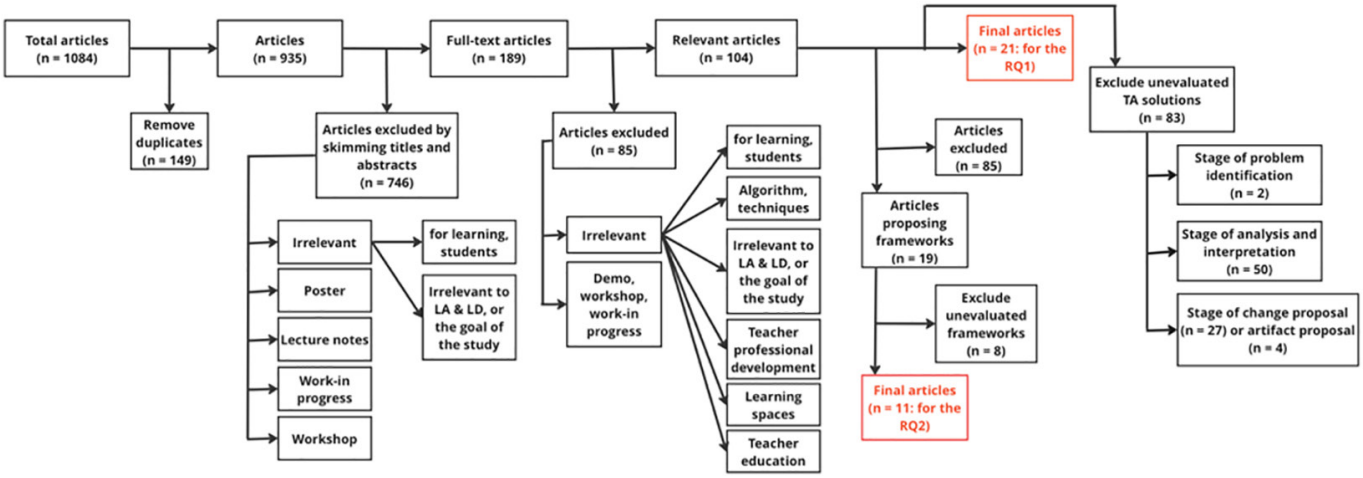

Fig. 1. PRISMA flow diagram of the screening and selection

2.3 Selecting a reference model for data analysis

To choose a method for data analysis, the researcher looked into the set of 104 relevant articles to explore a proper reference model as the baseline to measure the maturity and applicability of the TA solutions presented in the selected literature. The most common and specific methods that ten papers followed to develop an artifact or improve LD are design science research, design-based research, action research, or similar processes that were not explicitly named as the design cycle. The other methods are relatively generic and imply other various approaches included (more details in Table 2). Thus, we chose the design research cycle for the analysis of this SLR to investigate the differences between LA and TA based on this cycle and evaluate the applicability and maturity of TA solutions. For the papers that did not explicitly use the design cycle, we examined their studies based on the steps they had taken to discover how far their research had gone and how applicable the solutions were outside their own case studies. Some authors combined several methods in their studies (e.g. [11, 12]), leading to a total of more than 104 papers in Table 2.

Table 2. Methods with a respective number of papers

Qualitative method	7	Mixed method	8	Design science research/ design-based research/ action research	10
Case study	8	Review and theory	12	Flipped classroom	1
Multiple steps	9	Experiment	2	Phenomenological approach	1
SLR	9	Multimodal LA	2	Multiple studies	1
Non-specific method	36	Multimethod study	1		

To analyze the set of 21 papers for RQ1, we developed a taxonomy of elements following the design process (refer to Table 3). We did not apply this taxonomy to the set of 11 papers with frameworks for the RQ2 because we analyzed the frameworks in terms of applicability and generalizability. Regarding the taxonomy, one cycle means that authors systematically conceptualized, designed, developed, and evaluated the solutions once. Two cycles represent the solutions that are evaluated once and revised, or that led to interventions for improving the learning-related functionality that the articles address. The design research cycle, as a reference model, includes specific steps of awareness of problems, suggestion, development, evaluation, and conclusion [13]. Due to the distinction of this design cycle, only the papers producing artifacts were appropriate and able to be measured based on this design process. TA solutions and frameworks are artifacts in this context and embodied in different ways, such as insights, principles, tools, or prototypes. The contemporary research studies were analyzed to discover how many papers have reached the evaluation/intervention stage or how many cycles the papers went through, which shows the maturity of the models as described above.

The first element of the taxonomy is foundation, referring to whether a study is formed based on either theory, literature, or problems from authentic contexts, or even both. The second element, the design research cycle, signifies how many cycles of the design research cycle a study has gone through to evaluate the maturity of the development process of the study. The element of evaluation extent elucidates to what extent an artifact is tested and evaluated. The last element, applicability, alludes to the capacity that an artifact can be applied in reality, to a small or large extent.

Table 3. A taxonomy of elements following design research cycle

	Low	Medium-Low	Medium	High
Foundation	Non foundation	Problem or tendency with literature	Problem with potential solutions and strong literature/theory	Theory and empirical evidence
Design research cycle	1 incomplete cycle	1 complete cycle	2 cycles	>2 cycles
Evaluation extent	Test based on literatures or low-fidelity prototypes	Partly test or ongoing test in reality	Test with one course or limited group in reality	Test with more than one course or in wide scope
Applicability	Unsure applicability in authentic settings or do not know yet	Potential but uncertain or limited in reality	Considerable extent of applicability and readiness in reality with limitations or unexpected effects	Widely applied, high reliability, or high applicability with minor issues

2.4 An overview of the maturity of TA solutions

The set of 104 relevant articles has been read to capture an overview of the maturity of TA solutions. Among them, two papers have come to the stage of understanding the problem and context [14] or investigating design principles but have not reached the implementation stage [15]. Almost half of the review list—50 articles—only reported the outcomes up to the level of interpreting analytics results aligning to context and LDs, or proposed an artifact, even a handcrafted artifact or an incomplete artifact. These papers did not discuss intervention or evaluation to measure the applicability of the findings. Thus, these research studies did not show evidence for a complete design cycle, resulting in unanswered questions about the applicability of the outcomes or the reproducibility of the methods in other learning settings than the example showcased in the respective study.

Additionally, 27 papers proposed changes for LDs after analyzing and interpreting the results while four papers proposed an artifact with the illustration of use cases to show how the artifacts work. These papers have not come to the evaluation stage of the artifacts in reality or the intervention to apply proposed changes. The paper of [16] also needed further clarification although the authors used the term "intervention" in the paper. Referring to the design-based research approach that the authors used in the paper, the authors identified learning barriers and proposed revisions for the course design strategies in the stage of analysis and exploration. Next, the authors implemented the changes for the course design strategies, which were well-adopted in the stages of design and construction. However, the system construction and evaluation were in planning as future work. Thus, this paper was classified in the group that proposed changes. Another paper doing an SLR summarized the current landscape of LA and LD [17]. Although this paper did not produce any artifacts, the authors suggested several important areas of investigation to move forward from the current state. Thus, this paper was put in the category of proposing changes and used as the ground for our study.

Interestingly, 21 papers have reached the stage of evaluation or intervention. These papers are presented in detail in the result section. Figure 2 provides a comprehensive insight into classifying these 104 articles.

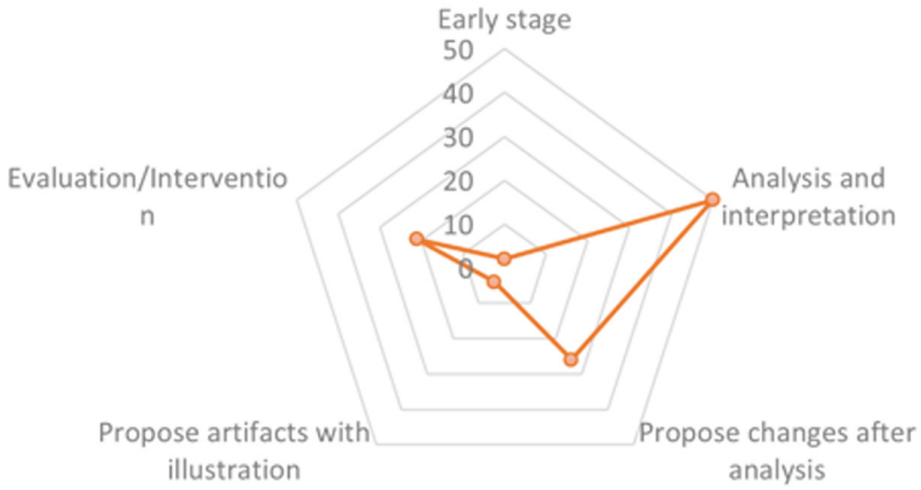

Fig. 2. A chart of articles classified by the design research cycle

2.5 An overview of existing frameworks for TA/LA and LD

As described in Figure 1, there were 19 papers proposing frameworks or models of TA/LA-integrated LD for teachers. These frameworks are listed in Figure 3.

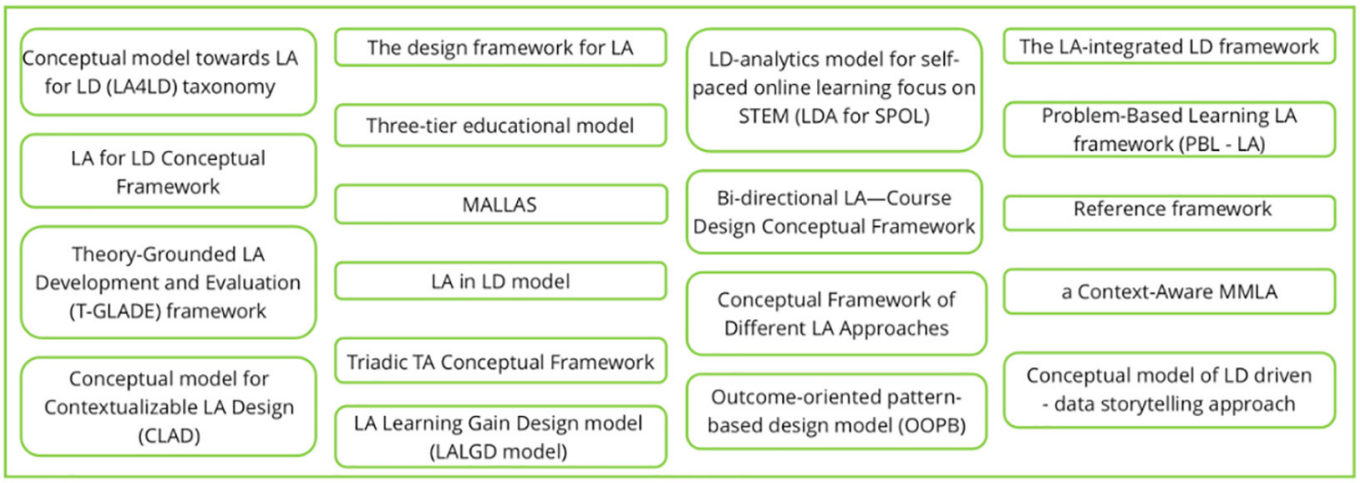

Fig. 3. Existing TA/LA and LD frameworks/models

Six papers proposed frameworks based on literature, which have not been evaluated. One paper evaluated their framework through the Loop tool, which was in progress [18]. [19] put forward a reference framework and used it as the analytical framework for the SLR of the same paper. The evaluation of this framework was not explicitly shown but implied potential. These eight frameworks have not been evaluated, so they were not analyzed. The remaining eleven frameworks have been evaluated either using use cases, literature, or real-world cases, which are presented in the result section.

3 RESULTS

3.1 RQ1: How mature are the TA solutions to be applied in practice?

The RQ1 has two parts. In this section, we respond to a part of the question about the maturity of TA solutions to be able to be applied in practice. 21 papers were found that have reached the stage of evaluation or intervention. The taxonomy details of these papers are summarized in Table 4. Among them, [20] brought up the analytical tool SNAPP which provides real-time visualizations of discussion activities. To examine the performance of this tool as reported in the literature, two more subsequent versions from these authors were found, which helped perceive the entire picture of the tool development process.

Among the articles in our corpus, three papers focus on designing learning objects or learning activities rather than the entire LD. Namely, [21] focused on the design of a writing activity with the support of an automated writing feedback tool; [22] worked on online asynchronous discussions with the support of Starburst; and [23] concentrated on revising content through the dashboard CoReaDa.

There is a sequence of papers that have connections in terms of the design process. The sequence starts with proposing design principles for edCrumble in [24],

followed by [25], and finally [26]. The papers were counted separately and presented in Table 4.

Table 4. Results of articles completing at least one design cycle

	Foundation	Design Process	Evaluation Extent	Effectiveness
Molina-Carmona et al. [27]	Medium-Low	High	Medium	Medium
Lockyer and Dawson [20]	Medium-Low	Not clear	High	Medium
Schmitz et al. [10]	Medium	High	High	High
Echeverria et al. [28]	Medium	Medium-Low	Low	Low
Blumenstein [29]	Medium	Medium-Low	Low	Low
Zotou et al. [12]	Medium	Medium-Low	High	Medium
Ahmad et al. [19]	Medium	Medium-Low	Medium	Medium-Low
Kaliisa and Dolonen [30]	Medium	High	Medium	Medium
Li et al. [31]	Medium	High	Medium	Medium
Eradze et al. [32]	High	Medium	Medium	Medium
de Menezes et al. [33]	Medium-Low	Medium	Medium	Medium
Kitto et al. [34]	Medium	Medium	Medium	Medium
Albó et al. [26]	High	Medium-Low	Medium	Medium
Hilliger et al. [35]	Medium	Medium	High	High
Albó and Hernández-Leo [24]	Medium-Low	Medium-Low	Medium-Low	Low
Albó et al. [25]	Medium	Medium-Low	Medium	Medium
Ortega-Arranz et al. [36]	High	Medium	Medium-Low	Medium-Low
Rodríguez-Triana et al. [37]	High	High	High	High
Sadallah et al. [23]	Medium-Low	Medium-Low	Medium	Medium
Shibani et al. [21]	Medium	Medium-Low	High	Medium
Dietrich et al. [38]	Medium	Medium-Low	High	Medium-Low

According to Table 4, three of 21 studies showed the high applicability and reliability of the outcomes, which were assessed based on their broad evaluations with various contexts, stakeholders, and their multi-iteration design processes. Among those three articles, [35] reported that the tool is being used by 20 Latin American universities to inform teachers about learning situations when redesigning course assessments and sequences. The other two still suggested future work to make the artifacts better at using TA to improve LD. Moreover, the SNAPP tool is also widely used as a reflective tool instead of for modification of the LD "on the fly" as the initial expectation [20]. The remaining papers need to make adjustments to enhance the alignment of TA and LD in their studies.

3.2 RQ2: How generalizable and applicable are the existing frameworks for TA and LD to come into use?

Eleven evaluated frameworks are presented here to answer RQ2. One framework was evaluated based on 13 selected studies from the SLR [29]. Three papers

demonstrated how to implement the frameworks through use cases [8, 39, 40]. One framework was offered based on the two-cycle design of an empirical study [6], another paper demonstrated three iterations to evaluate the frameworks [31], and five frameworks have been tested in reality from one course to multiple courses. Table 5 shows the details of the eleven frameworks evaluated in authentic settings or through use cases.

Table 5. The details of usability and applicability of the evaluated frameworks

Frameworks	LD	Subject	Learning Mode	Data Size
CLAD by Shibani et al. [21]	Writing activity	Various	Blended, online	90 and 302 university students
LDA for SPOL by Yan et al. [16]	Self-pace	Computer science	Online	University students
PBL-LA by Zotou et al. [12]	Problem-based learning	Various	Classroom with e-learning environment	32 postgraduate students
Context-aware MMLA by Eradze et al. [32]	LD for secondary teaching	Not specific	Classroom	1200 secondary students
LD driven-data storytelling approach by Echeverria et al. [28]	Group work	Database	Classroom with e-learning environment	15 undergraduate students
OOPB by Li et al. [31]	Not specific	E-learning leadership	Blended	21 master students
Design framework for LA by Seufert et al. [40]	**1.** Forum discussion **2.** Reflection **3.** The use of game elements **4.** With materials and problems	Not specific	Online	**1.** A group **2.** At individual level **3.** Community or individual learners **4.** Large number of learners
Multilevel framework for LA integrated LD by Law and Liang [8]	Task: observe the scenarios in the presented stimulus.	STEM	Classroom with e-learning environment	Individual student in grade 8
Bi-directional LA-course design by Kaliisa et al. [39]	Online social interaction activities and contexts	Not specific	Blended	University learners
T-GLADE by Wiley et al. [6]	Assessments: multiple choice items and open-response items	Global climate change	Classroom with e-learning environment	885 middle school students
LALGD model by Blumenstein [29]	Socio-communicative, cognitive/metacognitive, metacognitive/affective	Not specific	Face-to-face, blended, online	Not empirical evaluation but based on 13 selected studies, in higher education

According to Table 5, the LALGD model [29] was validated using literature but not in an authentic setting, so it is unclear to indicate for which subject or data size this model is valid, rather than the contexts applying the LDs of socio-communicative, cognitive/metacognitive, or metacognitive/affective. This model was created for higher education contexts; accordingly, the other educational contexts are not applicable. The frameworks described by [28, 39, 40] can be generalized to various LDs due to the popularity of these activities. However, the authors did not particularly describe how the activities should be designed and implemented. [40] put a heavier focus on LA design, while [39] demonstrated quite a general LD, and [28] emphasized the effects between explanatory and exploratory visualizations in the dashboard. The frameworks by [12, 16, 21] focused on specific kinds of LDs, which limits the generalizability of these frameworks. Context-aware MMLA [32] fits well in a physical setting rather than in

an online or blended context. The OOPB model [31] can be generalized since it can be applied to different educational levels, different modes, various subjects, and stresses on the activities that produce patterns. The authors of the OOPB model created four taxonomies of design patterns, including directed learning, explorative learning, productive learning, and reflective learning; thereby, instructional designers or teachers can freely refer to according to their design plans. Additionally, it is uncertain if the frameworks described by [6, 8, 32] function in higher education as they have been evaluated in secondary and middle schools. Five frameworks [8, 12, 28, 31, 40] can handle small datasets with a small number of students (<50), while the rest manage large datasets or do not mention this information explicitly.

3.3 TA or LA: which one supports teachers?

By synthesizing the knowledge captured from the SLR, we answer the remaining part of the RQ1 about the differences between LA and TA in sections 3.3 and 3.4. We start with the definitions of TA and LA introduced in the introduction, LA and TA are distinguished by two key actors: LA for learners and TA for teachers. We can examine two directions as follows.

In the first direction, the study of [21] used LA to build an automatic writing feedback tool tuned with pedagogical context to support personalized learning and to address students' dilemma: "How can students improve their writing skills without teachers?" The authors closely aligned the purpose of this study with the LA definition of aiming for students and their learning and emphasized contextualizable LA design to produce meaningful support for students.

In the second direction, the study of [27] also utilized LA to analyze students' data to support teachers in redesigning an instructional course and provide in-time assistance, thereby addressing teachers' question, which is "in which ways teachers can motivate students' learning, especially low-performance students." The other study by [41] used LA to analyze students' communication and collaboration in order to help teachers reflect on their practices and LDs, thereby anticipating problems and making informed interventions. This study also answered teachers' questions, which are "How can teachers actually design and evaluate their course design?" and "How can teachers provide in-time support to their students?"

Comparing these two directions, teachers' questions are different from students' questions although both types of studies used students' data. The goals of these studies aimed at different actors and answered different questions. Accordingly, it is recognized that the second direction is incongruous with the LA definition but consistent with the TA definition. [28] revealed the differences between students' and teachers' concerns and questions through student-facing dashboards and teacher-facing dashboards. LA dashboards allow students to evaluate some parts of their learning behaviors and may even assist them in better managing their study, while TA dashboards help teachers obtain a thorough grasp of their entire course or specific tasks, reflect on their teaching strategies, and identify students who need particular support. There are also disparities between learners' and designers' perspectives. Teachers or designers desire to communicate multiple insights or dimensions of data about student experience to make better-informed decisions on (re)designing learning activities while students want to see what they are supposed to do, how they perform individually and in comparison to their classmates, when activities are happening, and if there are alternative ways to achieve the same goal [14]. Moreover, there is also the opinion that LA was never intended to exclude teachers, and it is obvious since

teachers and students always need to go hand in hand to improve both learning and teaching. One cannot support students without considering teachers and LD, and vice versa. However, what we argue here is that the LA definition focuses on students and learning and addresses students' questions, while the TA definition actually answers teachers' pedagogical questions and directly supports teachers. The ultimate result of both TA and LA benefits students in a direct way for LA and in an indirect way for TA through supporting teachers. Therefore, it is important to demystify that if a study aims to support teachers using data analytics, TA should be used, and if a study aims to support learners using data analytics, LA should be used. The differences between LA and TA are also divulged when we dig into the analysis of developing TA solutions based on the design research cycle in the next section.

3.4 Differences between LA and TA – proposing a TA process framework

We continue to answer RQ1 about the differences between LA and TA by analyzing two more perspectives to distinguish LA and TA, which are recognized throughout the design research cycle.

The first aspect deals with the data. It is remarked that TA and LA both used student data to reflect on and evaluate either LD or students' learning or give feedback to teachers. Yet, this review explored further that TA uses not only student data but also the data of teachers using tools [25], LD data [42], physical traces of students or teachers [28], or qualitative data. TA can use LD data and teachers' data to reflect on teaching practices or evaluate LD, learning activities, or learning objects, while LA cannot use LD data or the data of teachers using tools to assess students' learning.

In the second aspect, if a design process just stops at the analysis and interpretation stages, TA and LA look the same. Nevertheless, the difference lies in the later stages of the design process when analytical results are transferred to changes or interventions. Regarding TA, only teachers themselves can implement the changes in their LD to observe the impacts while students cannot implement changes in LD or teaching practices, except that students can give feedback on LD. Similarly to LA, students themselves can change their behaviors or learning ways to improve their learning, which teachers cannot do, except that teachers can provide motivation or support. The later stages of the design cycle clearly show the differences: TA generates impacts on LD, or teaching, and directly involves teachers, while LA produces impacts on learning and directly involves students. This argument is supported by the 21 papers reaching the later stages reported above.

There are also differences between the TA process and the LA process. Currently, there is no well-established or well-defined TA process. [11] named a teacher inquiry cycle including problems and questions, design intervention and evaluation, classroom implementation, collected data and analysis, and reflection and changes. The first and last steps can go back and forth before starting a new cycle. Both teachers and students are engaged in the process. [41] described a teaching cycle as including design and planning, engaging with students, reflection, professional development, and then starting a new cycle. This cycle is valid for various levels of granularity, from learning activities to sessions, modules, or programs. [4] designed the teaching outcome model (TOM) – a TA life cycle, comprising data collection, data analysis, data visualization, and data action (course design and assessment). In this model, the teacher is the central actor. While both the teacher inquiry cycle and teaching cycle did not clearly show TA but demonstrated well the aspect of the teacher's role, TOM reflected the components of the data analytics process but lacked the teachers' practices. Thus, premised on these cycles and this SLR, we aggregated and supplemented to enhance

the TA process framework (Figure 4). Our TA process framework encapsulates the missing elements in the previous models described above by bringing the teacher role to the center of the didactics, teachers' actions into the TA process, and adding up-to-date needs relating to TA as well as relevant stakeholders in tandem.

The starting point of this TA cycle is that teachers capture interests in learning and teaching based on their LD and available data concerning LD, characteristics of learners, situations of learners, environments of learning and teaching, as well as challenges that learners or teachers face. Continued is extracting and analyzing the respective log data of teachers, learners, or LD data following the interests. The data collection and analysis need to be performed in (near) real-time to provide continuous insights to teachers throughout the courses. In addition, the choice of appropriate algorithms, techniques, or methods conforming to the data is essentially taken into account. TA results are visualized and interpreted by connecting back to the LD and context to be able to perform meaningful and timely interventions. Based on the interpretation of TA results, teachers alone or together with researchers and analysts propose appropriate changes that can enhance the LD for enhanced learning. Depending on the kinds of changes that will be applied to a course, teachers, together with relevant stakeholders such as a department, study administrators, learners, or institutions, will engage in planning and (re)designing the course. Stakeholders involved in this step need to consider learning objects in the LD in such a way that TA can be used to assess or validate the effectiveness of the learning objects. Additionally, the TA-integrated LD needs to be grounded in theory, as suggested in the previous literature. The next step is to implement the changes in authentic courses, followed by teachers' as well as the relevant stakeholders' reflections and evaluations on the changes. A new loop will be formed following teachers' needs for improvement. In this cycle, teachers, analysts, and researchers can be either different people or one person if the person can play the roles and have the competencies of teachers, analysts, and researchers at the same time.

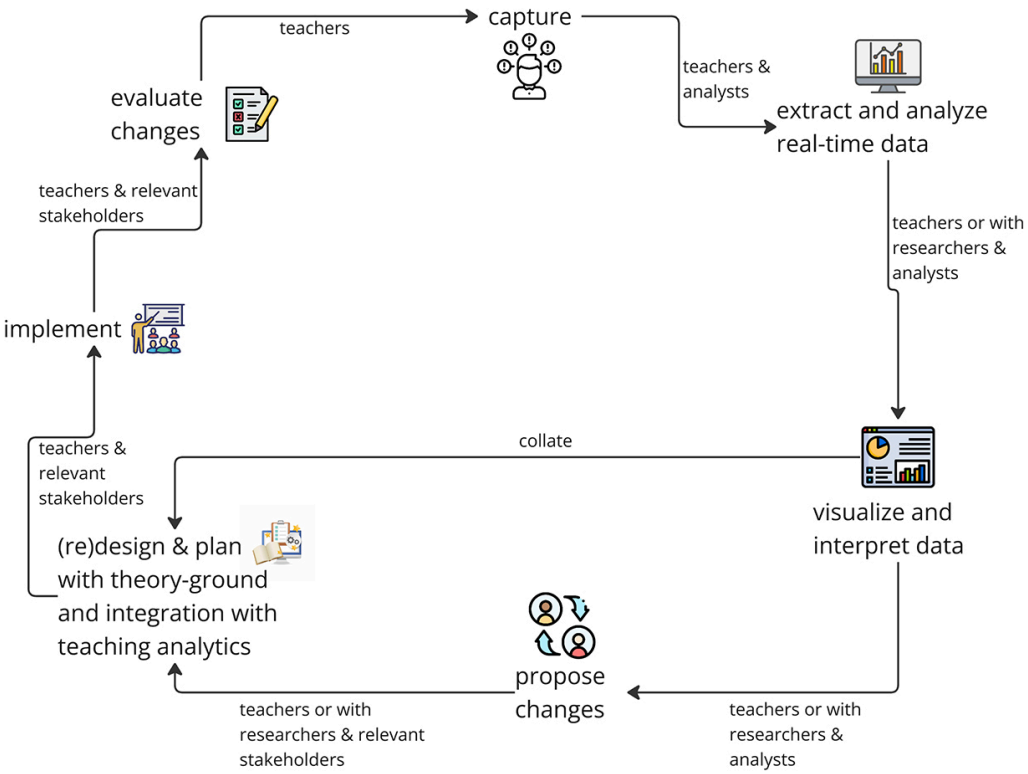

Fig. 4. TA process framework

4 DISCUSSION AND CONCLUSIONS

It is not uncommon to navigate students in the research of data analytics in education, but it is quite vague to see teachers as a key actor and their role. Although teachers still implicitly exist in this field, they should be emphasized and paid attention to as visibly and equally as students. Thus, we contribute this paper toward positioning teachers in this research field by presenting the results of an SLR aimed at demystifying the differences between TA and LA and delineating the applicability and maturity of TA solutions for teachers to improve LD and of the existing frameworks of TA-integrated LD. We selected and analyzed 21 articles developing TA artifacts to reinforce and supplement the points distinguishing between TA and LA in relation to LD. The design research cycle was applied for the data analysis as a reference model to examine the maturity and applicability of TA artifacts. This SLR showed that most of the existing efforts in TA focus on the first steps of this cycle, namely, data gathering, analysis, and visualization of certain learning processes rather than intervention or evaluation, which were illuminated in [7, 9]. However, some studies reached the intervention and evaluation steps, and three artifacts demonstrated high effectiveness or wide applicability in practice.

To differentiate between LA and TA, this paper revealed the ways, including (1) premised on the design research cycle, (2) kinds of data, and (3) definition, central actor, and actor's perspectives. According to the design research cycle, TA and LA are clearly distinguished in the later stages of the design process thanks to intervention while both TA and LA are quite similar in the early stages. Regarding the kinds of data, TA utilizes not only student data but also teacher data and data relating to teaching practices while LA works mostly with student data. Concerning the definitions, TA prioritizes teacher orientation whereas LA focuses primarily on learner orientation. The perspectives and questions of teachers and learners are different.

Moreover, this paper also synthesized and supplemented the elements to improve the TA process framework to be comprehensive and correlate with the recent highlights in the disciplines of TA and LD. Hopefully, this TA process framework combining teachers' practices and TA as well as highlighting teachers' roles can urge the studies using TA and aiming at teachers and LD to move forward closing the loop. Future suggestion is to evaluate the proposed TA process framework in real-world cases.

4.1 Implications for practice

Real-time feedback enhances the success of closing the loop [8]. Currently, a scarcity of real-time analysis hinders teachers from making quick decisions and accessing critical information. Based on the lessons learned from the case of the SNAPP tool [20] and the finding on the limited use of dashboards by teachers [30], to operate the real-time analysis and increase the possibility for adoption, this requires researchers' attention and the cooperation of teachers in designing TA-integrated activities and using tools to make it happen. Teachers' professional development in new pedagogies and data literacy should be prioritized to remove the barriers preventing teachers from using TA solutions and enable necessary intervention [43].

4.2 Implications for research

To develop TA solutions and frameworks, the design research cycle is a typical method that several papers have used compared to the other methods. The design research cycle is a rigorous process using theoretical knowledge and engineering design principles to construct socio-technical artifacts to solve identified problems. Evaluation is emphasized as crucial in this cycle [44]. Accordingly, the design research cycle is appropriate to use as not only an approach for developing artifacts but also a reference model to analyze the maturity of TA artifacts. The variety of artifact types and evaluation methods in this cycle facilitates the wide coverage of measuring the development and evaluation of TA solutions and frameworks.

There are existing frameworks combining TA and LD, as shown above. Nevertheless, the challenge is that many of them have not been evaluated; thus, the validity and reliability of these frameworks when applied in practice cannot be guaranteed. It is observed that most of the frameworks were implemented as tools. As a result, evaluating the frameworks connotes evaluating the respective tools; thereby, the evaluation of the frameworks is postponed until the technical implementation of the tools is accomplished [18]. Some of these frameworks were designed for specific learning activities such as writing or problem-based learning while others were tested in middle and secondary schools. This prevents these frameworks from being generalized; accordingly, these frameworks need to be evaluated in more contexts. Most of the existing frameworks support online learning or e-learning environments, which are comparatively popular in higher education. However, many courses in higher education have a small number of learners and, consequently, little data for building TA solutions. This is not supported or taken into account by most of the current frameworks. Conversely, there are potential frameworks that can be considered in the aspect of generalizability such as the OOPB model, bi-directional LA-course design, design framework for LA, or LD-driven data storytelling approach, yet they need more examination. Due to the limited contexts of evaluation, the maturity of these frameworks is not high for ubiquitous application. Consequently, there is an urgent need to explore the flexibility of LD for supporting diverse learners and teachers [17]. We also agree with [8, 10] that these frameworks are relatively complex and would not be ready to be adopted by practitioners. Hence, future work should consider the optimization of potential frameworks toward simplicity, generalizability, and applicability to support teachers, especially non-technical teachers.

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