Where is the Learning in Learning Analytics? A Systematic Literature Review on the Operationalization of Learning-Related Constructs in the Evaluation of Learning Analytics Interventions

Justian Knobbout and Esther van der Stappen

Abstract—**Learning technologies enable interventions in the learning process aiming to improve learning. Learning analytics provides such interventions based on analysis of learner data, which are believed to have beneficial effects on both learning and the learning environment. Literature reporting on the effects of learning analytics interventions on learning allows us to assess in what way learning analytics improves learning. No standard set of operational definitions for learning affected by learning analytics interventions is available. We performed a systematic literature review of 1932 search hits, which yielded 62 key studies. We analyzed how affected learning was operationalized in these key studies and classified operational definitions into three categories: 1) *learning environment*; 2) *learning process;* and 3) *learning outcome*. A deepening analysis yielded a refined classification scheme with 11 subcategories. Most of the analyzed studies relate to either *learning outcome* or *learning process*. Only nine of the key studies relate to more than one category. Given the complex nature of applying learning analytics interventions in practice, measuring the effects on a wider spectrum of aspects can give more insight into the workings of learning analytics interventions on the different actors, processes, and outcomes involved. Based on the results of our review, we recommend making deliberate decisions on the (multiple) aspects of learning one tries to improve by applying learning analytics. Our refined classification with examples of operational definitions may help both academics and practitioners doing so, as it allows for a more structured, grounded, and comparable positioning of learning analytics benefits.**

Index Terms—**Learning analytics interventions, learning metrics, operationalization, systematic literature review.**

I. Introduction

LEARNING technologies enable interventions in the learning process aiming to improve learning. Whenever such technologies are based on analytics of data on learners, the learning process and/or the learning environment, we speak of learning analytics.

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The authors are with the HU University of Applied Sciences Utrecht, 99 3584 Padualaan, The Netherlands (e-mail: justian.knobbout@hu.nl; esther.vanderstappen@hu.nl).

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Learning analytics is commonly defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" [1]. Interventions in the learning process based on data from that process are believed to have beneficial effects on learning and the learning environment. These interventions are an important step that "closes the loop" in the cyclic learning analytics process [2].

The largest challenge for learning analytics research and practice is to find out which types of interventions have a positive impact on learning [3]. In his comprehensive book on the field of learning analytics, Sclater [4] dedicated a chapter to interventions, with a focus on human-mediated interventions taken directly with learners while learning is taking place. He concludes that there is relatively little knowledge on how these interventions can be performed effectively, even though it is a vital part of the process to provide analytics that enable actions with a beneficial impact on learners [4].

These beneficial effects are increasingly subject of study [5]–[9]. These studies all support that there are relatively few studies that report on human-mediated interventions taking place directly in the learning process (at the microlevel), and there is little evidence available on the desired improvement of learning. Several recent studies call for more (longitudinal) empirical research in authentic settings as well as for a more systematic comparison of learning analytics interventions [5], [6], [8], [10]. To systematically design, implement, and evaluate learning analytics interventions, it is important to know how to measure the intended improvement of learning. Central to this article is the concept of "*affected learning,*" which denotes the observable change in learning caused by learning analytics interventions. A shared, transparent, and tested set of operational definitions for learning affected by learning analytics interventions is also crucial to enable comparison and generalization of studies on learning analytics interventions—and learning technologies in general—and eventually metastudies on effect sizes.

In this article, we study what operational definitions for affected learning can be identified in the existing literature on learning analytics interventions. We conduct a systematic literature review in order to provide an answer to the research question: In what way does existing literature on learning analytics interventions operationalize affected learning?

We structure the results of our study based on a high level preliminary classification scheme derived from learning theory. This classification scheme is subsequently refined in the analysis phase of the review. Our research supports both academics and practitioners in their work as it provides a refined classification scheme for operationalizing affected learning and actual operational definitions of affected learning which can be used to measure and compare the intended benefits of learning analytics interventions on learning. We structure the remainder of this article as follows. First, we provide an overview of the background of the study and related reviews from the field. We then describe the methodology, followed by an elaboration on the analysis and results. Finally, we provide recommendations for future research and discuss the limitations of this article.

II. Background

In this section, we give an overview of learning analytics interventions and recent reviews of the learning analytics field. Furthermore, we introduce a preliminary classification scheme which we use for the analysis in this review.

A. Learning Analytics and Learning Analytics Interventions

The Learning Analytics Cycle [2] describes the process of turning data into action and involves four steps: 1) learners generate data; 2) the infrastructure captures, collects, and stores this data; 3) the collected data are analyzed and visualized; and 4) feeding back these analytics and/or visualizations to stakeholders, such as learners and teachers. Such a learning analytics intervention is needed in order for learning analytics to have effect on learners. Learning analytics interventions can be defined as "the surrounding frame of activity through which analytic tools, data, and reports are taken up and used" [11].

These interventions can have a wide variety of appearances, e.g., automated visualizations of students' progress in the form of learning analytics dashboards [10], early warning systems for educators to identify students at risk [12], supporting adaptive learning pathways [13], and goal-setting recommendations based on labor market data analytics [14]. Learning analytics interventions are not restricted to formal educational settings, however, the number of studies in the context of nonformal or workplace learning is very limited [10], [15]. Examples of changes in the learning process achieved by these interventions are personalization of learning, enhanced instructor support of learners, or improvement of curricula [4], [16]. The effectiveness of learning analytics can be enhanced by increasing the speed of delivery of learning analytics interventions (e.g., real-time feedback to learners and teachers) [2].

In the definition of learning analytics, the goal described is twofold; we aim to understand and optimize learning [1]. Learning analytics takes place at the microlevel within educational institutes, so the focus is on the learner and its surroundings [17]. In this article, we focus on studies in which learning analytics interventions have been performed, in authentic settings, and empirically evaluated with respect to learning-related constructs. Studies in which, for instance, (advanced) analytics have been performed on learning data to measure the effects of a new instructional strategy or course design do not fall into our scope, since no "data-driven intervention" is performed.

B. Recent Reviews

In recent years, the number of (systematic) reviews of the learning analytics field is increasing rapidly. One of the first systematic reviews of learning analytics literature classifies studies by learning setting, analysis method, and research objectives [18]. That study shows that learning analytics uses a wide variety of techniques and is not limited to only virtual learning environments (VLEs), but can also be applied on, among others, web-based education, social learning, and cognitive tutors. The objectives of the studies are diverse and include, e.g., student behavior modeling, prediction of performance, prediction of dropout and retention, recommendation of resources, and increased (self-) reflection and (self-) awareness.

The learning analytics field is relatively young but steadily maturing, which is also noticeable in the increasing attention that is given to the evidence-based character of the field. Recently, Ferguson and Clow [5] analyzed the evidence in the LACE Evidence Hub [19] and they conclude that there is considerable scope for improving the evidence base for learning analytics. Among other aspects, they suggest paying more attention to the cyclic nature of learning analytics (closing the cycle) and to the validity, reliability, and generalizability of learning analytics research.

In 2017, Schwendimann *et al.* [10] presented a systematic literature review of research on learning dashboards. Based on their review, they define a learning dashboard as "a single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations" [10], clearly distinguishing dashboards from visualizations based on a single indicator. Interestingly, the indicators used in the dashboards in 60% of the papers included in the review were gathered from authentic educational situations, whereas merely 29% of the included studies actually evaluated the dashboard in such situations. Of all 55 analyzed papers, only four evaluated the impact of the dashboard on learning, whereas most others evaluated other aspects, such as usability and user satisfaction. Based on the results from their review, the authors conclude that large-scale studies on adoption and learning impact of dashboards are important yet underexplored. Schwendimann *et al.* also observe a lack of comparative studies in the field, partly due to "a lack of widely-accepted, specific evaluation constructs, beyond general ones like usability and usefulness" [10]. In this article, we aim to support the development of a set of operational definitions for the construct of affected learning.

Mangaroska and Giannakos [7] performed a systematic literature review on how learning analytics have been used to inform learning design. They aimed to gain insights on the intersection of these two research fields rather than the individual disciplines. The authors emphasize the need for actionable insights from learning analytics, i.e., data-driven interventions fed back to stakeholders in the learning process; thereby, closing the learning analytics loop effectively. Out of the 43 analyzed papers, just four reported learning analytics integrated into a learning environment providing real-time feedback. In their discussion, Mangaroska and Giannakos state that researchers should "know what data to collect in order to understand whether certain learning processes are activated, and what learning outcomes are associated with what design decisions" [7] and they urge learning analytics researchers to "evaluate and denote student learning outcomes, or any other learning-related constructs" [7].

Several recent systematic literature reviews focus on higher education as a specific educational context for learning analytics [6], [8].

Viberg *et al.* [8] performed a comprehensive review of 252 papers on learning analytics in higher education, analyzing the research approaches, methods, and evidence for learning analytics. With respect to the latter, they examined evidence for propositions 1 and 2 from Ferguson and Clow [5].

1) Learning analytics improve learning outcomes.
2) Learning analytics improve learning support and teaching.

They found that only 9% of the studies reported on evidence for proposition 1 and 35% found evidence for proposition 2. Interestingly, they include studies in their review, such as Guarcello *et al.* [20] and Gašević *et al.* [21], which both study an instructional approach (supplemental instruction and grading self-reflection video annotations, respectively) and apply advanced analytics to assess the effects of such an instructional approach rigorously. Viberg *et al.* include these studies as evidence for improvement of student outcomes by learning analytics, whereas they both fall outside our definition of learning analytics interventions, since the instructional interventions themselves were not based on data analytics.

Sønderlund *et al.* [6] performed a systematic literature review specifically aimed at studying the effectiveness of learning analytics interventions based on predictive models. From 689 papers, merely 11 studies reported on an evaluation of the effectiveness of such interventions. They conclude their review emphasizing the need for a solid knowledge base on the feasibility, effectiveness, and generalizability of the implementation and evaluation of learning analytics interventions. In order to replicate experiments, and to compare and generalize obtained results, we need to be transparent in the (operational) variables we use to measure the impact of learning analytics interventions on learning.

Most recently, Wong and Li [22] presented a review of 24 case studies of learning analytics interventions in higher education, analyzing objectives, data sources, intervention methods, obtained outcomes, and observed challenges. The review of these case studies suggests that learning analytics interventions have the potential for a broad application in terms of various purposes, as well as different learning contexts within higher education. Wong and Li conclude that to fulfill the recognized potential of learning analytics interventions, "more studies on empirical evidence, even with null or negative results, are needed to support its long-term effectiveness and sustainability" [22].

The previously mentioned studies note the importance to evaluate the effects of learning analytics based on learning constructs. In this article, we analyze in what way the effects on learning of learning analytics interventions (in all learning contexts) are measured by selecting key studies which report on empirical, quantitative results of the application of learning analytics interventions at the microlevel in the learning process in an authentic context. The outcome of this article is a classification scheme for constructs related to affected learning—with their operationalization—so in future research the effects of learning analytics on learning can be described comparably.

C. Preliminary Classification of Affected Learning

To evaluate the effects of learning analytics interventions on learning, the difference in learning caused by the provided intervention should be measured. This raises the fundamental question in what way(s) learning can be measured. Joksimović *et al.* [23] recently explored how learning is modeled in the MOOC research. They present a framework specifically suitable for open online contexts with a focus on student engagement. Along similar lines, we aim to analyze how learning-related constructs are operationalized in research on learning analytics interventions in all learning contexts (K-12, higher education, MOOCs, and the workplace).

Learning can either be described as a process or as the outcome of this process: a (relatively permanent) change in a person's behavior, knowledge and/or skills [24]. Not all learning theories award the same weight to both process and result. For example, the experiential learning theory by Kolb has a preference for a process-focused view: "learning is best conceived as a process, not in terms of outcomes" [25]. Behaviorism focuses mainly on learning outcomes, cognitivism made a shift toward taking the (cognitive) process more into account, whereas constructivism focuses mainly on the learning process [26].

This process-product duality is also present in the well-established 3P model of teaching and learning [27]. The framework on MOOC learning by Joksimović *et al.* [23] also distinguishes process and product, while adding a third category of learning-related constructs: learning contexts. The context in which learning takes place is also present in the 3P model in the factor Presage—Teaching context [27]. We argue that learning context should be an important aspect in research on learning analytics interventions, since the most commonly used learning analytics definition states we aim to optimize not only learning itself but also "the environments in which it occurs" [1].

Based on the discussion above, and in line with Joksimović *et al.* [23], we now discern three categories that we will use to classify operational definitions of learning affected by learning analytics interventions: 1) learning environment; 2) learning process; and 3) learning outcome. The 3P model not only describes the factors of learning (Presage-Process-Product), but also

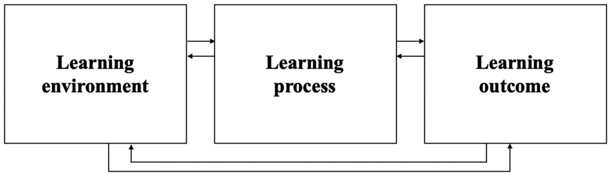

Fig. 1. High-level, preliminary classification scheme for operational definitions of learning affected by learning analytics interventions.

the relations between the factors and reciprocal influences. Our high level, preliminary classification scheme with categories, as well as their relations according to the 3P model, is shown in Fig. 1. During the analysis of our review, we will refine this scheme using the identified operational definitions.

III. Methodology

In this section, we provide a detailed description of the method used for our systematic literature review. The applied method in this literature review builds on other systematic literature reviews in the learning analytics domain (cf., [15], [16], [18], [28]). In this article, we aim to provide an answer to the following research question: In what way does existing literature on learning analytics interventions operationalize affected learning?

A. Literature Sources

During the literature review, papers from seven different databases are sourced as follows.

1) Learning analytics and knowledge (LAK) is the main conference in the learning analytics field. Organized for the first time in 2011, it produced an extensive amount of proceeding papers ever since. In this article, we include the LAK conference proceeding papers.
2) IEEE Xplore is a technical-oriented database and contains papers related to, among others, computer science.
3) SpringerLink is the Springer's online collection of scientific, technological, and medical journals, books and reference works.
4) The Association for Computing Machinery database is a large, comprehensive database focused on computing, and information technology.
5) ScienceDirect is Elsevier's information solution for researchers and includes over 3800 journals.
6) The Education Resources Information Center database is focused on educational literature and resources.
7) Learning Analytics Community Exchange (LACE) was a European Union funded project and one of the project aims was to collect evidence of the effects learning analytics have on education. In this article, we include papers which relate to the proposition "Learning analytics improve learning outcomes" [19].

B. Search Terms

To search the aforementioned databases for literature related to operational definitions of affected learning, different search terms are used. The search terms are formulated based on *a priori* analysis of relevant papers. Generally, the search includes the terms "learning analytics" AND student* AND (achievement OR "student learning" OR "learning goal" OR "learning outcome" OR performance OR "student success"). When allowed for by the search engine, we specifically search the abstracts for student[1] and ("learning analytics") to ensure we get learning analytics-related articles.

TABLE I
Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
Written in English	Full-text not available to researchers
Published between January 2011 and April 2019	Manuscript not peer-reviewed
Empirical study in an authentic context	Theoretical study
Performs an intervention in the learning process based on learning data analytics	Lacks reporting of quantitative results on affected learning
	Simulation study

C. Selection of Papers and Inclusion Criteria

The aim of this article is to identify operational definitions of learning affected by learning analytics interventions in an authentic context. We, therefore, focus on quantitative studies, as they provide us with actual metrics of learning, which can be calculated and compared in a standardized way. With this approach, we follow Joksimović *et al.* [23]. We concur with them that qualitative studies are fundamentally different in the way evaluation results are presented, which are worth of a separate literature review, potentially yield complementary insights, e.g., thick descriptions of the constructs, variables, and operational definitions we find in our review. The inclusion and exclusion criteria we used in this article are listed in Table I.

From the papers found in the previous step, the title and abstract are read to determine whether it meets the inclusion criteria, or it should be excluded based on the exclusion criteria. Papers clearly not meeting the criteria are dismissed. If the abstract and title do not provide enough information to make the selection, the article is scanned—especially the method and result section—to make a better-informed decision. In a second round of selection, the qualifying papers are entirely read and again gauged against our inclusion criteria. To ensure the objectivity of the selection, a random sample of ca. 10% of the retrieved full-texts was also handled separately by a second researcher and the results were discussed; interpretation of the selection criteria was calibrated. No conflicts were observed in the selection of key studies by the two researchers. The key studies are all included in the analysis phase of the review. From these papers, we extracted and collected author(s), title and subtitle, year, educational context, learning analytics intervention, research objectives, and operationalization of affected learning. These data synthesize the results of this article, as described in the following section.

[1] is a wildcard for characters so that extended words can be included in the search, e.g. student* can match search terms as students and studentship.

IV. RESULTS

This section presents the results of our literature review. From the 1932 hits on the search terms in the seven databases, 62 key studies meet the inclusion criteria (see Fig 2). A retention of just over 3% sounds rigid, however, other literature reviews in the learning analytics domain show similar results [6], [7], [15], [28]. This is also in line with the earlier statement that researchers agree there are relatively few studies reporting on human-mediated interventions taking place directly in the learning process [5]–[9].

A. Descriptive View of Key Studies

This section provides a descriptive overview of the 62 resulting key studies. All studies with their descriptive attributes are listed in Table II. To create this overview, we coded the key studies based on several attributes, which are as follows.

1) *Year*: Year in which the study was published.
2) *Country*: Country in which the study was conducted.
3) *Context*: Educational context in which the study was conducted.
4) *Intervention Type*: Category of the learning analytics intervention used in the study.
5) *Data Subject*: The (role of the) person whose data was collected, analyzed, and visualized in the intervention.
6) *User*: The user of the intervention, i.e., the (role of the) person that had access to the learning analytics intervention and could act upon this intervention in the learning process.
7) *Research Objective*: Goal of the key study, classified according to the classification proposed by Papamitsiou and Economides [18].

Since—to the best of our knowledge—no general accepted classification method is available for learning analytics interventions, we synthesized the categories for *Intervention Type* through open coding. Here, we adopted the proposed distinction between dashboards (consisting of visualization(s) of multiple indicators) and visualizations (based on a single indicator) [10]. Whenever information was presented to learners in a different form than visualization (e.g., plain numerical information), we coded this intervention as *Information for Learner*. Three intervention types may seem somewhat similar: 1) *information for teacher (IT)*; 2) *message from teacher to learner (MT)*; and 3) *learner support (LS)*. The difference is, that in type IT the intervention is passive, in the sense that information is presented to teachers (e.g., exercise completion rates for all students), whereas in intervention type MT, the teacher is supported by the intervention to actively reach out to students, e.g., to notify students at risk. In intervention type LS, the learning analytics intervention helped inform other ways of learner support, e.g., through academic advisors.

First, we analyzed the educational context of the key studies. More than half of the studies describe learning analytics interventions in higher education (38), followed by K12 education (15) with only a handful of other educational contexts (see Fig. 3).

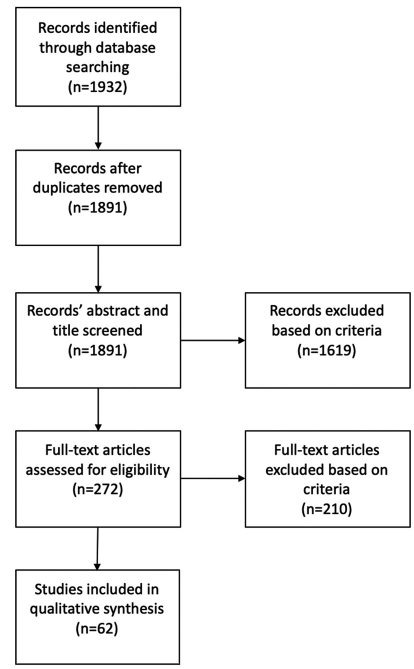

Fig. 2. Search process results.

Second, we analyzed the number of studies per year; see Fig. 4. We see that since 2015, the number of studies meeting our inclusion criteria has been approximately ten studies per year. In the first five months of 2019, this number is already 11, which gives hope of an even larger number of this type of study in the whole of 2019. We can conclude that the number of studies in which the effects on learning of learning analytics efforts are being analyzed empirically and quantitatively has increased since 2012.

B. Classifying Key Studies Based on Affected Learning

Using the preliminary classification scheme, we now classify the key studies based on the different categories of affected learning, i.e., learning environment, learning process, and learning outcome. To this aim, we searched the text of the key studies for description of what was measured exactly in order to analyze the effects on learning of the intervention discussed in that particular study.

We find that 53 out of 62 studies describe operational definitions that fit into a single category of our classification scheme. In Table III, we give an overview of these single-category studies per category per year. We observe that *learning outcome* is by far the largest category, followed by *learning process*. *Learning environment* is the smallest category with only seven single-category key studies.

Nine key studies contain operational definitions relating to more than one category. Table IV gives an overview of the number of cross-categorical key studies per year. The most occurring combination of categories is *learning process* and *learning outcome* with eight key studies, while the number of studies in this category combination is also increasing over the years. We observe that not a single key study includes operational definitions of affected learning in all three categories.

TABLE II
DESCRIPTIVE OVERVIEW OF KEY STUDIES

Ref.	Authors	Year	Country	Context	Intervention	Data Subject	User	Research Objective
[12]	Arnold & Pistilli	2012	US	HE	V	S	T	PP
[29]	Cheng & Liao	2012	Taiwan	HE	IT	S	T	SB
[30]	Smolin & Butakov	2012	Russia	HE	O	S	SD	IA
[31]	Lauría *et al.*	2013	US	HE	MT, PC	S	T	PP
[32]	McKenzie *et al.*	2013	Australia	HE	PC	S	L	PP, IR
[33]	Grann & Bushway	2014	US	HE	V	S	L	IR
[34]	Jayaprakash *et al.*	2014	US	HE	IT	S	T	PP
[35]	Kumar *et al.*	2014	India	HE	PC	S	L	IR
[36]	van Leeuwen *et al.*	2014	Netherlands	K12	MT	S	T	IA
[37]	Yamada *et al.*	2014	Japan	HE	PC	S	L	RR
[38]	Akçapınar	2015	Turkey	HE	O	S	L	IR
[39]	Berland, Davis & Smith	2015	US	K12	O	S	T	SB
[40]	Groba *et al.*	2015	Spain	HE	V	S	T	IA
[41]	Holman *et al.*	2015	US	HE	IL	S	L	PP
[42]	van Leeuwen *et al.*	2015	Netherlands	K12	MT	S	T	IA
[43]	Lonn *et al.*	2015	US	HE	IT, LS	S	AA	IR
[44]	Marcos-García, Martínez-Monés & Dimitriadis	2015	Unknown	HE	IT	S	T	IR
[45]	Martinez-Maldonado, Yacef & Kay	2015	Australia	HE	LS	S	T	IA
[46]	Melero *et al.*	2015	Spain	K12	V	S	T, L	IR
[47]	Nussbaumer *et al.*	2015	Austria	HE	V	S	L	IR, RR
[48]	Tabuenca *et al.*	2015	Netherlands	HE	MT	S	L	IR
[49]	Whitelock *et al.*	2015	UK	HE	AF	S	L	IR
[50]	Xiong, Wang & Beck	2015	Unknown	U	PC	S	L	RR
[51]	Arguedas, Daradoumis & Xhafa	2016	US	HE	V	S	T	PP
[52]	Beheshitha *et al.*	2016	Canada	HE	V	S	L	IR
[53]	Ben David, Segal & Gal	2016	Israel	K12	PC	S	L	RR
[54]	Khan & Pardo	2016	Australia	HE	V	S	L	IR
[55]	Harrison *et al.*	2016	Australia	HE	IT, LS	S	U	PD
[56]	Manske & Hoppe	2016	Germany	K12	V	S	L	IR
[57]	Papoušek, Stanislav & Pelánek	2016	International	All	AF	S	L	RR
[58]	Sharma *et al.*	2016	Switzerland	MOOC	V	S	L	IR
[59]	Siadaty, Gašević & Hatala	2016	International	W	PC	E	L	IR
[60]	Siadaty, Gašević & Hatala	2016	International	W	PC	E	L	IR
[61]	Davis *et al.*	2017	International	MOOC	V	S	L	IR
[62]	Dawson *et al.*	2017	Unknown	HE	MT	S	AA	PD
[63]	Diana *et al.*	2017	US	K12	V	S	T	PP
[64]	Faria *et al.*	2017	US	K12	IT	S	AA	PD

[65]	Herodotou *et al.*	2017	UK	HE	V	S	T	PD
[66]	Jing & Tang	2017	China	MOOC	PC	S	L	RR
[67]	van Klaveren, Vonk & Cornelisz	2017	Netherlands	K12	PC, AF	S	L	RR
[68]	Perikos, Grivokostopoulou & Hatzilygeroudis	2017	Greece	HE	AF	S	L	IR
[69]	Rosmansyah, Kartikasari & Wuryandari	2017	Indonesia	K12	V	S	T	IR
[70]	Seanosky *et al.*	2017	Unknown	HE	V	S	L	IR
[71]	Shimada & Konomi	2017	Japan	HE	IT	S	T	SB
[72]	Chen *et al.*	2018	US	HE	V	S	L	IR
[73]	Ciolacu *et al.*	2018	Germany	HE	MT	S	T	PP
[74]	Gong, Liu & Zhao	2018	China	HE	MT	S	T	IR
[75]	Guillot *et al.*	2018	Canada	HE	V, IL	S	L	IR
[76]	Klock *et al.*	2018	Unknown	HE	V, IL	S	L	IR
[77]	Mangaroska *et al.*	2018	Switzerland	HE	IL	S	L	IR
[78]	Michos & Hernandez-Leo	2018	Spain	HE, MOOC, W	V, D	T(L)	T(L)	IR
[79]	Aljohani *et al.*	2019	Saudi Arabia	HE	V	S	T, S	IR
[80]	Aslan *et al.*	2019	Turkey	K12	V	S	T	IR
[81]	Gong &Liu	2019	China	HE	AF	S	T, L	IA
[82]	Hubalovsky, Hubalovska & Musilek	2019	Czech Republic	K12	PC	S	L	RR
[83]	Jeon & Song	2019	Korea	K12	IT	S	T	IA
[84]	Jovanović *et al.*	2019	Unknown	HE	V	S	L	IR
[85]	van Leeuwen, Rummel & van Gog	2019	Netherlands	K12	D	SS	T	SB
[86]	Lim *et al.*	2019	Australia	HE	MT	S	T	IA
[87]	Swidan *et al.*	2019	Israel	K12	D	SS	T	SB
[88]	Syed *et al.*	2019	US	HE	LS	S	AA, T	SB
[89]	Vargas *et al.*	2019	Chile	HE	IT	S	T	SB

Context: primary/secondary school (K12), higher education (HE), massive open online course (MOOC), workplace (W).
Intervention type: automated feedback (AF), dashboard (D), information for learner (IL), information for teacher (IT), message from teacher to learner (MT), personalization of course materials (PC), learner support (LS), visualization (V), other (O).
Data subject (whose data is collected?): employee (E), student (S), simulated student (SS), teacher in the role of learner or employee (T(L))
User (who uses the intervention?): academic advisor (AA), learner (L), syllabus developer (SD), teacher (T), teacher in learner role (T(L)), unknown (U).
Research objective (according to classification of [18]): improve assessment & feedback services (IA), increase (self) reflection and (self) awareness (IR), prediction of dropout and retention (PD), prediction of performance (PP), recommendation of resources (RR), student behavior modeling (SB).

C. *Classification in Relation to Research Objective*

We also quantitatively investigated the relation between the classification of key studies and the respective research objectives according to the classification of Papamitsiou and Economides [18] (see Table V). Note that in this table, we included all combinations of classifications and research objectives to get a complete overview, i.e., if a key study relates to more than one category from our classification scheme or has more than one research objective, we counted all combinations. At first glance, the results do not look surprising; for example, key studies that measure affected learning in the category *learning environment* mostly aim to improve assessment and feedback services, while studies that aim to predict performance usually operationalize affected learning in the category *learning outcome*.

However, it might actually not be that straightforward. Consider those studies in which the research objective is prediction of performance. In only two out of nine key studies, the learner is the user of the intervention [32], [41], while in the other seven studies, the learning analytics intervention has teachers as target users. Equipping teachers with a learning analytics tool might be an indication that we are in fact trying to intervene on aspects of learning in the category *learning environment*, with the ultimate goal of increasing *learning outcome*.

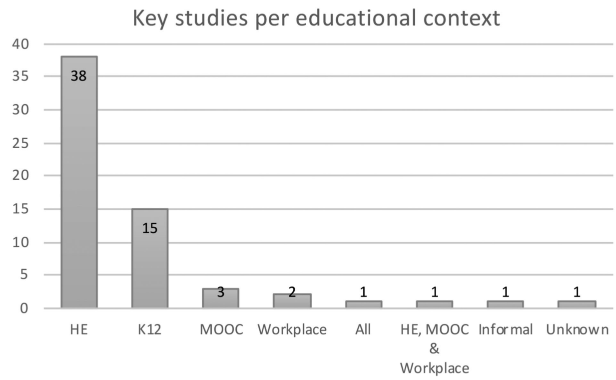

Fig. 3. Number of key studies per educational context.

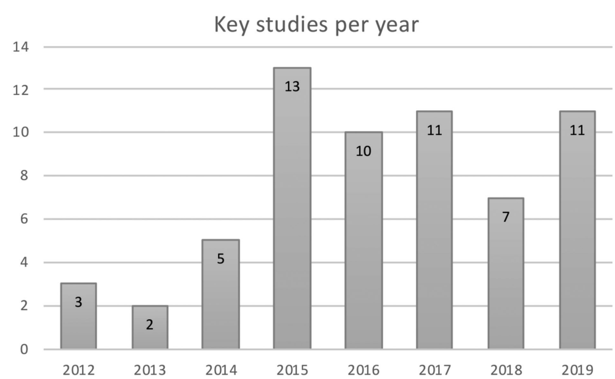

Fig. 4. Number of key studies per year.

TABLE III
SINGLE-CATEGORY KEY STUDIES PER CATEGORY PER YEAR

	2012	2013	2014	2015	2016	2017	2018	2019	TOTAL
LEARNING ENVIRONMENT	1		1	3				2	**7**
LEARNING PROCESS				5	4		2	1	**12**
LEARNING OUTCOME	2	2	4	4	5	9	3	5	**34**
TOTAL	**3**	**2**	**5**	**12**	**9**	**9**	**5**	**8**	**53**

In this chain of reasoning, we might need to consider measuring both the intermediate and the ultimate effects of our interventions by incorporating operational definitions from multiple categories in our studies.

D. Analysis and Refinement of the Classification Scheme

In this section, we analyze the retrieved operational definitions for each of the three categories of the preliminary classification scheme. We distilled subcategories through iterative open coding until convergence occurred, which we also link to relevant literature.

1) Learning Environment: Although the optimization of the learning environment is explicitly mentioned in the commonly accepted definition of learning analytics [1], with only

TABLE IV
CROSS-CATEGORY STUDIES PER CATEGORY SET PER YEAR

	2015	2016	2017	2018	2019	TOTAL
LEARNING ENVIRONMENT & LEARNING PROCESS			1			**1**
LEARNING PROCESS & LEARNING OUTCOME	1	1	1	2	3	**8**
TOTAL	**1**	**1**	**2**	**2**	**3**	**9**

TABLE V
CLASSIFICATION OF KEY STUDIES RELATED TO RESEARCH OBJECTIVE

	IMPROVE ASSESSMENT & FEEDBACK SERVICES	INCREASE (SELF) REFLECTION & (SELF) AWARENESS	PREDICTION OF DROPOUT AND RETENTION	PREDICTION OF PERFORMANCE	RECOMMENDATION OF RESOURCES	STUDENT BEHAVIOR MODELING
LEARNING ENVIRONMENT	5					3
LEARNING PROCESS	2	15		1	3	1
LEARNING OUTCOME	3	17	4	7	9	4
TOTAL	**10**	**32**	**4**	**8**	**12**	**8**

eight key studies this category is the smallest within our research. We found nine different operational definitions in this category, out of which we distilled three subcategories: 1) *teacher awareness*; 2) *teacher productivity;* and 3) *learning materials*.

Teacher awareness relates to operational definitions such as detection, attention, and interaction by teachers [36], [42], [45], [71], [85]. Schwendimann *et al.* also mention "teacher awareness (of students)" as a construct for the evaluation of learning analytics dashboard [10]. *Teacher productivity* relates both to efficiency and effectiveness: operational definitions in this subcategory include, e.g., the number of messages a teacher sends [36], [42], the time it takes a teacher to respond or assess time [40], [85] and the quality of assessment by a teacher [85], [87]. We also recognize this subcategory in a previous review, that identifies "productivity and effectiveness in teaching" as an outcome of learning analytics interventions [22]. A single key study does not fit into the abovementioned subcategories: Smolin and Butakov [30] used an operational definition related to the quality/suitability of learning materials. We, therefore, also include the subcategory *Learning materials* in our refined classification scheme. Considering the common learning analytics research goal "recommendation of resources" [18], we may expect more operational definitions in this subcategory in further research.

2) Learning Process: The learning process relates to learning activity-focused activities. We found a total of 21 key studies that measured to what extent different aspects of the learning process were affected by learning analytics interventions. We found 14 different operational definitions, from which we distilled five subcategories: 1) *learner awareness*; 2) *learner productivity*; 3) *self-regulated learning*; 4) *engagement*; and 5) *online activity and behavior*.

The first two subcategories are similar to the first two subcategories in *learning environment*; here the focus is on the learner instead of the teacher. Examples of operational definitions for *learner awareness* are plagiarized post ratios [38] and making predictions about grades by students [41]. Examples of operational definitions for *learner productivity* are study time, practice time, number of exercises made [48], [67], and time spent on solving questions [54]. We recognize these two subcategories in the earlier discussed reviews: "awareness of students by [..]other peers" [10], and "enhanced productivity/effectiveness in learning" [22].

We also found three key studies using operational definitions related to *self-regulated learning* (SRL). SRL has three important characteristics: 1) self-observation; 2) self-judgment; and 3) self-reactions [90]. Operational definitions in this subcategory include pre and postquestionnaire scores on the self-assessment and the application of SRL [46], [59] and the use of metacognitive tools [47]. SRL skills also can be the intended learning outcome of a learning process (see the discussion of the category *learning outcome* in the following section). In this subcategory, the focus is ON (evidence for) the application of SRL in the learning process. Measuring SRL is not straightforward; it is also argued that the measurement of SRL is intertwined with the intervention based on this measurement [91].

Engagement of learners is increasingly used as a measure of success of educational institutions [92]. Noticeable is the fact that in the 3P model, an affective learning outcome is involvement, which has a strong relation to engagement and the learning process. We decide to make *engagement* a subcategory of *learning process*—in which we follow Joksimović *et al.* [23]—however, we also recognize an ongoing discussion in the field on engagement, how to model, operationalize, and measure this construct [92], [93]. Examples of operational definitions we found in our review that relate to engagement are social interactions [44], [72], [78] and emotional changes [80]. We believe this is only a limited view of the complex construct of engagement; many other operational definitions of engagement are available. Joksimović *et al.* provide metrics for, e.g., academic, behavioral, cognitive, and affective engagement [23].

Finally, we decided to separate the two subcategories *engagement* and *online activity and behavior*, even though the latter is often used as a proxy for the former. We found a set of operational definitions in *online activity and behavior* such as event count [60], frequency of accessing the LMS [80], [87], quantity and/or quality of discussion board posts [52], [74], [76]–[79], and the use of note-taking functionality [71]. Measures of activity in a VLE or an LMS are also mentioned in many recent reviews as operational definitions of affected learning [6], [8], [10], [22]. *Engagement* can be measured in much more diverse ways than simple event counts, and we hope to emphasize this by separating these two subcategories in our refined classification scheme.

3) Learning Outcome: Containing 42 key studies, this last category is by far the largest in our research. We found 14 different operational definitions in this category, which we grouped into three subcategories: 1) *knowledge and skills*; 2) *learning gain*; and 3) *retention and dropout*. The first two subcategories are more focused on individual learners (at the course level), whereas the third relates to larger groups of learners (at the department level). In many of the key studies, we found concepts such as academic performance, academic achievement, and academic success. We argue that these concepts are too abstract for the transparent evaluation of learning analytics interventions (and for learning technologies in general), hence we used more explicitly named subcategories.

A learner can demonstrate the acquisition of *knowledge and skills* as a product of their learning process. Most key studies in this category operationalize affected learning through grades or test scores or scores [29], [33]–[35], [37], [49], [50], [53], [54], [57], [61], [63], [67]–[70], [74]–[76], which is a direct assessment of learning as performance on a task (e.g., an exam or final test) [94]. Although grades may seem to be a direct operational definition, this is debatable. Grades can be regarded as a proxy for learning, as they often comprise a combination of learning outcomes or include nonrelated corrections like extra credits for certain activities [95]. Other operational definitions might capture knowledge and skills more directly, such as the quality of an artefact created by the learner [39], [77]. Remarkably, some of the key studies claim to affect aspects which one would expect in one of the other categories—e.g., saving time for teachers in monitoring the progress of the learning process of students [69] but the operational definitions actually fall in the *learning outcome* category (e.g., grades or scores). That is, the product or outcome of the learning process is measured rather than the actions performed during this learning process or in the learning environment. Moreover, we observe that in some studies, researchers wish to improve higher order learning outcomes, such as self-regulated learning skills [32], [61]. Since these higher order skills are metacognitive and difficult—if not impossible—to measure, these researchers presumably chose to measure the effects in grades or test scores instead.

Knowledge and skills and the second subcategory *learning gain* are closely related; we separated them because the former relates to absolute operational definitions (such as grades) and the latter relates to relative operational definitions (such as the difference between pre- and a posttests [43], [58]), emphasizing the difference in learning a learner has achieved. The concept of *learning gain* captures the idea that learning is visible through a change over time in a learner's behavior, attitude, and/or knowledge. There is no standard definition, conceptualization, or measurement (instrument) to assess learning gain; a conceptual framework with a set of measurement tools is currently being developed for English higher educational institutes [96]. In the conceptual framework proposed in [96], a distinction is made between four components (cognitive, metacognitive, affective,

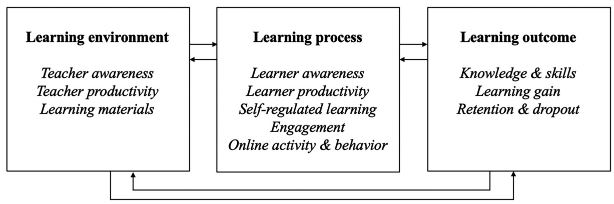

Fig. 5. Refined classification scheme for operational definitions of learning affected by learning analytics interventions.

and socio-communicative) and three cross-cutting dimensions (view of knowledge and learning, research attitude, and moral reasoning).

The final subcategory is *retention and dropout*, which relates to larger groups of learners and captures "academic persistence" in terms of, e.g., withdrawal rates and absence [12], [31], [34], [64], student retention [62], [65], and reregistration rates [33]. Siemens & Long [97] distinguish between learning analytics at course level and departmental level. Departmental variables may consider a more long-term effect of learning analytics, which has been posed as an important feature of future learning analytics research [9].

The above synthesis leads us to the refined classification scheme of Fig 5. We use this refined classification scheme to give an overview of all operational definitions identified in the key studies of this review (see Table VI).

V. Discussion

The aim of this article was to provide an answer to the research question: In what way does existing literature on learning analytics interventions operationalize affected learning? The first conclusion is that, from 1932 search hits on learning analytics, only 62 describe quantitative, measurable effects of complete learning analytics cycles in authentic learning context. This is a noticeable shortcoming and in line with previous research that concluded that not enough studies make a connection to the next stage of the learning analytics cycle, i.e., "not enough published work is making clear how the move will be made from researching the data to optimizing the learning" [5]. As we gathered evidence from a wide range of scientific databases, this article thoroughly underpins their conclusion, which was based on only those studies that were included in the LACE Evidence Hub. We concur with the conclusions of several other reviews in the field that the number of studies providing evidence for the (positive) impact of learning analytics on learning currently is low [8], [10], [22].

By analyzing these 62 key studies, we identified different operational definitions of learning which can be affected with learning analytics interventions. The operational definitions are positioned according to a classification scheme with three categories and eleven subcategories: 1) *learning environment*; 2) *learning process*; and 3) *learning outcome*. This article facilitates improved positioning of empirical research on learning analytics interventions based on concrete operational definitions, which, in turn, helps us to better compare and generalize studies. We hope to advance the field in this respect, motivated by recent calls for (the use of) a standard set of constructs evaluating the impact of learning analytics studies [6], [7], [10]. Our classification scheme with suggestions for operationalization could be used in conjunction with a framework for systematic development, implementation, and evaluation of learning analytics interventions [3]. Our results can also be used in the evaluation of learning technologies in general, since the impact on learning can be measured similarly for other technologies.

This systematic literature review shows that key studies mostly relate to the following two subcategories: 1) *learning process—online activity and behavior*; and 2) *learning outcome—knowledge and skills*. This is not surprising, since grades, test scores, and LMS log data are easily gathered. Merely nine key studies report on operational definitions in more than one category, even though cross-categorical learning analytics provide a better, multiperspective view on learning. The need for multidimensional metrics for learning is supported by Joksimović *et al.* [23]. Moreover, given the complex nature of applying learning analytics interventions in practice, measuring the effect of learning analytics interventions on a wider spectrum of aspects can give more insight into their workings on different actors and processes involved. We believe this is not exclusively important for learning analytics research, but is crucial in the development of learning technologies in general because of the shared goal of optimizing learning through technological interventions. We observe that all cross-categorical studies have appeared in the most recent years (since 2014), which might be an indication that the need for this type of study is increasingly acknowledged in the learning analytics field.

A. Recommendations

In order to justify the use of data analytics within educational processes, the effects of learning analytics interventions on learning must be clear and well defined. In a recent book chapter, Wise [98] described the various pedagogical uses for which learning analytics are used. All of them focuses on improving either the learning process or the learning environment. It makes sense to empirically evaluate whether learning analytics efforts indeed have done so, by measuring effects of learning analytics interventions on these particular aspects directly.

Finding the operational definition(s) of affected learning in a research paper was not always straightforward; these operational definitions could be found in Section III, the analysis or the result section. Often, the dependent variable of a study would be named as an abstract construct in most of the article (e.g., academic achievement or engagement), whereas the concrete operational definition or measurement instrument would only be mentioned explicitly once in the section, without justification on why this specific operationalization was adopted. We share this observation with Joksimović *et al.* [23], who state that a lack of specificity on used concepts and measures posed a significant challenge for their article. We recommend researchers to be clear and transparent throughout the article on which operational definitions are used to measure learning affected by learning analytics interventions.

TABLE VI
OPERATIONAL DEFINITIONS OF AFFECTED LEARNING POSITIONED WITHIN OUR REFINED CLASSIFICATION SCHEME

Category	Subcategory / construct	Operational definition	Key studies
Learning environment	Teacher awareness	Detection of problematic student groups	Van Leeuwen *et al.* [36], Van Leeuwen *et al.* [42], van Leeuwen, Rummel & van Gog [85]
		Teacher attention, teacher interaction	Martinez-Maldonado, Yacef & Kay [45]
		Synchronization between teacher and student	Shimada & Konomi [71]
	Teacher productivity	Number of messages sent by teacher	Van Leeuwen *et al.* [36], Van Leeuwen *et al.* [42]
		Time it takes a teacher to assess a student	Groba *et al.* [40]
		Percentage of correct answers (identification) regarding group work	Swidan *et al.* [87]
		Response time	Van Leeuwen, Rummel & van Gog [85]
		Number of correctly detected problem types	Van Leeuwen, Rummel & van Gog [85]
	Learning materials	Validity, reliability of exam	Smolin & Butakov [30]
Learning process	Learner awareness	Plagiarized post ratios	Akçapınar [38]
		Making predictions about grades by students	Holman *et al.* [41]
	Learner productivity	Revision of artefact made	Manske & Hoppe [56]
		Study time, practice time, number of exercises made	Klaveren, Vonk & Cornelisz [67], Tabuenca *et al.* [48]
		Time spent on solving questions, higher level of difficulty of questions	Ben David, Segal & Gal [53]
	Self-regulated learning	Self-assessment pre- & post-questionnaire scores Self-regulated learning pre- & post-questionnaire scores	Melero *et al.* [46], Siadaty, Gašević & Hatala [59]
		Use of metacognitive tools, application of SRL cycle (plan, learn, assess, reflect)	Nussbaumer *et al.* [47]
	Engagement	SNA indicators, social interactions and engagement	Chen *et al.* [72], Marcos-García, Martínez-Monés & Dimitriadis [44], Michos & Hernandez-Leo [78]
		Emotional duration changes	Aslan *et al.* [80]
	Online activity & behavior	Counts of events, centrality measures	Siadaty, Gašević & Hatala [60]
		Number of posts, threads, messages or discourse features	Beheshitha *et al.* [52], Gong, Liu & Zhao [74], Klock *et al.* [76], Michos & Hernandez-Leo [78], Aljohani *et al.* [79]
		Utilization ratio of note-taking functionality	Shimada & Konomi [71]
		Online learning behaviors (Discussion posts, Resources browsing, Self-evaluation, Peer evaluation, Tasks submission)	Gong & Liu [81]
		Online activity, frequency of accessing LMS, frequency of accessing discussion board	Aljohani *et al.* [79], Lim *et al.* [86]
Learning outcome	Knowledge and skills	Grades	Diana *et al.* [63], Grann & Bushway [33], Guillot *et al.* [75], Jayaprakash *et al.* [34], Khan & Pardo [54], Klock *et al.* [76], Kumar *et al.* [35], McKenzie *et al.* [32], Rosmansyah *et al.* [69], Seanosky *et al.* [70], Tabuenca *et al.* [48], Whitelock *et al.* [49], Syed *et al.* [88], Gong & Liu [81], Lim *et al.* [86], Arnold & Pistilli [12], Davis *et al.* [61], Lauría *et al.* [31], Vargas *et al.* [89]
		Answers to reference questions	Papoušek, Stanislav & Pelánek [57]
		Depth, rarity, quality, and specificity of program	Berland, Davis & Smith [39]
		Number of unit tests passed	Mangaroska *et al.* [77]
		Quiz scores, test scores, final exam scores	Ben David, Segal & Gal [53], Cheng & Liao [29], Gong, Liu & Zhao [74], Klaveren, Vonk & Cornelisz [67], McKenzie *et al.* [32], Xiong, Wang & Beck [50], Yamada *et al.* [37], Jovanović *et al.* [84], Lim *et al.* [86]
		Score of the game	Arguedas, Daradoumis & Xhafa [51]
		Exercise performance (completion time & success rate)	Hubalovsky, Hubalovska & Musilek [82]
		Course completion or failure rates	Ciolacu *et al.* [73], Davis *et al.* [61], Faria *et al.* [64]
	Learning gain	Difference between pre- and post-test	Perikos, Grivokostopoulou & Hatzilygeroudis [68], Sharma *et al.* [58], Aslan *et al.* [80], Jeon & Song [83]
		Mastery scores (pre- and post-)	Lonn *et al.* [43]
	Retention and dropout	Withdrawal rates, absence	Arnold & Pistilli [12], Faria *et al.* [64], Jayaprakash *et al.* [34], Lauría *et al.* [31]
		Student retention	Dawson *et al.* [62], Herodotou *et al.* [65]
		Reregistration rate	Grann & Bushway [33]
		(Revenue from) student enrollment	Harrison *et al.* [55], Jing & Tang [66]

Some of the papers we encountered during this article do report on potential improvements gained by learning analytics interventions, but do not quantify the actual effects by operationalizing and measuring affected learning. This is in line with the observations from the review by Viberg *et al.* [8]. By describing those effects, more evidence about the benefits of learning analytics on education can be gathered, consequently strengthening the field in general. We suggest the use of our research outcomes for reporting on and comparing learning analytics results in both research and practice. It is a first step to be clear and transparent about the operational definitions and measurement instruments we use in our empirical evaluations, before the learning analytics field as a whole can standardize these operational definitions in order to ultimately compare effect sizes in the same way this is done in research fields with a longer tradition such as medicine and psychology.

As mentioned before, grades can be regarded as a proxy for learning. Recently, Guillot *et al.* [75] also concluded that grades (alone) are no suitable way to operationalize the impact of learning analytics systems. The problem that operationalizing affected learning results in shallow proxies for learning extends well beyond grades, since the data that are available to the researchers often limits which measurements can be used; this need not be a huge problem, as long as researchers are transparent on which operational definitions are used. Rienties *et al.* gave a good example of such transparency: in their study they state "LMS activity should only be regarded as a proxy for student engagement in formal online activities, as at this point in time the OU does not systematically collect data about formal or informal offline activities" [99]. We emphasized this perspective by separating the subcategories *engagement* and *online activity and behavior*.

Moreover, we observe that higher order learning outcomes, such as self-regulated learning skills, are difficult—if not impossible—to operationalize and measure. Further research could explore alternative operational definitions that fit the higher order nature better than grades or test scores do.

Gašević *et al.* [9] urged us to remember that "learning analytics are about learning." In line with this statement, and based on the outcomes of this article, we recommend learning analytics researchers and educational institutes to move away from mere performance-based evaluation of learning analytics projects and include measurements related to learning processes and learning environment as well, as that is also a core objective of learning analytics [97]. Regardless of the dominant learning theory within an institute, a more complete view on learning is taken by adopting a multiperspective operationalization from more than one category of our classification scheme.

B. Limitations

We used a classification scheme based on the 3P model—-in line with the approach of Joksimović *et al.* [23]—to categorize the operational definitions we found. Other approaches to classify could lead to different insights, since a choice for a specific classification scheme introduces a level of subjectivity. In relation to our category *learning outcome,* Viberg *et al.* [8] used similar, but slightly different categories in their review of learning analytics evidence: knowledge acquisition, skill development, and cognitive gain. Rienties *et al.* [3] proposed to evaluate the impact of learning analytics interventions using the attitude, behavior, and cognition model. Attitude and behavior have the strongest relation with our category *learning process* and cognition with *learning outcome*. However, although cognition is often measured through summative assessments, operational definitions also can incorporate more formative learning activities, such as discussion forum activity or blog postings [3].

Our goal was to systematically review in what way literature on learning analytics interventions operationalizes affected learning. In order to do so, we only included empirical, quantitative results from the evaluation of learning analytics interventions in this article in the same way Joksimivić *et al.* did in their study on modeling learning in the MOOC research [23]. However, several studies use tools, techniques, or methods as an intervention, even though they do not rely on data analytics itself. These papers then use data (analytics) to describe the effect the intervention has on learning. Although this provides insight in the variables used to measure affected learning, these studies were disregarded as they do not meet our inclusion criterion demanding interventions based on learning analytics, which is an important step within the learning analytics cycle and the focus of this article. Furthermore, qualitative studies will probably yield complementary, rich insights; we believe such studies are worth of a separate literature review. Future research might adopt broader inclusion criteria and extend the current findings with a larger set of key studies, thereby enhancing our results and identifying more and different operational definitions of affected learning.

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Justian Knobbout received the M.Sc. degree in supply chain management from Erasmus University Rotterdam, Rotterdam, The Netherlands, in 2013. He is currently working toward the Ph.D. degree in learning analytics from Open University, Heerlen, The Netherlands.

He has been a Lecturer of Business Engineering with the HU University of Applied Sciences Utrecht, Utrecht, The Netherlands, since 2014.

Esther van der Stappen received the M.Sc. degree in computer science from the University of Groningen, Groningen, The Netherlands, in 2003, and the Ph.D. degree in computer science from Utrecht University, Utrecht, The Netherlands, in 2008.

She is currently an Associate Professor with the HU University of Applied Sciences Utrecht, Utrecht. Her research interests include learning analytics, technology-enhanced learning, specifically the design and evaluation of technology supporting learning processes in the workplace.