A Systematic Review of Empirical Studies on Learning Analytics Dashboards: A Self-Regulated Learning Perspective

Article *in* IEEE Transactions on Learning Technologies · May 2019

DOI: 10.1109/TLT.2019.2916802

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***Abstract*—This paper presents a systematic literature review of learning analytics dashboards (LADs) research that reports empirical findings to assess the impact on learning and teaching. Several previous literature reviews identified self-regulated learning as a primary focus of LADs. However, there has been much less understanding how learning analytics are grounded in the literature on self-regulated learning and how self-regulated learning is supported. To address this limitation, this review analyzed the existing empirical studies on LADs based on the well-known model of self-regulated learning proposed by Winne and Hadwin. The results show that existing LADs i) are rarely grounded in learning theory; ii) cannot be suggested to support metacognition; iii) do not offer any information about effective learning tactics and strategies; and iv) have significant limitations in how their evaluation is conducted and reported. Based on the findings of the study and through the synthesis of the literature, the paper proposes that future research and development should not make any a priori design decisions about representation of data and analytic results in learning analytics systems such as LADs. To formalize this proposal, the paper defines the model for user-centered learning analytics systems (MULAS). MULAS consists of the four dimensions that are cyclically and recursively interconnected including: theory, design, feedback, and evaluation.**

***Index Terms*—Dashboards, empirical research, feedback, information visualization, learning analytics, self-regulated learning**

I. Introduction

Over last several years, the role of technology increased significantly in different educational settings from the widespread use of learning management systems to social media, interactive simulations, and serious games to name a few. The growth in the use of technology propelled the development of the capacity for capturing data about various aspects of learning experiences. This is done through the collection of digital footprints learners leave behind whenever they interact with technology. These digital footprints have been recognized as a promising source of data (also known as trace of log data) that can be leveraged to inform and optimize decision making of a wide range of stakeholders such as learners, teachers, and administrators.

To harness the potential of digital footprints, the field of learning analytics focuses on the collection, analysis, and reporting of data about learners and contexts in which learning occurs [1]. Learning analytics make use of data science methods to analyze data and report the results of the analysis with different visual and textual approaches [2]. Within learning analytics, dashboards have received much attention as tools that can provide users with relevant insight, prompt user reflection, and potentially inform interventions that are aimed at optimizing learning and the quality of the student experience [3]. Schwendimann and colleagues [4] define (LAD) as "a single display that aggregate different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualization" (p. 8).

In spite of some promising results, critical limitations in the existing research and design of LADs have been identified [5]. Some studies suggest that learners find it hard to interpret the data presented in dashboards and to make use of feedback presented in dashboards to inform the choices of their learning strategies [6]. The actual impact of learning dashboards and recommendation systems is found to be relatively low [7]. Moreover, some authors question whether feedback presented in LADs could be translated into a meaningful actionable recommendation to guide students in their learning [5], [8], [9].

Given the growing interest in LADs, several systematic literature reviews have recently been published (see Section 2.1 for a summary). These reviews identified key themes that emerge in the literature including the focus on metacognitive, cognitive, affective, and behavioral aspects of learning [10], [11]. The focus on metacognition and self-regulated learning has particularly been emphasized. The conclusions of the existing literature reviews suggest that current LADs should i) have theoretical grounding to overcome some of the limitations in the existing LADs [10], [11], ii) support all phases of self-regulated learning [10], iii) significantly improve how evaluation is conducted [4], [10], [11], [12], and iv) establish closer connections

Manuscript received August 12, 2018; revised February 17, 2019; accepted April 12, 2019. Date of current version April 16, 2019.

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with the literature on open learner modeling [13].

Although the limitations are reported in the current literature reviews, there have been a shortage of systematic analyses of the existing LADs based on an established theoretical model of (self-regulated) learning. This is a significant limitation, as some of the findings in the existing reviews may not be completely aligned with the contemporary understanding of self-regulated learning in the learning sciences. For example, metacognition in the reviews of LADs is only linked to the reflection phase on self-regulated learning [10]. This exclusive link is not consistent with the Winne and Hadwin [14] model of self-regulated learning. The key reason for the misalignment is the fact that metacognition is not a phase of self-regulated learning. Instead, metacognition is exercised by two key processes – monitoring and control. These two processes underline the engagement with all four phases of the Winne and Hadwin model (see Section 2.2 for details). Therefore, to be able to draw conclusions about the extent to which LADs support metacognition and self-regulated learning, there is a need to perform a systematic literature review of LADs against in a well-established theoretical model. This motivated our first research question:

1. *What is the support of LADs for the elements of self-regulated learning based on a well-established theoretical model?*

In this review, the analysis of the LADs reported in the literature was performed based on the Winne and Hadwin [14] model of self-regulated learning. The Winne and Hadwin model is particularly suitable for the analysis of LADs, as the model is derived from the well-known synthesis of the literature on learning feedback [15]. Our results of the literature show that existing LADs i) are rarely grounded in learning theory; ii) cannot be suggested to support metacognition; iii) do not offer any information about effective learning tactics and strategies; and iv) have significant limitations in their evaluation. Note that, in this systematic literature review, the effectiveness of individual SRL element on the learning outcome were not discussed.

In addition to the theoretical analysis of LADs published to date, the current study also aimed to replicate and complement some of the findings published in the previous literature reviews through two additional research questions.

2. *What types of information is offered as feedback in LADs?*

This research question corroborated the findings of the previous literature reviews [4] about the techniques used for presentation of data and results of analysis in LADs. The findings showed that individual references frames were most prevalent in the existing dashboards followed by comparisons with group average scores. The use of chart bars is the most relevant.

3. *What is the quality of study designs and reporting the literature that reports on empirical evaluations of LADs?*

The final research question expanded the existing literature reviews by critically appraising the quality of design and reporting of empirical research on LADs. This appraisal was performed by using an instrument adapted from medical research. The findings suggest that no studies discuss generalizability of their findings, while limitations of study results are rarely reported. Causal effects of the use of LADs can hardly be made due to the limited used of experimental designs and mixed-methods.

To guide future work of developers, researchers, and adopters, a model for LADs has been proposed in this paper (Section 5). The model integrates the findings of these three research questions.

II. Background

This section summarizes the findings of the previous reviews of the literature on LADs. The section also introduces the Winne and Hadwin model of self-regulated learning.

A. Reviews of LAD Literature

The initial review of the 15 LADs was carried out by Verbert et al. with the aim to illustrate the conceptual framework proposed by the authors of that review. The review analyzed target users of dashboards, data that were tracked, and evaluations performed. This review was further extended by Verbert and her colleagues [16] who ranked existing papers based on categories of LADs that had been deployed in face-to-face lectures, face-to-face group work, and blended learning settings. Then, they analyzed the dashboards in terms of the data sources, data tracking, target users, devices used and evaluation to support the four elements of the conceptual model (awareness, reflection, sense making, and behavioral change) originally proposed by Verbert et al. [17]. Although these two reviews provided useful categorizations of the literature, the two reviews did not perform a systematic search of the literature as a guarantee for a comprehensive representation of the state-of-the-art.

The first systematic literature review of learning dashboard research is reported by Schwendimann et al. [4] and included a total number of 55 papers. The review presents the result based on four categories: types of contribution (e.g., theoretical proposal or framework), learning context (e.g., target users and learning scenarios), learning dashboard solution (e.g., purpose and data sources), and evaluation. Although it has some similarities with the review reported by Verbert et al. [16], the Schwendimann et al. review additionally scrutinized the types of indicators presented in individual dashboards into six broad groups and categorized the types of visualization used in LADs. The main finding of the study was that existing papers on LADs rarely reported on results of empirical evaluations, because dashboards were mainly developed as part of exploratory work and built as proof-of-concepts.

The systematic literature review conducted by Bodily & Verbert [12] focuses on student facing learning analytics reporting systems. Such reporting systems include LADs but can also include recommender systems and textual messages with feedback generated based on learning analytics. Building on the previous three literature reviews, 94 papers were included into the review and coded according to five dimensions: functionality, data sources, design analysis, perceived effects and actual effects. The review concluded that further research is needed on the process of design of LADs and recommender systems and not only on the final products of design. The review also suggested that more rigorous experimental studies are needed to determine effects of LADs and recommender systems. Although these suggestions are of critical importance, the review did not analyze the relevance of learning theory and the role of learning sciences in the design and evaluation of LADs.

The systematic reviews conducted by Jivet and her colleagues [10], [11] provide important steps towards bridging the gap between the literature on LADs and the learning sciences. Specifically, Jivet et al. analyzed how theories and models that have been integrated at learner-facing LADs. They found six clusters of papers based on their general theoretical tendencies, including, cognitivism, constructivism, humanism, descriptive models, instructional design, and psychology. Of these, the cognitivist cluster had the highest number of papers with the subcluster of self-regulated learning being the largest. From the perspective of the types of competences promoted, the reviews found the following categories of papers – metacognitive, cognitive, behavioral, emotional, and self-regulation. Given the growing recognition that LADs can be a helpful tool for providing reference frames [18], the Jivet et al. reviews classified papers into those providing social, achievement, and progress reference frameworks.

Although the existing literature reviews offer valuable contributions toward incorporation of the learning sciences into the design and evaluation of LADs, there is a need for more rigorous examination of the existing dashboards from the perspective of specific theoretical models of learning. Given the overwhelming recognition of the role of LADs to support self-regulated learning, the current study was set out to scrutinize systematically the existing literature based on a well-known model of self-regulated learning.

B. Self-Regulated Learning and Feedback

Self-Regulated Learning (SRL) research aims to optimize learning skills by exploring cognitive and metacognitive processes that encompass several internal and external factors. Zimmerman defines self-regulated learning as "the process whereby students activate and sustain cognitions, behaviors, and affects, which are systematically oriented toward attainment of their goal" as cited by [19] (p. 465.). Several SRL models were proposed. Zimmerman developed several versions of SRL models based on socio-cognitive theory. Boekaerts' model was developed based on the role of goal and emotion [20]. Winne and Hadwin developed SRL model based on the Information Processing Theory [14]. Regardless of the difference foundation that built up the model, the proposed SRL models involve cognitive, metacognitive, motivational factors and goal that drive the learning process. In this study, we based our systematic literature review around Winne and Hadwin model, as the model has been broadly adopted in the computer supported learning [21], [22], the cognitive and metacognitive components were described in more details as compared to other models [21] and the role of external feedback was clearly highlighted in the model [15]. Winne and Hadwin [14] state that a self-regulated learning process involves four cyclical recursive phases including *task definition*, *goal setting and planning*, *enactment of tactics and strategies*, and *adaptation*. They highlight that within these four phases, five components are running recursively. These five components are conditions, operations, products, evaluation, and standards, to form the COPES model. Figure 1 illustrates the COPES model developed by [14].

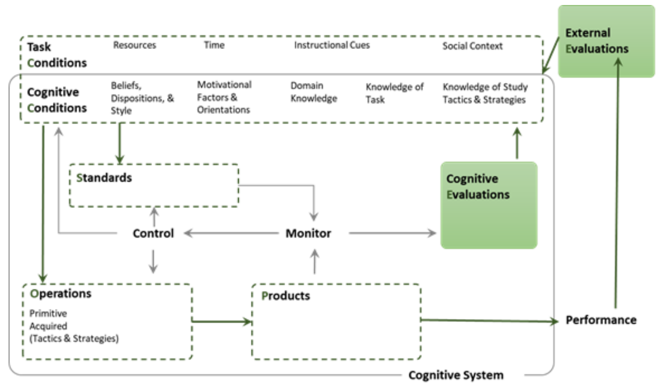

Fig. 1. Representation of the COPES model [14].

Learning tasks are designed to guide the learner to achieve a specific goal. Understanding the task definition is important as it will affect the selected learning strategies [23]. In the early phase of learning, learners define the tasks and set learning goals by considering several constraints. These constraints are referred as conditions in the COPES model. Condition can be internal ones such as knowledge of tasks, domain topics, learning tactics as well as motivational factors. External conditions can be resources available, learning environment, instructional cues and time constraints to complete a given task. Based on these conditions, students make judgements that drive setting goals, planning their learning, and setting expectations or standards. That is, according to Winne and Hadwin, goals can be considered as a vector of different standards learners will use for metacognitive monitoring (e.g., how long they expect to study to recall some information or how they will self-assess the coherence of the argument in their learning activities). Learners operate their learning by the learning strategies and tactics. As they progress with their learning, products of learning will be created (e.g., memory recall or essay). As the learning process unfolds, learners evaluate the learning products and learning processes with the standards they had set earlier. The evaluation can lead to the choice of new learning strategies, maintenance of the current learning strategies, or updating their standards and thus revising existing and setting new goals [14].

Supporting learners to regulate their learning requires understanding and incorporating the self-regulated learning process into the supporting system. Feedback is one of the crucial elements in any SRL processes. In the COPES model developed by [14] feedback occurs internally when learners evaluate their learning against the standards that define their goals. Whereas, external feedback could also be implemented and provided by instructors or other external agents. External feedback can confirm, add to, or alter the internal feedback perceived by students, which subsequently effects on the learning process [15]. However, [24] states that students are inaccurate in judging their performance. Students with good performance tend to underestimate their learning process whereas students with lower performance tend to overestimate it [24]. Moreover, Winne and Jamieson-Noel [25], [26] found that what students' self-report about own learning was not in accordance with their action. These misperceptions of the learning progress and performance can lead to selecting an ineffective or inadequate learning strategy [23]. Hence, external feedback, especially from teachers or learning technologies, could enhance the accuracy of judgments made by students regarding their progress and performance.

This systematic literature review is based on the assumption that LADs are a form of feedback that aims to equip learners to take control over their learning and thus better self-regulate their learning [27]. LADs can play a role of feedback for students and teachers. A conceptual model has recently been proposed to show how LADs can be used to "provide cognitive and behavioral process-oriented feedback to learners and teachers to support regulation of learning" [28] (p.1). LADs are also suggested to provide cues to support the evaluation on students' current state of self-regulated learning and progression towards their goals [29] . Other authors propose that the LADs have a potential to reduce negative affect, motivate students, and assist them to reflect on their self-regulated learning process [30]. Specifically, this review aims to examine the role of learning analytics as a form of feedback by using the COPES model proposed in [14].

III. Method

The process of the systematic review followed in this study is summarized in Figure 2. The review focused on the existing literature published between 2010 and 2017 until the time the search was completed (September 1st, 2017). By following guidelines proposed by Kitchenham & Charters [31], three steps were taken in order to conduct the systematic literature review and these steps were repeated twice during 2016 and 2017 to ensure that the relevant papers were included.

The first step in the systematic review was keyword search. Five main academic databases were selected: ACM Digital Library, IEEE, SpringerLink, Science Direct, and Wiley. Google Scholar was included as an additional database to detect other research resources. A total of 488 papers were obtained by running the query: dashboard AND ("learning analytics" OR "educational data mining" OR "educational data mining") (initial search in 2016 = 382 papers and revised search in 2017 = 488 papers). A total of 488 also includes top 100 papers from Google Scholar.

The second step was carried out to filter insufficient and irrelevant papers by screening paper titles, keywords, and abstracts to identify those that were describing LADs. Only papers related to LADs were included. Papers that were not written in English and papers containing less than 3 pages (e.g., posters) were excluded. As a result, 140 papers were selected (initial search in 2016 = 110 papers; revised search in 2017 = 140 papers).

Finally, papers that solely shared opinions, provided reviews or designs of dashboards, offered proposals or conceptual frameworks and the duplicate papers or preliminary versions of papers (conference papers compared to extended journal papers) were removed (unless they presented new and different aspects). Lastly, a total of 29 papers successfully passed all the inclusion criteria and were included in the final analysis.

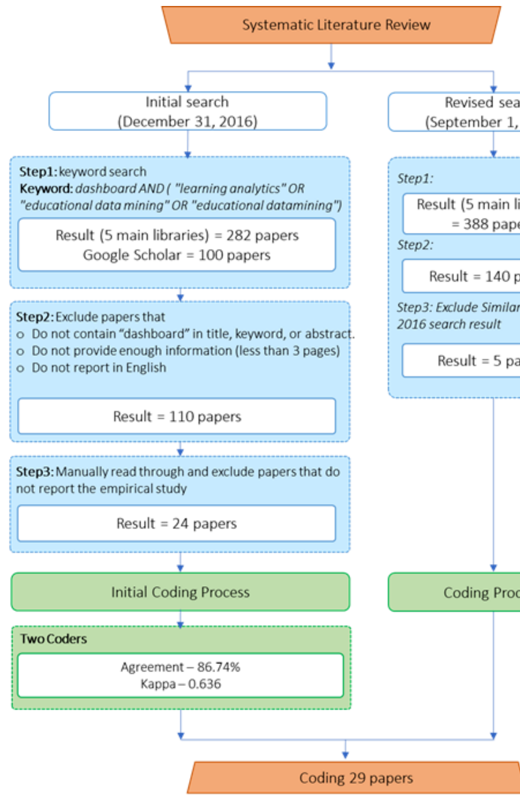

Fig. 2. Methodology used in this systematic literature review.

In the analysis, we also referred to the screenshots of dashboards presented in the papers to scrutinize the indicators presented in the dashboard. Then, we coded the papers according to several dimensions based on the three research questions as summarized in Table I. The papers were manually coded by two independent coders (the first two authors of the paper) and the coding process is detailed in the remainder of this section. Out of 822 coding items, the percent agreement between two coders was 86.74% and Cohen's Kappa = 0.64. All initial differences in coding were then discussed and reconciled. The results presented in the paper are based on the reconciled coding.

To answer the first research question, the study focused on whether the papers mentioned the theoretical or relevant models that were used to guide the choices of indicators that should be presented to the users. Furthermore, we also examined if the papers mentioned any educational theory used to guide the design and development of LAD. Then, each indicator described in the papers and presented in the figures/screenshots of the LADs was mapped to its corresponding elements of the COPES model. Table II presents the description of SRL constructs used in our analysis of the selected papers.

The indicators presented in the dashboards were retrieved from the results of each learning phases. Therefore, these indicators can be considered products of learning in each phase.

Hence, products in the COPES model were analyzed according the four phases of self-regulated learning as shown in Table III [14]. LADs aim at providing feedback for different purposes. We identified eight themes of feedback support (Table IV).

TABLE I
CODING DIMENSION USED FOR ANALYSIS OF LAD PAPERS FOR THE THREE RESEARCH QUESTIONS

Research Questions	Elements in Dashboard	Coding Category
1. What is the support of LADs for the elements of self-regulated learning as established in the learning sciences?	Indicators Selection Methods	Method used in selection of the indicators in dashboards (based on previous work/Users centered design)
	Theory Reference	Mention of theory on the selection of indicators in dashboards (Yes/No)
	Indicators in the dashboards	SRL constructs and Items (Conditions, Operations, Products, Evaluations, Standard)
	Learning Phases	4 Learning phases according to COPES model (Refer to Table III)
	Theme of Dashboard	Theme of dashboard (Refer to Table IV)
2. What type of information is offered as feedback in LADs?	Reference frames	Social Norm (individual viewing and average class comparison)
	Types of visualization	Type of chart used
3. What is the quality of study designs and reporting the literature that reports on empirical evaluations of LADs?	Target users	Stakeholders (student, teacher, administrator, designer)
	Participants demographics	Participants (Expert, Student, and number of participants)
	Evaluation method described	Evaluation instruments used
	Quality of study reporting	Assessment based on a 12 questionnaire for research quality appraisal

The analysis of information presented in LADs as asked in research question 2 looked at two key dimensions. First, it examined the extent to which different reference frames were supported in LADs [18]. Similar to the approach followed by Jivet and her colleagues, references frames included individual (self) and social (average comparison and course-wide including the provision all information available about other users and environment) as follows: a) individual – students can only see their own individuals' activities; b) average comparison (social) – students are provided with the average comparison against their peers, classmates or course mates; c) course-wide information (social) – all information is available to all target users.

Quality of study design and reporting was assessed by using the instrument for appraisal of empirical research specifically developed for this study, given that there is no generally accepted instrument for assessment of empirical research in education or educational technology. The instrument used in this study was informed by the MERSQI (Medical Education Research Study Quality Instrument) instrument [32] and the coding scheme used in [33]. The MERSQI instrument is a 10-item coding instrument often used to evaluate the quality of the research studies in the medical field, focusing primarily on the quality of double-blind clinical trials.

TABLE II
DESCRIPTION OF THE SRL CONSTRUCT AND ITEMS BASED ON THE COPES MODEL

SRL Construct	Items	Description	Example of the indicator(s)
Task Condition	Resource	Indicators that show the available resources or learning materials	List of course and relevant competency
	Instructional Cues	Indicators that represent the structure of the courses or learning materials	Student's weekly workload; Structure of learning environment (e-book); Learning Concept
	Time	Time available; ability of student to manage the time	Students' time divided among learning space (face-to-face & online); Time utilization
	Social Context	Indicators that are related to group participation, collaboration, connections, students' interaction with teacher, or role of students in learning environment	Roles adapted by learner from discussion (using Classification); Collaboration
Cognitive Condition	Domain Knowledge	Indicators that represent the knowledge of student in certain topic or learning performance	Quality of post in discussion board; Scores
	Beliefs, Dispositions, & Style	Indicators that represent the student's beliefs, disposition and learning style	Deep/surface learning; Result of writing habit by a single student
	Motivational Factors & Orientations	Indicators that aim to motivate learning; such as by using of badges and awards	Achievement badges and details; Total stars earned
	Knowledge of Task	Indicators that represent the task related knowledge	Task Value
	Knowledge of Study Tactics & Strategies	Indicators that represent the tactics of study	Remediation
Operation	Primitive	Indicators that represent actions of students in learning environment e.g. numbers of video watched	Group progress in their task; Assignment Progress; Total no. of comments; Total no. of tweet
	Acquired (tactics & Strategies)	Indicators that indicate if students had achieved the specific learning skills	Average skill mastery plotted against average amount of practice
Product	-	The result of the operations; coded based on learning phases	-
Evaluation	-	Indicators that indicate if student had achieved their target outcome	-
Standard	-	Indicators that specify the student's target outcome	-

Similarly, the instrument from [33] focuses on assessing the methodological quality of the studies that compared distance education (DE) and face-to-face (F2F) education. The [33] instrument includes 13 items that focus on the quality of reporting of statistical results and equality of comparison groups (e.g., did DE and F2F conditions have the same instructional approach, same instructors, and assessment instruments). The final instrument used in this study included 13 questions, which are shown in Figure 11. The responses to each of the questions were “Yes” indicating some presence of the dimensions of the study design and report in the papers, and “No” indicating the total of the discussion or indicators pertaining to the dimensions analyzed.

TABLE III
PHASES OF SELF-REGULATED LEARNING BASED ON THE COPES MODEL

Learning phases	Description	Example of Indicator(s)
Phase 1: Task identification	Indicators that present information to guide students on their learning tasks	Grading criteria; Student’s weekly workload;
Phase 2: Goal setting and planning	Indicators that represent the goal of learning activities and conditions that are relevant to learning strategies selections	Goal on table
Phase 3: Enactment of learning strategies and study tactics	Indicators that represent the actual behaviors and interactions of students	Group progress in their task; Level of engagement with videos;
Phase 4: Adaptation	Indicators that represent the continuation of certain learning strategies (maintain of action) or changing of learning strategies over time	Most spent timing website; Result of writing habit by single student;

TABLE IV
THEMES FOR WHICH LADS ARE USED

Theme	Description
Competency	Any dashboards that aim to track competency development progress (set of knowledge or skills that students are required to achieve)
Emotions	Any dashboards that track students’ emotions while learning
Game-based learning	Any dashboards that track learning activities retrieved from informal game-based learning system
Learning progress	Any dashboards that track learning activities retrieved from formal face-to-face, blended or online learning context
Learning design	Any dashboards that track the activities in the course design process
Learning difficulty detection	Any dashboards that were developed to detect students who diagnose with learning difficulty
Study plan	Any dashboards that were developed to assist the students and/or study advisers to plan their learning for a given period (semester)
Teamwork progress	Any dashboards that track students’ learning activities in group-based learning

IV. RESULTS

In this section, we present the results of the article review according to the three research questions. Figure 3 shows that there has been a steady increase in the number of empirical evaluations on LADs over past few years. The amount of empirical publications on the LADs research peaked during 2016. Meanwhile, the number slightly declined in 2017. Note that, the search conducted in September 2017 and the amount of empirical publications on the LADs research is likely to increase during the final quarter of year 2017. Appendix C provides summary of the research studies included in this systematic literature review.

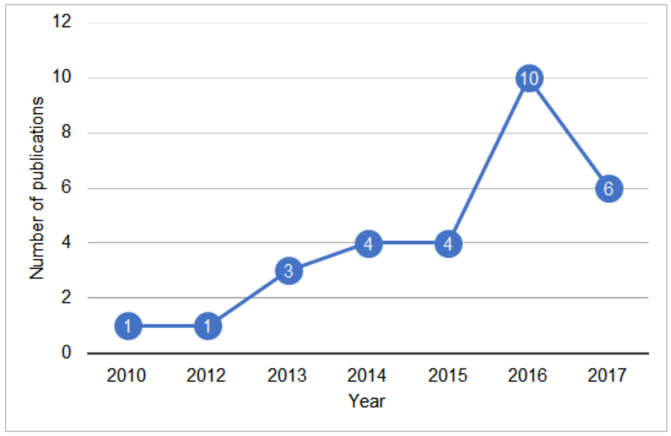

Fig. 3. Publications included in this review according to years of publication.

A. *RQ1: Support of LADs for the Elements of Self-Regulated Learning*

1) *Indicator*

An indicator represented the state or level of a student’s actions and performance. Selection of indicators is recognised as one of the most important steps in the design of LADs as dashboard provides users with the feedback via the selected indicators. Figure 4 presents the sources and the approaches used for the selection of indicators as reported in papers included in this study.

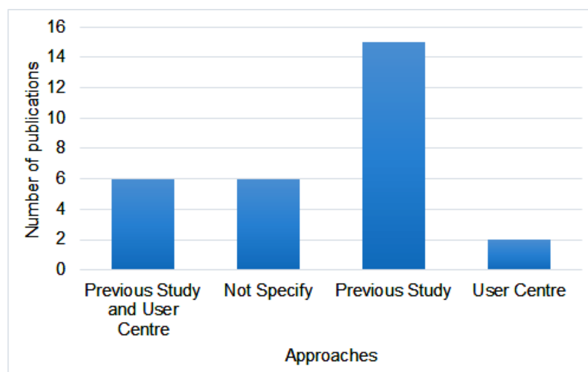

Fig. 4. Indicators selection approaches used in the design of LADs.

Two main approaches were followed: referring to the previously published papers and/or following user centered design. A total of 52% of the included papers mentioned that they solely selected the indicators based on the previously published works. A total of 20% of the included papers referred to previously published papers and in combination with user-centered design to select which indicators should be presented. A small number of the papers (7%) relied on the users’ input alone in the selection of the indicators. Whereas, 21% did not provide any justification on how the indicators were selected.

2) *Theory and Learning Model Application*

A main criticism of the literature on LADs is that many of them do not have grounding in a sound theoretical foundation

[5], [34]. Thus, this review looked at the theory or related learning model referenced in the papers as sources that informed the design of LADs. Table V provides details of educational or pedagogical models used in each category. Despite the importance of educational theory, most of the LADs were not grounded in any established educational theories (69 percent). Open Learner Models (OLMs) were used by three research papers [31], [32], [33]. OLMs present to students the information such as knowledge, preferences, and skills which previously were not available to the student. This information is often extracted and computed by an analytic algorithm [35]. OLMs have been used by many systems with the proposition that by unveiling this information through OLMs to students, students can improve their awareness and reflection on their learning [36]. Florian-Gaviria et al. [37] and Mejia et al. [36] incorporated OLMs with activity theory [38] to develop a framework that was used for the design of LADs.

Two dashboards were developed to detect the emotion of learners with the assumption that emotion impacts learning. The TEA model was proposed by [39] which was informed by the work of Pekrun, Goetz, Frenzel, Barchfeld, & Perry [40] and Arroyo et al. [41]. The TEA model defines six positive emotions and six negative emotions that affect learning. Based on the TEA model, a self-report instrument was developed to track students' emotion according to teachers' defined events [39]. The data collected in this way were then presented to learners in the dashboard. Another study that emphasized emotion tracking was carried out by Ez-zaouia & Lavou [42]. They stated that two most commonly used theoretical viewpoints for consideration of emotions are discrete and dimensional. To capture discrete and dimensional emotions, the Automatic Emotion Recognition process (AER) based on facial expression and voice recognition was used in combination with self-reported data and trace data to automate detection of students' emotion and shown the results in a LAD.

Theories of achievement goal orientation and motivation are also used in the papers included in this literature review. Beheshitha, Hatala, Gašević, & Joksimović [43] developed three LADs that promoted participation in online discussions by considering achievement goal orientations (AGO) of students. Self-reported measures of AGOs were used to explore the association among three different LADs, individual differences, and learning behavior. Broos, Peeters, Verbert, & Soom [44] employed an extensively and widely used Learning and Study Strategies Inventory (LASSI) questionnaire [45] to capture students' learning skills and motivation in order to present feedback and recommendations to support the development of learning skills. The dashboard was focused on five out of ten scales that were detected from the LASSI instrument including performance anxiety, concentration, motivation, the use of test strategies, and time management.

The fully-embedded assessment model (FEAM) was developed by Capella University to measure students' competency development [46]. The FEAM identified a set of learning goals and grading criteria. The dashboard was then developed according to FEAM to offer feedback to students. Tarmazdi, Vivian, Szabo, Falkner, & Falkner [47] relied on Dickinson and McIntryre's [48] teamwork model to capture the role and emotion of students working in a group. Dickinson and McIntryre's [48] identified seven core components of teamwork based on practical teamwork including team leadership, team orientation, monitoring, coordination, communication, feedback and backup behavior. The measurement of these core components was based on how the team responded to the critical events according to the seven core components.

TABLE V
EDUCATIONAL THEORIES AND MODELS USED TO DERIVE THE DEVELOPMENT OF THE LADS

Related learning model used in the design and development of dashboard		Number of papers
No	Not specified	20
Open Learner Model (OLM)	Open Learner Model (OLM)	1 [35]
	Open Learner Model; Activity-based Learner-Model (Engeström's Activity Theory and Actuator-Indicator Model)	2 [36], [37]
Emotion	The TEA Model (TEAM)	1 [39]
	Discrete and dimensional emotions theories by using Automatic Emotion Recognition process (AER)	1 [42]
Motivation and Goal Orientation	Goal Orientation	1 [43]
	Learning and Study Strategies Inventory (LASSI)	1 [44]
Competency	Fully-Embedded Assessment Model (FEAM)	1 [46]
Teamwork	Dickinson and McIntryre's teamwork model	1 [47]

3) Indicators and SRL Constructs

Since no paper explicitly considered SRL theories in the design of LADs, the current study coded the indicators presented in the papers based on the descriptions of the dashboards provided in the papers (including screenshots) according to the elements of the COPES model (Tables 2 and 3). There was a total of 266 individual indicators from the 29 dashboards presented in the 29 papers. A majority of indicators represented Cognitive Conditions and Operations as shown in Table VI. The indicators related to Operations – Primitive (66 indicators) indicated actions such as a number of log-ins, number of message posts, and number of questions answered. However, there was no indicator representing the skills or tactics acquired by students. A total of 74 indicators represented domain knowledge as part of learners' cognitive conditions. These indicators were test or exam scores, correctly completed exercises, or quality of message posts. A total of 80 indicators represented motivational factors. Most of these indicators were based on the use of badges to create game-based learning such as a number of badges earned or level of participants in games. Other types of SRL constructs were relatively low. Six indicators represented beliefs, dispositions, and styles, one indicator represented the knowledge of study tactics, and one displayed the knowledge of tasks.

Task conditions in the Winne and Hadwin model of SRL indicate the constraints in external conditions (e.g., group task or open book exam). Only 16 indicators were about task conditions, of which 10 indicators represented time utilization, five indicators reported about social context, and one indicator addressed the resources available. Based on our review, two elements of the COPES model were completely missing in the papers describing LADs, namely standards and evaluation.

TABLE VI
INDICATORS REPRESENT BASED ON THE CORRESPONDING LEARNING PHASES AND SRL CONSTRUCT

COPES Model	Item in COPES	Learning Phase					Total Number of indicators
		Phase 1	Phase 2	Phase 3	Phase 4	Not Related	
Cognitive Conditions	Beliefs, Dispositions, & Styles	2		1	3		6
	Domain Knowledge	19		53	2		74
	Knowledge of Study Tactics & Strategies	1					1
	Knowledge of Task	1					1
	Motivational Factors & Orientations	24	2	54			80
Task Conditions	Instructional Cues	11		5			16
	Resource	1					1
	Social Context			5			5
	Time	2		8			10
Operations	Primitive			63	3		66
	Acquire (Tactics & Strategies)						0
Others	Demographic Information					6	6

4) Indicators and Self-Regulation Phases

We coded the indicators present in the LADs based on the four phases of self-regulated learning of the Hadwin and Winne model (Table III). Table VI presents the cross-tabulation of the numbers of indicators according to the COPES elements and the phases of self-regulated learning.

Phase 1 – Task identification: In this stage, students develop their perceptions and understanding of what tasks need to be done [14]. The indicators in this phase represent the constraints and conditions of their learning such as grading criteria, previous learning difficulty, previous grades, and successful rate of previous year's students. Based on this literature review, the indicators at this stage focused on the task conditions and cognitive conditions. Other elements in COPES model were absent. Cognitive condition primarily included domain knowledge along with motivational factors and goal orientations (19 and 24 indicators, respectively). Knowledge of study tactics and strategies [49] and knowledge of task [44] each had only one indicator in the reviewed dashboards. Knowledge of study tactics and strategies was represented by the indicator that was called the 'level of test strategies usage (respective norm scales) of a student' and knowledge of task was presented by indicator called 'task value'. Instructional cues were the most represented indicators in task conditions (11 indicators). Task conditions were represented by two indicators of time: i) the level of time management (respective norm scales) of a student and prediction of academic year based on historical data; and ii) resources had one indicator, which offered information about dynamic question text editing and indexing.

Phase 2 – Goal setting and planning: In this stage, students set goals for their learning, select learning strategies, and create a plan to achieve their target. There were only two indicators that represented the COPES elements in phase 2. These two indicators were related to goals which fall under cognitive conditions - motivational factors and goal orientation – in the COPES model [49], [50].

Phase 3 – Enactment of learning strategies: Most of the learning activities occur during this phase where students enact the learning strategies that they have selected in phase 2 [14]. The most frequently presented indicators were operations – primitive (63 indicators); cognitive conditions – domain knowledge (53 indicators) and motivational factors and orientation (54 indicators). Whereas, knowledge of tasks, resources, and tactics and strategies that students acquired were completely absent in the dashboards presented in the papers included in this study.

Phase 4 – Adaptation: Adaptation refers to a large-scale adjustment of students' learning behavior based on the performance of metacognitive monitoring and control. There are generally two types of adaptation – i) adaptation of learning strategies, and ii) updating standards that constitute goals set in phase 2. The changes of standards can also affect students' motivation, and self-efficacy, belief, or disposition. The indicators of operations from the COPES model related to phase 4 were focused on primitive operations. Examples of such indicators included the most frequently visited sites and most frequently active documents (three indicators). Cognitive conditions were represented by indicators of domain knowledge including 'reflection on mastery level' and 'competency achieved'. No other elements of the COPES model were present in the dashboards to support phase 4 of the Winne and Hadwin model.

TABLE VII
INDICATORS BASED ON THE THEME OF DASHBOARDS AND THE CORRESPONDING COPES ELEMENTS

OPES Model	Item in COPES	Theme of the dashboard							
		Competency (2 LADs)	Emotion (2 LADs)	Game-Based (2 LADs)	Learning Design (1 LAD)	Learning Difficulty Detection (1 LAD)	Learning Progress (18 LADs)	Study Plan (2 LADs)	Teamwork Progress (1 LAD)
nitive ditions	Beliefs, Dispositions, & Styles					3	1	2	
	Domain Knowledge	5		6		10	35	18	
	Knowledge of Study Tactics & Strategies							1	
	Knowledge of Task						1		
	Motivational Factors & Orientations	7	23	14			13	21	2
ditions	Instructional Cues	2			4		2	8	
	Resource				1				
	Social Context						3		2
	Time						8	2	
rations	Primitive	1	3	9			53		
	Acquire (Tactics & Strategies)								
ers	Demographic Information					5	1		

5) Theme and SRL Constructs

We categorized 29 dashboards according to the themes of the dashboards as described earlier in Table IV. As shown in Table VII, a large number of the dashboards tracked students' learning progress in face-to-face, online and blended learning environments (18 papers).

Other themes of dashboards that were captured in this study were competency tracking [35], [46], game-based learning [51], [52], emotion tracking [39], [42], and study planning [44], [53] (two dashboards in each theme) while learning difficulty detection [36], teamwork progress tracking [47] and learning design tracking [54] were supported by a single dashboard in each case.

Competency: Two dashboards were developed to track the competency development of students [35], [46]. The indicators presented in the competency tracking dashboards focused on cognitive conditions – domain knowledge and motivational factors and orientations (five and seven indicators, respectively). For cognitive conditions, domain knowledge related indicators focused on grade and performance. Similarly, as part of cognitive conditions, motivational factors and orientations related indicators represented the ranking (based on the course completion and performance) of individual students against the peer and course. That is, they were primarily focused on social reference frames [11]. Task conditions highlighted instructional cues by using grading criteria and lists of relevant competencies. Only one primitive operation was tracked in this type of the dashboards and it was about the progress on assignments.

Emotion: The dashboards that tracked emotions [39], [42] mostly used the indicators fell under the category of cognitive conditions – motivational factors and orientations (23 indicators). Some of the primitive operation were also presented in the dashboards such as learner's audio record or facial expression during a certain learning period (three indicators). Other types of indicators from the Winne and Hadwin model were not used in the dashboards included in the review.

Game-based learning: Most of the game-based dashboards [51], [52] used badges with the aim to motivate students (14 indicators). Cognitive conditions focused on domain knowledge through the use of indicators like the level of achievement in certain rounds of games (six indicators). Operation were primitive and included indicators such as total number of activities and total number of badges awarded to the class (nine indicators).

Learning Progress: There were 18 dashboards which fell under the learning progress tracking theme. A variety of feedback types were provided to users. The most common indicators represented information about primitive operations such as number of logins, posts, or tweets (53 indicators). The second most frequently provided information to students was about domain knowledge (35 indicators). Cognitive condition was represented by motivational factors and goal orientations through 13 indicators. Task conditions were highlighted by a small number of indicators, including eight indicators about time – time spent on course site, time spent on different kinds of activities, time before the first attempt, and time of submission of before a deadline [57], [58], [59] whereas three indicators showed social context – collaboration and communication [49] and two indicators represented instructional cues – feedback on overall performance and recent behavior and behavioral activities [30], [58]**.**

Learning Design: A single dashboard that captured the activities of students to inform teachers' design of courses included the information such as concept connections [54]. Four indicators about instructional cues (i.e., concept count, concept connections, correct answer indication, and question marks assignment) and one about resources (i.e., dynamic question text editing and indexing) were presented in the dashboard.

Learning Difficulty Detection: The learning difficulty detection dashboard [36] only displayed information on domain knowledge (i.e., the previous diagnosis of learning disabilities, the number of associated difficulties with reading) and belief, disposition and styles (the result of writing habit by a single student and the result for a single student with learning style: active, sensory, visual and sequential) with ten and three indicators respectively. Beliefs, dispositions, and styles were represented by using indicators that reflect learning styles and were collected with self-reporting instruments.

Study Plan: This type of dashboard aims to help the study advisers and students to plan learning and course enrolments [44], [53]. Of cognitive conditions, motivational factors and goal orientation as well as domain knowledge were the most frequently presented indicators for this type of dashboard (21 and 18 indicators, respectively). Other types of cognitive conditions were observed such as two indicators of beliefs, dispositions and styles and one indicator represented knowledge of study tactics and strategies [44]. Task conditions were observed through the indicators that represented instructional cues and time condition (eight and two indicators, respectively).

Teamwork Progress: The teamwork dashboard [47] provided information about the role played by a student in a group learning activity (i.e., two indicators represented social context within task conditions) and one emotions of team members (i.e., two indicators represented motivational factors and orientations within cognitive conditions).

B. RQ2: Types of Information Offered as Feedback

1) Types of Reference Frames

Types of reference frames used in LADs are presented in Figure 5. Some dashboards were designed for several target user groups. Therefore, the retrieved indicators were counted independently for each target user group.

Most of the indicators represented the individual-related learning activities (80 indicators from students' dashboards, 81 indicators from teachers' dashboards, and seven from others' type of users' dashboard). The dashboards that were designed for students provided with the average comparison (so called social reference frames) against their peers and class (31 and 32 indicators, respectively) while there was only one indicator that presented the students against the top performers.

Course-wide information indicators allow users to view all the information available in a learning analytics system. Most of the dashboards in this dashboard type were designed for teachers who can view a whole class's related information (33 indicators) [52], [55], [57], [59], [60]. The dashboards that were developed to track team progress also presented all information to all students in a given team as well as some of the indicators that aimed to display levels of achievement to motivate the students and help them plan their learning (17 indicators) [50], [51], [52]. A dashboard that was developed to track the design of exam questions displayed the structure of each exam questions to teachers (five indicators) [54]. Two study plan tracking dashboards also offered some course-wide information such as the success rate of those who previously took the course (17 indicators from students' dashboards; 11 from teachers' dashboards, and 14 from other users' dashboards) [44], [53].

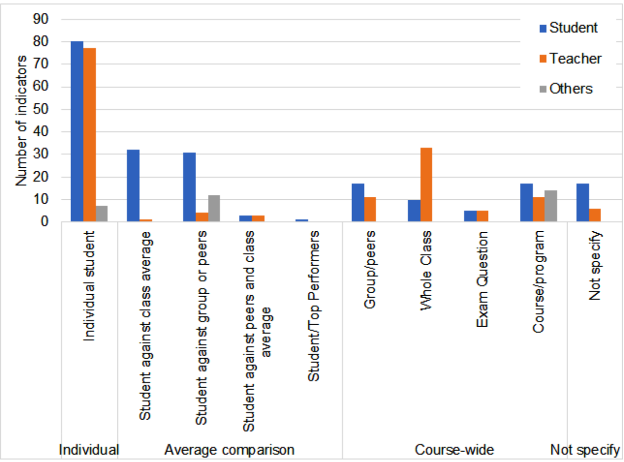

Fig. 5. Type of reference frames used in LADs for each target user group.

Data representation is another debated issues in LADs. Based on our research, common graphs used to represent data was bar chart as presented in Figure 6. The use of simple visualizations aims to aid students in interpreting the result. However, some research reports that students face a problem in interpreting graphs available in contemporary dashboards [61], [62]. Similarly, Corrin, Kennedy, & Mulder [63] stress the concern of teachers regarding the ability of students to interpret the feedback presented in dashboard. Yet, there have been few empirical studies to inform on the selection of visual display to represent the identified indicators in the dashboard and the influence of these representation on students' level of understanding and motivation (if any) of feedback [4].

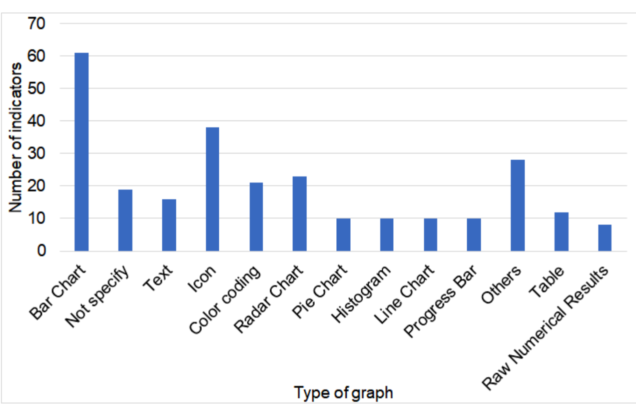

Fig. 6. Visualization Type.

C. *RQ3: Quality of Study Design and Reporting*

1) *Participants*

Figure 7 illustrates the dashboards' target users. Based on the 29 dashboards described in the papers, the main target users were students (22 dashboards in total) and teachers (18 dashboards in total). Among these, some dashboards were designed to be viewed by both teachers and student (10 dashboards). Other audiences of dashboards were administrators, other faculty members, study advisers, and designers (three dashboards in total).

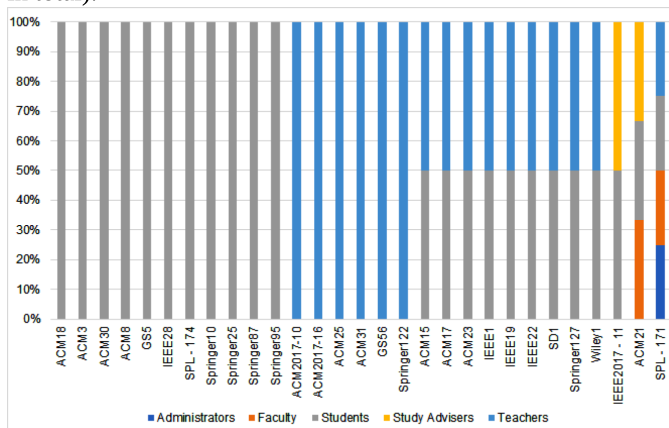

Fig. 7. Target user of LADs.

Based on 29 papers, the number of participants involved in each study varied, range from one to more than 500 participants. Figure 8 presents the number of participants involved during the empirical studies.

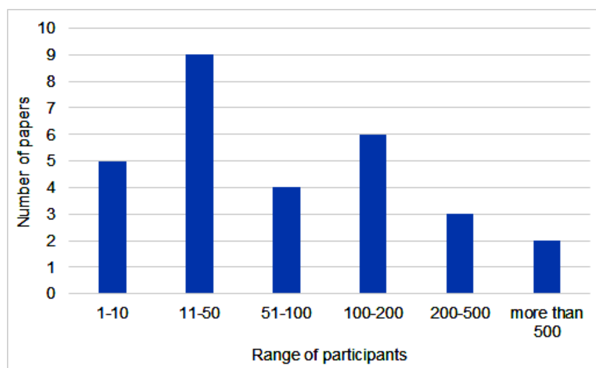

Fig. 8. Range of participants.

Five papers involved between one to ten participants. Nine papers included participants between 11 to 50 persons. Four papers reported the number of participants from 51 to 100 and 11 papers included more than 100 participants. Based on the different numbers of participants, we further explored if the participants referred to students or experts. Experts in this context refer to both teachers and other audiences such as learning/course designers and study advisers.

Figure 9 shows the percentage of students and experts participated in LAD evaluation. Most of the papers included students in their studies (20 studies). There were nine papers that involved experts alone in their studies. Four papers included both experts and students in their studies.

2) *Course Demographics*

Most of the papers reported that students were from a single course in their studies (12 papers). Another group of papers (11) reported that students were from two to five courses. Four papers reported that their participants were from diverse background courses and two papers did not report the academic context in which their evaluations took place. The courses were diverse and a majority of them were computer science and engineering related courses such as C programming, human-computer interaction, and object-oriented programming. Other courses included Japanese, law, psychology, and Chinese literature.

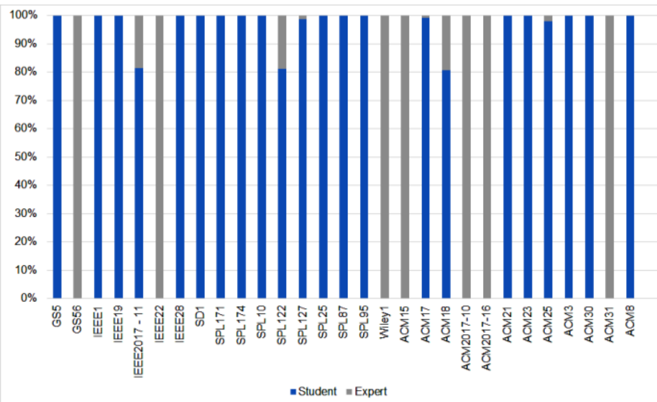

Fig. 9. Participants included in each study.

3) *Data Collection Approaches*

The approaches used to gather data varied. Figure 10 shows the methodology used by each paper. Most of the papers used more than one instrument to gather the required data. The main approaches that had been used to gather data were questionnaires, trace data, and interviews (19, 12 and 8 papers, respectively). The evaluation of LADs was based on usability studies mostly and self-report instruments. There was a lack of solid evidence in terms of observational data in real class setting on how LADs, as a form of feedback provision, influenced behavioral change, learning strategy, and learning performance.

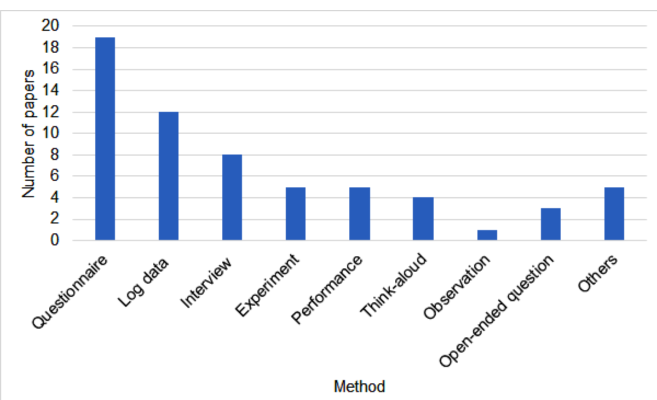

Fig. 10. Research approaches used for data collection.

4) *Quality of Study Designs and Reporting*

Figure 11 shows the results of the quality of study design and reporting as presented in the papers to evaluate the impact of LADs. The analysis showed that less than half of the studies (11 papers) reported limitations. We also observed that there was no discussion on the generalizability derived from any of the studies. However, slightly more than half of the studies interpreted the results with respect to the current literature (16 papers). Just under a half of the studies (14) studies discussed implications for research and 20 studies addressed some implication for practice. Only five studies reported the use of experimental study designs that involved the use of control and treatment groups. The use of quantitative research based were reported by 17 studies. The main methods of data collection were questionnaires as highlighted earlier in the paper. Most of the research studies (19 studies) provided some description of the courses in which the evaluations were conducted and clearly stated the number of participants involve in the studies. However, the demographics of participants were not stated by many research studies (only 13 studies reported the demographics of participants). Besides quantitative methods, there were four papers that solely employed qualitative methods in their studies which involved collecting data from interview (2 studies), interview and think-aloud protocols (1 studies) and case studies (1 study). In addition, there were only eight research papers conducting and reporting on mixed methods studies (combination of qualitative and quantitative research methods). The most common mixed method research designs were a combination of surveys and interviews (4 studies) followed by survey and think-aloud protocol (1 study), survey and focus group (1 study), survey and log data (1 study) and log data and interview (1 study).

V. Discussion

Based on the insights obtained from this systematic literature review, we highlight four dimensions that should be considered when researching and developing user-centered learning analytics systems. These dimensions include theory, design, feedback, and evaluation. These dimensions are included in the model for user-centered learning analytics systems (MULAS) (Figure 12). The model assumes the cyclical and recursive nature of the four dimensions. Each of the four dimensions is discussed in the remainder of the section.

At the core of MULAS is the recommendation that future research and development should make any a priori design decisions about representation of data and analytics results in learning analytics systems such as LADs. Instead, the focus should be on developing user-centered learning analytics systems with the emphasis to support users with learning analytics to accomplish set tasks in the most effect way. Therefore, the reminder of the discussion section draws recommendations for user-centered learning analytics systems as a class of systems that subsumes LADs.

A. *Theory*

The most striking finding of this study is that a great majority of the existing dashboards (68%) are atheoretical in their choices of indicators and content to be shown in Table VI. The arguments for the importance of theory and the use of learning sciences for informing learning analytics have already been made by several researchers [2], [5], [28], [34], [64]. In a nutshell, without building on what is already known about learning and teaching and instead, using design- or data-driven approaches will likely result in ineffective or even deteriorating effects on learning. Unsurprisingly, several authors have already reported negative effects of existing LADs on learning [6], [65], [66]. Possible reasons for this can be derived from the results of this study that analyzed the existing learning dashboards against a well-known theoretical model of self-regulated learning [14]. The analysis against the COPES models revealed that the existing LADs did not support knowledge of learning strategies and tactics, and knowledge of tasks under cognitive conditions, acquisition of learning tactics and strategies under operations, and standards and evaluation. Failing to capture knowledge of and operations associated with learning tactics and strategies makes it hard if not impossible to understand and optimize learning; understanding and optimization of learning are the ultimate purposes of learning analytics [67].

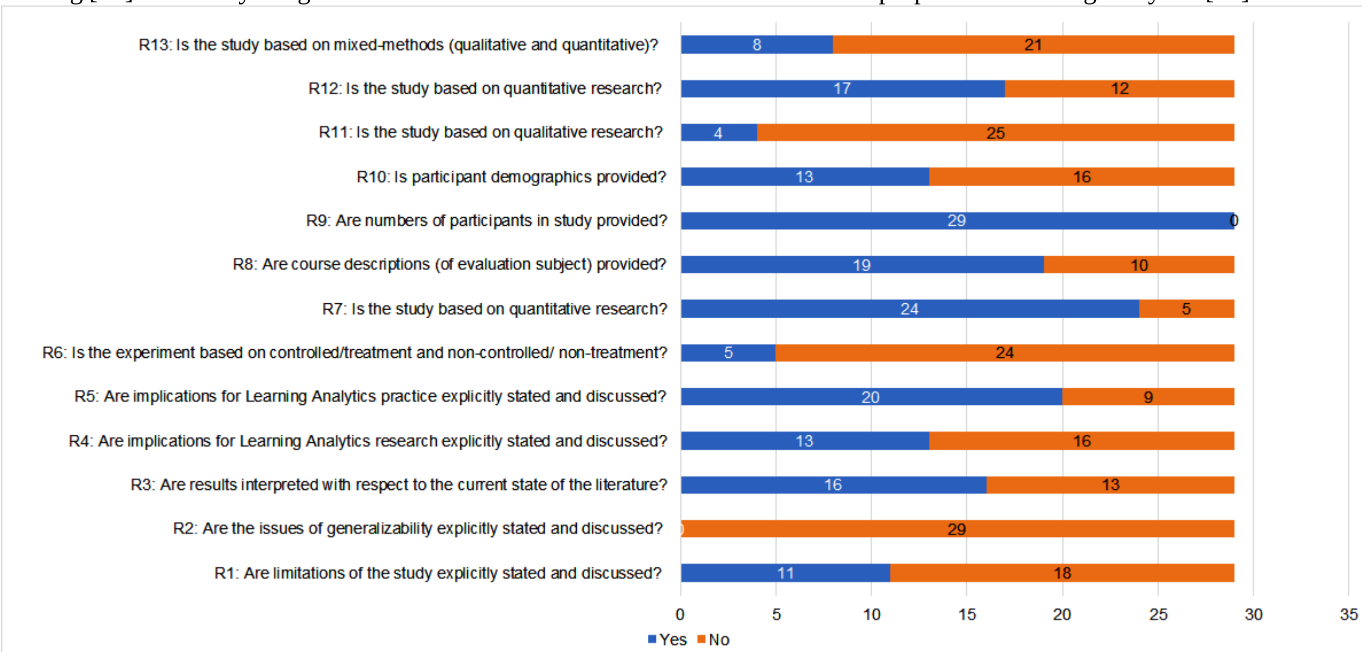

Fig. 11. Quality of reporting of the empirical studies with LADs.

Current educational psychology research indicates that learners use suboptimal learning tactics and strategies and many are even unaware of the effective study tactics (e.g., self-testing and spaced learning significantly enhance memory retention in comparison to reading and rereading) [24], [68]. Just informing learners of the benefits of some of the effective tactics and strategies significantly increases the chances of learners to adopt them in their learning [69], [70]. Therefore, LADs are likely to be less effective if they are ignorant of what learning tactics and strategies learners follow, and if they do not increase their awareness and offer recommendations for more optimal approaches. The recent approaches to mining tactic and strategy from trace data [73], [74], [75] are highly promising for the future work on user-centered learning analytics systems. The important next step for research is to find the right mechanisms to communicate the learning tactics and strategies discovered with data mining to learners and educators along with some recommendations on how to optimize the learning process.

Capturing knowledge of tasks is as important as knowledge of learning strategies and tactics. Awareness of the benefits of a tactic or strategy is not sufficient for the learners to adopt the tactic or strategy for a given task. Winne [74] suggests this steams from the fact that learners need to be aware that the tactic or strategy is beneficial in a context different from the original context in which the learners experienced the use of the tactic or strategy [75]. Therefore, for dashboards to unlock the full potential of learning analytics, they need to incorporate indicators of knowledge of tasks the learners are working on. This clearly indicates a need for building long-term learner profiles that gradually capture knowledge of tasks over time. Ideally, learner profiles that underlie user-centered learning analytics systems will go beyond a single learning context (e.g., course) and capture longitudinal changes in knowledge of tasks and knowledge of learning tactics and strategies. Even if a potential cold start problem may exist (e.g., enrolment into a university), learner profiles can still gradually be built as the students are progressing in their learning. Given the wealth of experience in building and using learning profiles, developers of user-centered learning analytics systems should pay close attention to the research done on open learner modelling [13].

The total absence of support for standards and evaluation from the COPES model in contemporary LADs has several negative consequences. First, standards are used by learners to evaluate the products of their learning and the choices of their study strategies. If standards and evaluation are not supported, it is very unlikely that metacognitive monitoring and control support can effectively be supported too [14], [76]. Therefore, we question whether the choice of terminology used in the previous reviews of LADs [10], [11] can be considered adequate considering the lack of evidence found to support the references to metacognition. Second, standards underlie the definition of goals learners set according to the Winne and Hadwin model of SRL. Unsurprisingly, no support for standards in LADs was also associated with no support for phase 2 (goal setting) of the Winne and Hadwin [14] model of SRL. Likewise, no support for standards and evaluation led to rather limited support for phase 4 (adaptation) of the Winne and Hadwin model of SRL. Phase 4 is where metacognition is fully exercised in terms of the choices of learning tactics and strategies upon evaluating learning progression against standards encoded in learning goals. Given that our findings identified no support for acquisition of learning tactics and strategies, the potential of support for phase 4 is additionally limited. Therefore, future research and practice on user-centered learning analytics systems should prioritize the incorporation of indicators of standards and evaluation from the COPES model if the intention is to inform and enhance decisions of self-regulated learners, especially if the goal is to scaffold and enhance goal setting and adaptation.

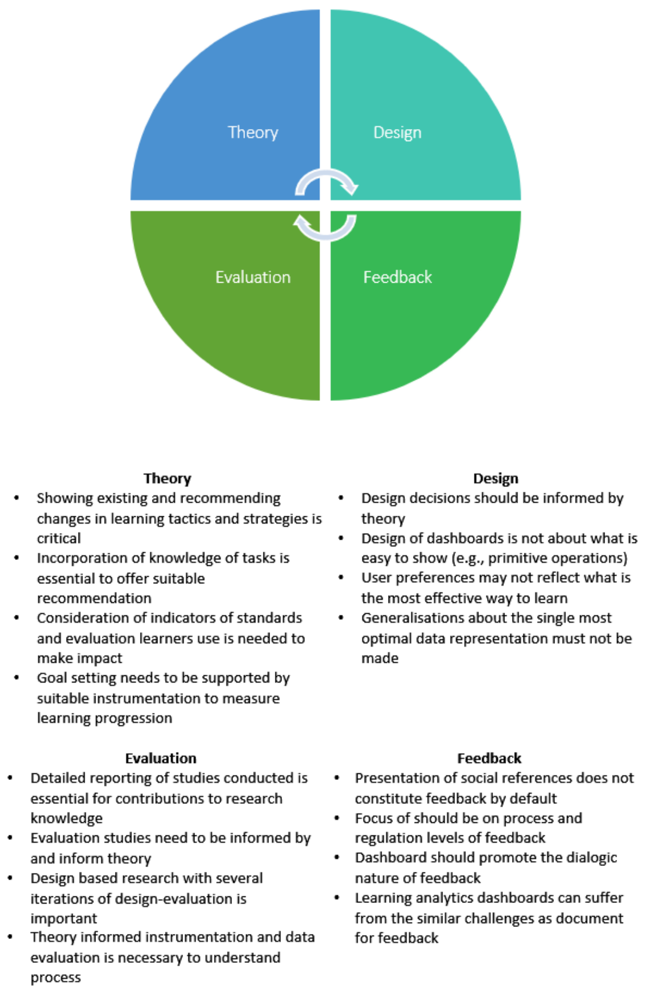

Fig. 12. Model for development, research and evaluation of LADs (MLAD).

It is difficult to capture indicators of standards and evaluation from the COPES models given that learning is driven by many internal and dynamic feedback loops [15]. Providing students with the features in learning environments and/or LADs to set their learning goals is a promising direction that can be used to capture standards of the student. However, goal setting functionality needs to be connected with a data collection mechanism that can track whether learners are working effectively towards their goals and how effectively they evaluate the products of their learning and choices of learning tactics and strategies. For example, Santos, Govaerts, Verbert, & Duval [50] presented a goal-oriented dashboard which allowed students to keep track if the learning goals had been achieved. Yet, their dashboard did not provide any mechanism for detailed collection of data that are related to standards based on which students evaluated their learning products and learning processes. That is, the presence of a goal setting functionality is not sufficient without the presence of a detailed instrumentation of the learning environments to collect data that can be used as feedback for a) enhancing students' evaluation against standards they set in the goals and b) informing the choices of study tactics and strategies. A promising example how user-centered learning analytics systems can benefit from more granular data that can support metacognitive monitoring and control is proposed by Marzouk et al. [77]. Marzouk et al. discussed the six scenarios in which user-centered learning analytics systems are informed by the learning sciences. One of their scenarios suggested goals should be presented in terms of indicators that promote the use of proven study tactics – note taking, summarization, and highlighting [24], [75]. Moreover, the Marzouk et al. approach suggests the importance of setting so-called SMART (specific, measurable, achievable, relevant, and time-bound) goals that can increase student motivation while maintaining their autonomy [28], [78], [79].

The weaknesses identified in theoretical underpinnings have implications for design, feedback, and evaluation dimensions of the MULAS.

B. Design

MULAS posits the importance of theory-informed design of user-centered learning analytics systems to maximize their effects on learning. Theory-informed design has implications on specific themes across which user-centered learning analytics systems, including LADs, are implemented, choices of indicators of learning that are incorporated to support the entire learning process, and the ways how information is presented to users.

The thematic analysis of the LADs showed significant limitations in the support of different elements of the learning process as theorized in the COPES model (see Table VI and Table VII). For example, dashboards that aim at informing the learning design cannot provide a complete insight to the stakeholders without taking into consideration aspects of task conditions. Currently, task conditions are only minimally presented at the level of instructional cues and resources, but they do not offer any insights into social context and time. For example, time defined for task completion of learning tasks and the order in which learners complete the tasks is essential to be considered if effectiveness of learning designs is to be assessed [80]. Learning difficulty in the current dashboards is considered without accounting for task conditions, knowledge of study tactics and strategies, knowledge of tasks, and motivational factors and orientations. Learning difficulty cannot adequately be assessed if these factors are not considered. Dashboards that considered affective states did so only in consideration of a single dimension of cognitive conditions (motivational elements and orientations) but without any dimension of cognitive conditions. Our entire sample of the dashboards across all the themes showed a complete shortage of attention paid to tactics and strategies students have acquired or performed. There was some limited attention paid to primitive operations mostly around the theme of learning progression but with little information across other themes.

Possible reasons for the weaknesses in the current LADs can be found in the design approaches followed in the selection of the indicators and formats for presentation. Most of the designs were based on the references to some of the previous studies, usually in learning analytics, and user-centered design methodologies (Figure 4). Although the references to the previously published papers and user-centered design for the indicator selection are important, there are some potential challenges that need to be considered. Previous research indicates that much of the existing literature on LADs has not been evaluated robustly [4], [7], [11]. Very few of those studies indeed used theory-informed decisions in the choices of their indicators, which triggered questions of validity [2], [5]. Relying on the input of the users only might not be the most robust approach either. The use of learner preferences only for adaptation of learning resources is commonly criticized in the literature given the insufficient evidence to support such approaches [81], [82]. Sometimes, users are not clear on what they can expected from the system, especially if they are not aware of a) possibilities learning analytics can afford or b) mechanisms how data can effectively be collected. Instead, we suggest that the choices of indicators should be theory-driven, while input of the users should be sought to understand the extent to which those indicators are practically useful to optimize learning and teaching. The discussion provided in Section 5.1 offers a comprehensive overview of the elements that need to be considered if the optimization of self-regulated learning, metacognition, and the overall learning process and outcomes is the target.

The major challenge for the designers of user-centered learning analytics systems is to address some of the potential tensions that may come from a combined use of user-centered approaches and theory. For example, while the use of effective study tactics and strategies has consistently been proven to promote effective learning, research has also shown that learners may not prefer to adopt them due to perceived difficulty in their use. This is the reason why they are commonly referred to as desirable difficulties [83]. Design of user-centered learning analytics systems, including LADs, should not only be informed by theories centered on cognition and metacognition but also by those that consider motivation dimensions that are also recognized to play a significant role in adoption of new learning tactics, strategies, and tools [74], [84], [85]. A promising direction is the use of self-determination theory that can inform the creation of conditions to motivate learners to engage with uninteresting tasks [86]. Self-determination is relevant to maintain and grow the sense of agency of learners by moving the decision making power to the learner while offering the reason why something can be beneficial for their learning [77]. This can also be a promising direction for the entire field of learning analytics to mitigate concerns suggesting that learning analytics may increase external control over and suppress the agency of learners.

The design of user-centered learning analytics systems, including LADs, should not make assumptions that only one representation of data universally works for all tasks as argued by Gašević et al. [2] by referencing the theory of cognitive fit [87]. Recent studies suggest that strong positive effects on learning outcomes and satisfaction with feedback can be achieved if analytics-based feedback is provided in form of weekly emails [88]. We recommend that future work on the design of user-centered learning analytics systems, including LADs, should consider multiple forms of information presentation in order to maximize the value of the insight provided by analytics.

C. *Feedback*

The results of this study suggest that the existing generation of dashboards is unlikely to meet any recommendations for effective feedback provided in the literature. Feedback can be defined in different ways and we highlight two recent definitions that effectively summarize the present body of research knowledge. According to Boud and Malloy [89] (p. 6), feedback is “a process whereby learners obtain information about their work in order to appreciate the similarities and differences between the appropriate standards for any given work, and the qualities of the work itself, in order to generate improved work”. Carless [90] (p. 190) further extends this definition and suggest that feedback is “a dialogic process in which learners make sense of information from varied sources and use it to enhance the quality of their work or learning strategies”. These two definitions clearly suggest that learners are agents, feedback is dialogical not unidirectional from educators to learners, and the use of standards and learning strategies is essential. As already established in the previous subsections, all these elements are either highly underrepresented or non-existent in the existing dashboards. As long as the design does not incorporate these elements, it is unlikely to expect user-centered learning analytics systems, including LADs, to provide potent and actionable feedback. For example, presentation of the number of logins or the number of posts can hardly offer sufficient guidance on the quality and strategy of learning [91]. It should also be stressed that the presence of reference frameworks (social, normative, or individual as shown in Figure 5 and [10]) is insufficient to consider LADs as feedback if reference frames are not grounded in and comprehensively capture relevant elements of the COPES model. That is, rather than focusing on what information is easily available, the provision of feedback should focus on what information is required in order to provide meaningful feedback to the students.

The recommendation for the designers of user-centered learning analytics systems, including LADs, is to use established frameworks for feedback such as the one proposed by Hattie and Timperley [92] who distinguish four levels of feedback: task, process, regulation, and self. While the literature indicates little support for the value of the self-level, the process and regulation levels of feedback are the most effective while the task level feedback is beneficial when combined with process and regulation levels of feedback. However, effective provision of feedback on the process and regulation levels can only be enabled if information about standards, evaluation, and learning tactics and strategies is considered [15]. As well, the design of particular features of a dashboard should address questions on all four levels of feedback: where am I going, how am I going, and where to next. Future work on user-centered learning analytics systems, including LADs, should consider recommendations provided by Pardo and colleagues [93], [94] on provision of feedback in data-rich environments. Finally, for user-centered learning analytics systems, including LADs, to exhibit the dialogic nature of feedback, some lessons learned from the literature in open learner modelling should be considered [13] by allowing users to update their user models when they potentially disagree or find discrepancies in data or results of data analysis. Not only will such an approach promote the agentic behavior of learners, promote reflection, and open the dialogue between learners and educators, but it can also increase the validity of learning analytics as an important side effect.

Research and the development of user-centered learning analytics systems can potentially face common issues as reported in the literature on feedback. The key challenge for future research is to study the extent to which learners understand and can act on feedback received through a dashboard or other representation of data/analytics. The literature suggests that good quality feedback reflects students' performance correctly, provides information about the task, and offers suggestions how to proceed or enhance learning [95], [96]. Feedback can achieve its potential benefits when students understand it and take some actions based on it. Very frequently, students struggle to make a clear interpretation from feedback externally provided [97]. As highlighted by many researchers, students who receive their feedback sometimes do not understand it, are not able to make use of it, or do not recognize benefits steaming from it [96]. The work by Corrin and de Barba [6] precisely highlights this lack of understanding of feedback communicated through dashboards that may affect even top performing learners.

D. Evaluation

Evaluation of the impact of user-centered learning analytics systems, including LADs, is an area that requires immediate attention. The studies on the impact of LADs as feedback are limited [17], [54]. Moreover, the evaluation on how LADs act as a mediator of feedback is under-explored. Most of existing research evaluates dashboards in terms of perceived usefulness. There were only a few studies that observed the real impact of implementing dashboards in field studies. As observed by Pardo and Khan [98], no significant association between the number of dashboard views and midterm scores of students was found in a large enrolment computer engineering course. Kim et al., [29] found that students who received feedback through a dashboard showed significantly higher final scores than those who did not receive dashboard feedback. However, the frequency of dashboard views had no significant association with performance. Similarly, Brouwer, Bredeweg, Latour, Berg, & Huizen [56] compared a group of students who received a dashboard intervention with another group that did not receive it. They found a significantly higher performance on the group of students who were provided with the dashboard, but there was no statistically significant association between the frequency of usage of the dashboard and performance.

The analysis of the quality of study design and reporting has revealed some significant limitations in the current studies. The most striking limitation is the total absence of discussion about generalizability, which should serve as a key source for informing future studies and inviting other researchers to pay attention in their future research endeavors. Even more importantly, the discussion of the study limitations is essential to inform practitioners who need to understand the extent to which the results reported in the studies are applicable to practice and be translated to policy. When this is coupled with very few studies that reported on their generalizability, the extent to which empirical studies on LADs can inform practice and policy is questionable. Therefore, there should be an expectation made that each study reporting empirical findings on the effects of the use of user-centered learning analytics systems, including LADs, provide a detailed discussion about study limitations and the extent to which study results can be generalized. We particularly refer to some technology-related fields such as empirical software engineering from which empirical research on user-centered learning analytics systems can learn and which have guidelines how results should be reported and threats to validity discussed [99], [100].

The analysis of empirical research revealed the shortage of the studies that provide some discussion on the implications for learning analytics research and interpretation of the results with respect to the existing literature and most importantly theory. This finding is consistent with the predominant atheoretical nature of the designs of the LADs. However, if research on user-centered learning analytics systems, including LADs, aims to contribute to the body of research knowledge that advances understanding of human learning and learning environments, not only do studies need to discuss its findings against the related literature, but the study objectives and research questions need to be informed by and advance relevant theories and previous research [2].

The shortage of experimental and mixed-method studies suggests that causal inferences cannot be made from the existing literature. Experimental studies or correlational studies complemented with qualitative methods to form mixed-methods afford for opportunities to identify specific effects that the user-centered learning analytics systems may have on particular learning processes or outcomes. Conducting experimental studies with user-centered learning analytics systems can be challenging due to ethical and practical implications. This is the space where we see a need for more attention to be paid to design-based research when developing and evaluating user-centered learning analytics systems [2], [101]. The papers included in this review did not offered any representative examples of design-based research on LADs. Design-based research would involve several iterations of designs where each iteration introduced a new intervention that was tested in practice [102]. Although most of the papers indeed were motivated to address problems in practice, their weak grounding in theory and ambition to advance the body of research on human learning would likely reduce the potential of existing studies to fold under the design-based research umbrella. Therefore, a strong integration of existing theory to inform the work on solving practical problems while conducting several design-evaluation cycles is a key recommendation for future empirical studies on user-centered learning analytics systems, including LADs.

The effects of LADs on different learning processes and outcomes have been discussed in previous learning analytics reviews [7], [11]. Our study corroborates their findings in terms of the general focus on quantitative measures of perceived usability and association with learning outcomes. Few studies attempted to assess the relationships between the use of LADs and learning outcomes or relevant cognitive conditions (e.g., motivation and approaches to learning) [43], [98]. However, even the findings of these studies cannot offer sufficient understanding about learning processes. The instrumentation and analysis did not extract indicators or proxies that were theoretically grounded to identify which exact learning processes and how were affected by certain components of LADs. The work presented by Siadaty and colleagues [103] offers a promising direction how technological interventions, including LADs, can be evaluated to assess impact on learning processes. Siadaty et al. proposed a theory-informed pre-analysis of digital traces in order to identify indicators of relevant process. In the case of the work proposed by Siadaty et al., processes based on Zimmerman's [104] model of self-regulated learning were extracted from trace data. Once extracted from trace data, temporal relationships between such processes and interaction with technological interventions including LADs are studied with techniques from areas such as social network analysis, process mining, or sequence mining to reflect on the temporal nature of learning.

VI. Limitation

The primary limitation of this study is related to the searching process in which we restricted our search to papers that only contain term "dashboard". This could possibly exclude papers that did not explicitly use that particular term although could be considered related to LADs.

Second, we faced several challenges during the coding process because some of the papers provided insufficient information to describe LADs adequately. For example, there is a paper which indicated that the dashboard presented targeted both teachers and learners; however, the paper only provided description for the teacher's viewpoint. Furthermore, we often relied on the figures or screenshots of the dashboards to extract relevant indicators. Moreover, some papers may have not included complete information about the dashboards under study in the figures or screenshots included in the papers. Thus, we might have missed some important indicators in the review process.

Finally, there is a possible limitation related to the analysis of the reporting of the evaluation results. Some papers did mention the use of mixed method in conducting their study (e.g., survey and interview) but they only presented results of interviews and did not report the results of the survey analysis. Therefore, our information about the quality of study designs and reporting might not include complete information about the papers.

VII. Conclusion

The review provided in this paper highlighted significant limitations in the existing literature on LADs. The model of user-centered learning analytics systems (MULAS) is proposed to guide developers, researchers, evaluators, and practitioners in their endeavors that aim to understand and optimize learning and environments in which learning occurs. The model reinforces the need for strong grounding of user-centered learning analytics systems, including LADs, in the literature on learning processes, effective study methods, and feedback. Only when those aspects are systematically combined with user-centered design approaches, user-centered learning analytics systems are posited to provide effective support for learning. The review also emphasizes the need to grow rigor in the empirical evaluation of user-centered learning analytics systems, including LADs, especially in authentic learning contexts through several iterations where the use of design-based research offers a solid methodological foundation. It should be also acknowledged that the research on learning analytics requires strong interdisciplinary teams that can come with expertise in learning sciences, human-information interaction, design, and research methods. Although forming and coordinating such teams can often be a complex task, the proposed MULAS model offer some guidance for team competencies necessary to develop and evaluate user-centered learning analytics systems, including LADs.

Appendix A

W. Matcha and N. Ahmad Uzir are joint first authors and had equal contributions to this paper.

Appendix B

This work was in part funded by the LALA project (grant no. 586120-EPP-1-2017-1-ES-EPPKA2-CBHE-JP), EMBED project (grant no. 2017-1-NL01-KA203-035288), and Smart-Data Schools discovery project (grant no. DP190102286). The LALA and EMBED projects have been funded with support from the European Commission and Smart-Data Schools with support from the Australian Research Council (ARC). This publication reflects the views only of the authors, and the Commission, the Agency, and ARC are not responsible for any use which may be made of the information contained therein.

Appendix C

TABLE VII
Research Papers Included in This Study

Paper ID	Theme	Theory	Target User	Context
ACM15 [54]	Learning Design	No	Teacher	Blended Learning
ACM17 [39]	Emotion	TEA Model	Teacher, Student	Traditional Classroom
ACM18 [50]	Learning Progress	No	Teacher, Student	Computer Supported

Paper ID	Theme	Theory	Target User	Context
				Collaborative Learning
ACM2017-10 [42]	Emotion	Discrete and Dimensional emotion theory (Automatic Emotion Recognition process)	Teacher	Online Learning
ACM2017-16 [57]	Learning Progress	No	Teacher	Online Learning and Blended Learning and Flipped Learning
ACM21 [46]	Competency	Fully-Embedded Assessment Model (FEAM)	Student, Faculty, Study Advisor	Online Learning
ACM23 [55]	Learning Progress	Open Student Model (OSM)	Teacher, Student	Blended Learning
ACM25 [47]	Teamwork Progress	Dickinson and McIntyre's teamwork model	Teacher	Blended Learning
ACM3 [98]	Learning Progress	No	Student	Flipped Learning
ACM30 [49]	Learning Progress	No	Student	Online Learning
ACM31 [59]	Learning Progress	No	Teacher	Blended Learning
ACM8 [43]	Learning Progress	Achievement Goal Orientation	Student	Blended Learning
GS5 [6]	Learning Progress	No	Student	Blended Learning
GS56 [60]	Learning Progress	No	Teacher	Intelligent Tutoring Systems (ITS)
IEEE1 [35]	Competency	Open Student Model (OSM)	Teacher, Student	Online Learning
IEEE19 [36]	Learning Difficulty Detection	Open Student Model; Activity-based Learner-Model (Engeström's Activity Theory and Actuator-Indicator Model)	Teacher, Student	Academic Supporting Tool
IEEE2017 – 11 [53]	Study Plan	No	Student; Study Adviser	Academic Supporting Tool
IEEE22 [37]	Learning Progress	Open Student Model; Activity-based Learner-Model (Engeström's Activity Theory and Actuator-Indicator Model)	Teacher, Student	Online Learning and Blended Learning
IEEE28 [105]	Learning Progress	No	Student	Blended Learning
SD1 [51]	Game-Based	No - Flow Theory; Analogical Reasoning Theory; Pragmatic Constraint Theory in the game development	Teacher, Student	Online Game-based Learning
SPL – 171 [106]	Learning Progress	No	Student, Teacher, Administrators, Faculty	MOOC
SPL – 174 [44]	Study Plan	Learning and Study Strategies Inventory (LASSI)	Student	Academic Supporting Tool
Springer 10 [29]	Learning Progress	No	Student	Online Learning
Springer 122 [52]	Game-Based	No	Teacher	Blended Learning
Springer 127 [107]	Learning Progress	No	Teacher, Student	Blended Learning
Springer 25 [56]	Learning Progress	No	Student	Blended Learning
Springer 87 [30]	Learning Progress	No	Student	Intelligent Tutoring Systems (ITS)
Springer 95 [61]	Learning Progress	No	Teacher, Student	Online Learning
Wiley1 [108]	Learning Progress	No	Teacher, Student	Blended Learning

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