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A Systematic Review

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Open Learner Models and Learning Analytics Dashboards: A Systematic Review

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ABSTRACT

This paper aims to link student facing Learning Analytics Dashboards (LADs) to the corpus of research on Open Learner Models (OLMs), as both have similar goals. We conducted a systematic review of literature on OLMs and compared the results with a previously conducted review of LADs for learners in terms of (i) data use and modelling, (ii) key publication venues, (iii) authors and articles, (iv) key themes, and (v) system evaluation. We highlight the similarities and differences between the research on LADs and OLMs. Our key contribution is a bridge between these two areas as a foundation for building upon the strengths of each. We report the following key results from the review: in reports of new OLMs, almost 60% are based on a single type of data; 33% use behavioral metrics; 39% support input from the user; 37% have complex models; and just 6% involve multiple applications. Key associated themes include intelligent tutoring systems, learning analytics, and self-regulated learning. Notably, compared with LADs, OLM research is more likely to be interactive (81% of papers compared with 31% for LADs), report evaluations (76% versus 59%), use assessment data (100% versus 37%), provide a comparison standard for students (52% versus 38%), but less likely to use behavioral metrics, or resource use data (33% against 75% for LADs). In OLM work, there was a heightened focus on learner control and access to their own data.

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CCS CONCEPTS

• Human-centered computing~Visualization application domains • Human-centered computing~Visualization systems and tools

KEYWORDS

Learning analytics dashboards, open learner models, open student models, literature review

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1 INTRODUCTION

Learning analytics promises to have a profound impact on educational practice. One way in which this area of research might bring about beneficial change for learners is through "learner awareness tools," that is, tools that provide up-to-date information to learners about their learning status, often in an interactive manner. The tools may provide this information as the learning activities are ongoing (e.g., as students are enrolled in a course or in real-time as they work through course materials) or after learning activities have been completed.

Examples of such tools are student-facing learning analytics dashboards (LADs) [6, 51], early warning systems [2, 30, 37, 53, 56], and open learner models (OLMs) [10, 11, 12, 39]. A key assumption is that learners will carefully use the information provided by the awareness tool to help them monitor, reflect on, and regulate their own learning, and that this will boost their academic achievement.

In this article, we review an important class of learner awareness tools, namely open learner models (OLMs). An Open Learner Model "…makes a machine's representation of the learner available as an important means of support for learning" [10]. Such a model might represent variables regarding "student's knowledge, interests, affect, or other cognitive dimensions," which typically are "inferred based on the learner's interactions with the system." [10]. Over decades of past research, many different OLMs have been developed, with a variety of content, designs, and visualizations. These OLMs are often embedded in advanced learning technologies such as intelligent tutoring systems [34, 41, 44, 50, 55].

2 PREVIOUS WORK

2.1 A History of OLMs

At first blush, OLMs are very similar to LADs, which may be more familiar to the learning analytics and knowledge (LAK) community and which have been defined as "a single display that aggregates multiple visualizations of different indicators about learners, learning processes, and/or learning contexts" [45]. Although this definition overlaps considerably with that of OLMs, these two lines of work have different roots and have proceeded largely independently, with very limited cross-fertilization. As a result, we hypothesize that the typical OLM is quite different from the typical student-facing dashboard, in spite of the shared goals of these types of systems.

A key difference is that OLMs are grounded on work in "student modeling", "learner modeling", and even the broader "user modeling", where dashboards are more broadly grounded in data-driven decision making which often includes goals, stakeholders, and decision making outside of the context of the learner model. The line of work in OLMs has a long history in the research areas of intelligent tutoring systems (ITSs), artificial intelligence in education (AIED), and adaptive hypermedia (AH). Learner models are a central component of many such systems. Much of the adaptive capabilities of these systems derive from having and maintaining an up-to-date model of the learner. One key role of such a learner model is to automatically drive personalization of teaching or recommendations to the learner.

Among OLMs, there is great variety in the kinds of student variables used to capture a learner's learning state. A few examples are (i) simple progress measures (i.e., number of problems completed), (ii) measures of a student's knowledge and knowledge growth (i.e., mastery of knowledge components, often modeled as a latent, or unobservable, construct, for example in cognitive tutors [19]), (iii) affective state, or (iv) effort expended on recent problems.

Work on student modeling and OLMs is often grounded in artificial intelligence techniques and methods, especially in terms of the way that a student's learning state can be represented so as to support a system's adaptive pedagogical decision making. For example, some of the older work in this area has focused on how to represent students' possibly incomplete and inaccurate knowledge. More recent work has focused on, for example, how to decompose knowledge targeted in instruction so that the student's performance on activities in the system (i.e., the targeted knowledge) can be accurately tracked [40, 43].

Over the years, a great variety of student modeling techniques, or methods have emerged for keeping learner models up-to-date, based on student interactions in learning activities. Nowadays, accurate student modeling is a key focus in the field of educational data mining [4, 22, 43], although "close the loop" studies, in which novel student modeling methods invented in EDM or other results of analytics-focused research rarely make it into educational software, and their effect on student learning or other outcomes is rarely rigorously tested (but see [35, 40]). A number of studies provide strong evidence that having a student model can make a system more effective in helping students learn, by using the model to adapt to learner differences (e.g., cognitive mastery, which is a form of individualized problem selection based on modeling individual students' skill mastery [18]).

Within the fields of ITS and AIED, much research has focused on how a student model can be made directly beneficial to students by "opening" it up to them, thus leading to the notion of OLMs [28, 49]. A key way of doing so is simply to display the student model in the software's student-facing interface. The earliest of these interfaces did not use the term "OLM" [8, 13, 17, 32, 54]; this terminology emerged in the late 1990s.

There were many driving forces behind this idea, including the notion that OLMs might support useful reflection and self-regulation by learners. Also, in systems that implement a mastery learning criterion (e.g., cognitive tutors [3, 34, 42]), meaning that each student gets an individualized problem sequence depending on their performance with the software, the student model (often displayed in the form of "skill bars" that capture the level of mastery of the targeted knowledge components) communicates progress more effectively than the number of problems solved. Further, it was thought that exposing the system's inner workings (and in particular its conception of the student) to students would inspire confidence and learner self-awareness. Taking this idea one step further, researchers developed the notion of a "negotiable student model" [13] in which the student could "appeal" the student modeling decisions made by the system. The ensuing negotiations between student and system about the student's actual current level of knowledge were likely to result in more accurate student modeling, and potentially also helped the learner better understand their own understanding and misconceptions. Another approach allowed the student to provide their self-assessed knowledge so that this self-assessment could serve as one source of evidence, used in conjunction with evidence based on their actual performance tracked by the system [14, 33]. Broadly, OLMs have been created for many roles, including: (i) improving the accuracy of the learner model; (ii) supporting metacognitive processes of reflection, self-monitoring and planning; (iii) facilitating navigation and decisions of what to learn next; (iv) assessment; and (v) addressing the diverse issues around a learner's right of access to, and control of, their personal learning data and its use [9, 12]. There has been a host of empirical work to find out how OLMs influence student learning.

2.2 Purpose and Research Questions

Given the common goals of LADs and OLMs, it is desirable that these two lines of work influence each other more strongly, and perhaps even merge. As a first step in that direction, a review of the OLM literature would be helpful. While overview articles exist of LADs [5, 6, 31, 45, 51, 52], we are not aware of a similar comprehensive overview of the work on OLMs. Such a comprehensive review would help researchers to better understand what OLMs are and what empirical results have been obtained with OLMs. It would also help inform the discussion about how research on OLMs and research on LADs could be more synergistic. We particularly set out to do this in a manner that facilitates comparison with LADs [5].

The current paper bridges this gap with a systematic review of the literature on OLMs. We here seek to answer the following guiding research questions:

1. What data is collected in OLM systems, and what type of modeling methods are used?
2. What are the current trends in OLM research in terms of publication venue, publications over time, authors, and top cited articles?
3. What are the central themes or topics that have emerged from OLM research articles?
4. What is the nature of OLM system evaluations?
5. What similarities and differences exist between OLMs and learning analytics dashboards?

3 METHODS

3.1 Article Search Method

We initially developed a set of keywords to identify relevant OLM research articles. The list of keywords included "Open Learner Model*", "Open Social Learner Model*", "Open Student Model*", and "Open Social Student Model". An asterisk denotes a variable ending to the word (i.e., "model*" can be "models" or "modelling" or "modeling"). We focused our search for OLM research articles in the following databases: Computers and Applied Sciences, Education Resources Information Center (ERIC), IEEE Xplore, ACM digital library, and Google Scholar. We searched for the keywords in both the title and the abstract of the articles. Each of the keywords listed above was either used as a separate search query or was joined together with an "OR" statement with the remaining keywords. These searches yielded 190 articles.

Once we had this initial list of OLM articles, we counted the number of times each author appeared as an author of a paper and then analyzed the publication lists of the top ten authors to make sure we did not miss relevant research that did not list one of our keywords in the title or abstract. Lastly, to check that we did not miss large pockets of OLM research, two OLM experts, Judy Kay and Vincent Aleven, listed authors who they perceived to be top authors in the OLM field. We searched the previous work of these recommended authors and added articles that discussed introducing an OLM. These author searches yielded 44 additional articles for a combined total of 234 articles.

3.2 Inclusion Criteria

In our analysis, we only included articles that introduced a new OLM or a new version of an OLM. Articles where the authors simply cited an OLM from prior work were not included. We used these inclusion criteria so that we could compare the results of this analysis to previous learning analytics dashboard literature reviews that have been conducted. Four coders reviewed the 234 articles based on this inclusion criteria, which resulted in 114 articles.

3.3 Coding Process

Four researchers participated in the article coding process. First, the four coders discussed and agreed upon a code book (defined below). Next, each coder coded a set of five articles and all then met to discuss the differences in their codes. After refining the code book, each coder recoded the initial five articles as well as a new set of five articles. Coder agreement metrics were then calculated using the codes on the five new articles. Table 1 shows the results of the coder agreement.

Table 1: Interrater agreement metrics from four coders.

Name	Metric
Average Pairwise Percent Agreement	89%
Fleiss' Kappa	0.78
Average Pairwise Cohen's Kappa	0.78
Krippendorff's Alpha (nominal)	0.78

Previous research suggests a Krippendorff's Alpha of greater than 0.80 is excellent, and a value greater than 0.67 is acceptable for four coders [36], so our value of 0.78 satisfies the acceptable threshold. Moving forward, each coder then coded a different set of about 28 articles each. If any coder experienced difficulties coding a particular article, the article was flagged and double coded by another coder. Seven additional articles were removed during the coding process because they did not fit the inclusion criteria, even though they had made it through our previous evaluation. This resulted in 102 articles (107 OLMs, as five articles introduced two OLMs instead of one) for the final analysis.

The final list of articles can be viewed here: https://docs.google.com/spreadsheets/d/1k0VszbOfEDgYUASOdePyHUaIs3eCkMA8XylIjCQVeig/edit?usp=sharing.

3.4 Code Book Category Definitions

The code book used in our coding process was iteratively developed from previous OLM literature review work [9, 12] as well as previous learning analytics dashboard literature review work [6, 45]. Furthermore, the categories defined in the code book were chosen based on the research questions for the review. The final categories, along with the guiding questions for each of them, are:

- **User input:** Did the OLM allow the user to provide input to the learner model? For example, OLMs that satisfy this criterion included the ability for learners to negotiate with the model over their assessed knowledge state or progress (as is the case in [14, 23, 33]). If an OLM allowed a user to provide input, but this was not reflected in the learner model, it would not be coded as "User Input".
- **Visual**: This coding indicates that a screenshot showing what the learner would actually see in the OLM was included in the paper. If the paper included an example table or figure of what the system may have looked like, but did not include a screenshot of what the learner would actually see, it was not counted in this category.
- **Single type of learner data**: Did the OLM only utilize a single type, or class, of learner data? For example, if a system estimated knowledge mastery and exclusively used that data type shown in the OLM, the system would only have one type of learner data. However, if an OLM tracked more sources, e.g., knowledge mastery and affective state, then it would not be coded as "Single type of learner data".
- **Multiple applications**: Did the OLM aggregate data from more than one source? For example, if an OLM uses data from an intelligent tutoring system and a learning management system, it would be coded as "Multiple applications". However, if a virtual learning environment tracked multiple types of data, it would not count as "Multiple applications" because all data types originated from the same system.
- **Complex Modelling**: Did the OLM (1) explicitly mention the method used to determine the learner model, AND (2) use a modelling technique that was more sophisticated than using a formula based on a simple summation of variables?
- **Behavioral Metrics**: Did the OLM include measures of learner behavior in terms of resource use, such as discussion board views, page views, number of assignments submitted, duration of time spent, etc.? For example, if an OLM made use of the number of questions a student completed, it would count for this category.
- **Interactive interface**: Did the OLM allow the learner to interact with the OLM in some way? If the learner could filter, click on hyperlinks, choose which visualization they preferred, or challenge the system to negotiate on their learner model, the system was coded as "Interactive." Systems not coded as "Interactive" provided a static interface with no ability to engage with it.
- **Comparison**: Did the OLM provide a comparison between the learner and their peers or some sort of course standard defined by the instructor?
- **Evaluation**: Was any type of system evaluation conducted? This category was defined quite broadly and included any type of validation study. Examples include usability tests, perception surveys, and randomized control trial experiments. If an evaluation was not conducted, the evaluation, sample-size, multiple evaluation, authentic evaluation, formal domain, tertiary education, and secondary education categories were coded as "not applicable" and not included in our analyses.
- **Sample-size**: The number of participants in an evaluation study was coded. In the rare case that multiple evaluations were conducted, we coded the sample size as the sum of all sample sizes listed in the paper.
- **Multiple evaluations**: Does the paper discuss multiple evaluations of the OLM?
- **Authentic evaluation**: Was the evaluation conducted in an actual classroom environment as part of the standard coursework rather than a research lab or other controlled environment?
- **Formal domain**: Was the evaluation conducted within a STEM-related discipline (science, technology, engineering, mathematics, or programming)?
- **Tertiary education**: Is the evaluation domain in tertiary education (college or university)?
- **Secondary education**: Is the evaluation domain in secondary education (high school, middle school)?

4 RESULTS AND DISCUSSION

The results of our analyses address each research question.

4.1 Research question 1: What data is collected in OLM systems, and what type of modelling methods are used?

For the first research question, we calculated the number of OLM systems that were coded for each of the categories shown in Table 2. We calculated both the total number of OLM systems that were coded for each category, as well as a percentage of the category in comparison to all OLM systems in the analysis (Table 2 below).

Table 2: The number and % of articles coded in each category.

Category	# of OLMs	% of OLMs
Single type of data	62	57.9%
Behavioral Metrics	35	32.7%
Multiple applications	6	5.6%
Input provided by the user	42	39.3%
Complex Modelling	40	37.2%

One of the notable insights from this analysis is that about half of OLMs used a single type of data to model the learners. This included multiple-choice question scores or data generated from intelligent or cognitive tutors to model a learner's level of assessed knowledge. About one third of the OLMs we investigated included behavioral metrics on the OLM display.

OLM systems rarely use data from multiple applications, but rather pull their data from only one application. This is not surprising, since many of the OLMs included in our analysis are embedded into an intelligent tutoring system or a cognitive tutor. Apart from using data automatically collected by the system, several OLMs also requested additional input from the users themselves. This was usually done by requesting learners to agree with or challenge/persuade the OLM when they did not agree with the model's representation. The proportion of papers that explicitly stated what type of complex modelling they were using was smaller than we expected. This does not necessarily suggest that most OLMs use simple modelling approaches, but rather that authors were not discussing their modelling techniques in OLM papers. As trust is an important factor to consider in the adoption and use of OLMs, being more explicit about the method used to infer the learner model has potential to advance OLM research.

4.2 Research Question 2: What are the current trends in OLM research in terms of publication venue, publications over time, authors, and top cited articles?

To answer the second research question, we identified trends in OLM research using Google Scholar to track citation counts for each of the final 102 articles. We then filtered the articles to display the top 10 based on citations (Table 3).

We next conducted an analysis of the top authors in terms of paper quantity by counting the number of times each author appeared as either one of the first three authors or the final author of a paper. We did not include all authors because we wanted to more accurately represent significant contributions to the OLM field by key actors (gauged by appearing earlier in the list of authors or as last author). Last author was included because many prominent scholars are listed as the last author indicating their leadership role and that the research came from their lab or research group. We next counted the number of times each author was represented in the dataset and filtered to only display the top 10 authors (Table 4). We also counted how often these authors appeared in the systematic review of LADs [6], in which the authors analyzed LAD research published between January 2005 and June 2016. The author and venue counts of LAD publications are therefore not entirely up to date. But in general, we can observe that work of many prominent OLM authors is not well picked up in reviews of LADs (Table 4).

For the top publication venue analysis, we standardized the text for each of the conferences or journals, and then counted the number of times each venue, conference name or journal name appeared in our dataset. All venues with more than one published article were included in our results (Table 5). The new venues for publishing analysis are represented by a list of all venues that were included only once in the dataset. These may provide additional opportunities for OLM scholars to publish their work (Table 6).

To represent the publications over time, the articles were grouped by year and displayed in a line chart (Figure 1).

Table 3: The top-cited articles based on Google Scholar citations.

Article Title	Citations
STyLE-OLM - Interactive open learner modelling	215
Multi-agent multi-user modelling in I-Help	187
Evaluating the effect of open student models on self-assessment	149
Active open learner models as animal companions motivating children to learn through interaction with my-pet and our-pet	77
CALMsystem - a conversational agent for learner modelling	76
Integrating open user modeling and learning content management for the semantic web	73
Alternative views on knowledge - presentation of open learner models	73
Student preferences for editing, persuading, and negotiating the open learner model	70
Supporting learning by opening the student model	69
Inspecting and visualizing distributed bayesian student models	68

Table 4: The top authors of our analysis compared with top LAD authors.

OLM Author	# of OLM Publications	# of LAD Publications
Bull, S.	31	2
Brusilovsky, P.	13	1
Johnson, M. D.	7	1
Hsiao, I. H.	7	0
Greer, J. E.	6	0
Guerra, J.	6	0
Dimitrova, V.	5	0
Mitrovic, A.	5	0
Zapata-Rivera, J-D.	5	0

Although OLM and LAD research have a number of similarities, there are still several gaps between the two fields which stem from the different communities from which each field has emerged. LAD research is connected to the learning analytics and knowledge community, while OLM research is centered in the intelligent tutoring system and artificial intelligence in education communities. An illustration of the gap between these two fields can be seen in Table 4, showing the number of OLM and LAD papers each of the top OLM authors have published. Table 4 also shows that LAD review papers to date have not included OLM research in their inclusion criteria ([5, 6, 31, 51]). Another gap between the fields can be seen in Table 5, which shows the most common venues for each of the two fields. There are a few small overlapping venues (e.g., EC-TEL, AIED, LAK, IEEE TECT), but for the most part, the communities are separate.

Table 5: The top venues of our analysis compared with top LAD venues.

OLM Venue	# of Publications	LAD Venue	# of Publications
AIED	13	LAK	16
IJAIED	12	Expert Systems	6
ITS	9	CEUR	4
UMAP	9	ETS	4
ICCE	5	Artel	3
EC-TEL	5	ICALT	3
ICALT	4	Knowledge Based Systems	3
IEEE TLT	3	AIED	2
VL/HCC	2	PCS	2
IUI	2	EC-TEL	2
UMUAI	2	C&E	2
UM	2	Educon	2
IEEE DGIT	2	IEEE TETC	2
LAK	2		
IEEE TETC	2		

Table 6: New publishing venues OLM researchers and LAD researchers may want to consider.

New Venues for Publishing
Journal of Learning Analytics
Caspian Journal of Applied Sciences Research
ALT-J, Research in Learning Technology
Tech., Inst., Cognition and Learning
ReCall
Adaptive Hypermedia and Adaptive Web-Based Systems
Journal of Computer Assisted Language Learning
International Journal on E-Learning and Higher Education
The second International Conference on Internet of Things, Data and Cloud Computing
International Journal on Artificial Intelligence Tools
International Journal of Information and Education Technology
International Journal of Interactive Mobile Technologies
Advances in Web-Based Learning
E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education
Computers and Education
e-Proceeding of Engineering
New Venues for Publishing
ACM/IEEE International Conference on Human-Robot Interaction
International Journal of Computer Applications
New Review of Hypermedia and Multimedia
European Conference on e-Learning
IEEE MultiMedia
Interactive Learning Environments
FECS
ACE (Australasian Computing Education Conference)
Ibero-American Conference on Artificial Intelligence
Int. J. Cont. Engineering Education and Lifelong Learning
SGAI International Conference on Innovative Techniques and Applications of Artificial Intelligence
Proceedings of CSCL
Int. J. Human-Computer Studies
User Modeling Conference
Workshop on Personalisation on the Semantic Web
Red-Conference - Rethink Education in the Knowledge Society

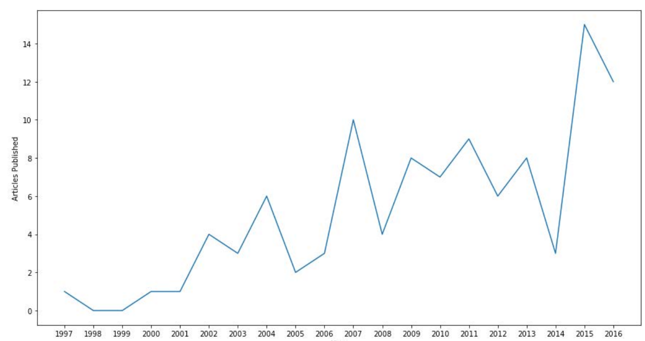

Figure 1. A line chart showing the number of OLM publications per year.

The OLM research trends analyses (Table 3, Table 4, Table 5, Table 6, Figure 1) are provided to give readers unfamiliar with the OLM field a snapshot of the top authors, venues, and papers in OLM research. The publication over time figure shows the recent growth of OLMs, which is similar to the recent growth in LADs, suggesting there is a growing interest in the development of OLMs and LADs. This common enthusiasm highlights a potential for collaboration between LA research and OLM research.

4.3 Research question 3: What are the central themes or topics that emerge from OLM research articles?

To identify central themes or topics within OLM research, we looked at the top occurring keywords, top occurring words in the abstract, and top occurring words in the title. First, all text was made lower case. Next, stop-words (e.g., of, a, and, the, etc.) were removed. Obvious words (e.g., Open Learner Model, Student Modelling) were then removed because these do not provide valuable new information. The final list of words in each category (keywords, abstract, title) was tabulated to find the most commonly occurring words (Table 7).

Table 7: Top keywords, words in abstract, and words in title. Ordered by descending frequency.

Keywords	Abstract	Title
intelligent tutoring systems	paper	social
learning analytics	system	adaptive
self-regulated learning	approach	using
self-assessment	study	support
learner model	results	reflection
reflection	social	visualizing
visualization/visualisation	support	language
intelligent tutoring system	based	self-regulated
user trust	knowledge	system
learner independence	learners	environment
education	adaptive	views
metacognition	data	user
open student models	OLM	interactive
data visualization	information	intelligent
collaborative e-learning	two	inspectable
student modelling	different	interaction
adaptive hypermedia	presents	trust
open learner models	tutoring	learners
meta-cognitive skills	research	environments
information visualisation	help	students

Intelligent tutoring systems, learning analytics, and self-regulated learning were the top three keywords in OLM research. This highlights an interesting overlap between OLM and learning analytics, as many OLM articles used learning analytics as a keyword. This may indicate that the OLM community was more aware of the learning analytics community than vice versa (see Table 4 above). Self-regulated learning and reflection also seem to be a focus for many OLM articles, suggesting a key purpose of opening the model to the learner. Social and adaptive are two interesting words used in abstracts. The appearance of "social" is likely indicative of the rise of open social student models [7, 29]. The presence of the word "adaptive" in abstracts shows the intent of OLMs to personalize or adapt instruction to learners. Many of these words occur again in the title analysis: social, adaptive, reflection, self-regulated, interactive, inspectable, and trust. OLM research, in part, has focused on inspectable or negotiated models which require understanding student trust of the learner model and the OLM. This has yet to be thoroughly investigated in LAD research.

4.4 Research question 4: What is the nature of OLM system evaluations?

Each OLM was coded on six evaluation categories: authentic evaluation, evaluation, multiple evaluations, formal domain, secondary education, tertiary education, and sample-size (see Section 3.4). The total number of OLMs that fit into each of these categories is displayed in addition to the percentage of the total OLMs for each category (Table 8). Figure 2 shows the sample-sizes distribution in a histogram.

Table 8: The number and % of articles from evaluation categories.

Category	# of OLMs	% of OLMs
Authentic evaluation	42	39.3%
Evaluation	80	74.8%
Multiple evaluations	11	10.3%
Formal domain	53	49.5%
Tertiary education	58	54.2%
Secondary education	12	11.2%

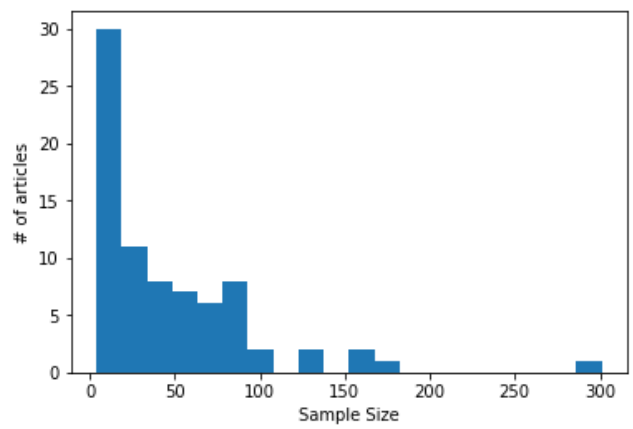

Figure 2. A histogram showing the number of articles (y-axis) describing evaluations with a given sample-sizes (x-axis).

The numbers show that a large majority of OLMs were evaluated, and in some cases (data not shown), several evaluations of the same OLM with different participant samples. The fact that more than one-third of these OLMs were evaluated in an authentic setting is encouraging and indicates that many OLMs may be close to classroom-ready. When we looked at the domain in which the OLMs were evaluated, our results indicate that the formal domain category, indicating a STEM subject, and tertiary education category, indicating higher education, only appeared about half of the time. Our hypothesis was that the large majority of OLMs would be implemented in higher education contexts in a STEM subject. While this prediction was essentially correct, clearly, there is more work in other course subjects and grade levels than we predicted.

4.5 Research question 5: What similarities and differences exist between OLMs and learning analytics dashboards?

To compare and contrast the LAD field with the OLM field, five metrics were calculated for both LADs and OLMs: evaluation percentage, behavioral metrics, assessment data, comparison, and interactivity (see 3.4). The LAD metrics were calculated from a previous LAD review ([6]) and the OLM metrics were calculated from the coded OLMs in this paper (Table 9).

Table 9: A comparison of LAD and OLM research from the metrics in two literature reviews.

Category	LAD	OLM
Evaluation percentage	59%	75%
Behavioral metrics	75%	33%
Assessment data	37%	100%
Comparison	38%	52%
Interactive	31%	81%

Of interest for this paper is how the rich body of research performed by the OLM community can inform researchers and practitioners in the LAK field. Our preliminary comparison in Table 9 indicates that, overall, OLM research has been more extensively evaluated than work in learning analytics. The difference might be explained by the fact that OLM is a more mature research field, with first publications using the term in our review dating back to 1997 (though some work was published even earlier than that), whereas the first LAK conference was organized in 2011. Since then, we have seen an uptick in the evaluation of learning analytics tools with end-users, but there is still a need to assess the effect of LADs in real-life settings with large sample sizes and different stakeholders involved [6].

An interesting observation is that behavioral metrics are used more extensively in LADs, as opposed to assessment data in OLM (see Table 9). Tracking activity traces of learners is indeed at the core of learning analytics, and several researchers have demonstrated the utility of different behavioral metrics based on resource use, social interactions, and time spent [52]. In addition, assessment data is used in 37% of LADs, which seems low. Although not a prerequisite for useful dashboards, recent work in the learning analytics field has demonstrated that visualizing assessment data that is available at hand in every institution can provide a solid foundation for learning analytics dashboards to support student retention, one of the core objectives of many learning analytics applications [15].

Comparison with peers or a standard for the course is supported in both OLM and LA work, although we see a higher number of OLM tools that include such functionality as opposed to LADs. Comparison with peers has been identified as an important feature for LADs by several researchers [6]. Leony et al. [38] found that students particularly requested such features to enable interpretation of learning analytics data. Charleer et al. [15] defined three levels of insights that learning analytics dashboards provide: factual, interpretations, and reflections. Also in this work, comparison with peers was identified as a key element to support interpretation and reflection, beyond the presentation of facts that are the first steps towards achieving behavior change [51]. Hence, a similar larger support for comparison as in OLM work may be a good step forward in LAD work.

Interaction is supported more frequently in OLM work, and we see this as integral to the advancement of LAD work. The majority of LADs (69%) rely on a static representation of behavioral metrics. This may reflect a belief that there is benefit from a dashboard as a single screen of important information, presented to a stakeholder that can be understood at a glance [27]. Whereas a single-screen representation may provide a user with useful data and potential insights, there are several shortcomings to the approach that are likely to hinder the adoption of LADs. First, trust is an important issue that needs to tackled in the LAK field: whereas dashboards have been used in real-life settings, a commonly raised concern of different stakeholders is to what extent the data is trustworthy to support decision making. The LAK field can benefit from a rich body of OLM research to support user trust [1] and to see the way the learner model has been used to personalize teaching [20]. Here the OLM gives learners access to their personal data in the learner model and its use, as advocated by the EU Privacy Directive [26]. A second shortcoming of the single-screen representation in many learning analytics dashboards is the lack of support for user control. Data that is collected in LAD applications is often noisy, and predictions may be error-prone [16]. Interaction is needed to enable learners, instructors, or other stakeholders involved to provide additional input and feedback to improve the analytic process. Future research on learning analytics dashboards should increase interaction support to address these shortcomings.

6 LIMITATIONS

Our inclusion criteria included articles that introduced a novel OLM or a novel version of an OLM. There were, in addition, many articles comparing existing OLMs or adding to the theoretical literature on OLMs, but these papers were excluded given our research questions and motivation. For this reason, we do not claim the results presented in this paper to represent the entire body of work on OLMs. To address this limitation, we acknowledge the scope of our conclusions as within the OLM literature that introduces novel OLMs.

In the LAD and OLM comparison section (research question five) we compared the results of this OLM review with a previously published LAD review. The present study adopted a slightly modified version of that review's methodology, and we acknowledge that these differences could potentially affect the conclusions drawn from the LAD and OLM comparisons. We attempted, to the best of our judgment, to reproduce the methods and inclusion criteria in order to produce accurate, reliable results of the comparative analyses. The LAD review is also slightly older, and analyzed papers published between January 2005 and June 2016. The low number of LAD publications in some of the venues, such as IEEE TLT, may be attributed to the fact that the review is not entirely up to date.

Our article search process identified OLM articles with specific keywords in the title or abstract. Because we used keywords found only in the title and abstract, we may have missed OLM articles that discussed an OLM but did not use our keywords. To add rigor to our search process, we included OLM experts as a spot check to make sure we did not miss prominent scholars or articles in our review.

In our search, we may have missed articles that discussed OLMs in particular journals or conference proceedings stored in databases outside of the scope of our search. The conclusions that we draw in the paper are subject to the rigor of our search criteria. We present these conclusions with confidence given our methods and the use of Google Scholar as well as OLM experts to ensure we did indeed capture a representative body of work within the scope of the review.

7 RECOMMENDATIONS TO MERGE OLM AND LAD RESEARCH FIELDS

Our first recommendation is that LAD and OLM scholars conducting student-facing learning analytics research begin to build on literature in both LAD research and OLM research. Furthermore, combining open learner models and learning analytics dashboards into an umbrella term may be helpful. For example, there should be discussion of a term such as student-facing learning analytics to help bridge the awareness gap between these fields. Both communities, LAD and OLM, could begin to use common terminology for these systems.

Our next recommendation is that learning analytics researchers begin using the term learner model, defined as a machine's representation of the learner, more frequently. The term learner model is used often in the OLM community, and we believe it can be correctly used in learning analytics contexts. This will help bridge the gap in terminology between OLM and LAD research.

One challenge in merging these fields is determining how the methods and metrics between the two fields can be standardized to enable more synergistic research efforts. We recommend that a more in-depth systematic review should be conducted to gain a deeper understanding of the methods and metrics used in OLM research. This review can compare OLM research methods and metrics to LAD research methods and metrics. This review can serve as a starting point for a standardization and best practice recommendations for metrics and methods in these two fields.

8 CONCLUSION

In this paper, we have presented a review of OLM research along several dimensions as well as similarities and differences with current work in the LAK field. We report the following key results from the review: in reports of new OLMs, almost 60% are based on a single type of data; 33% use behavioral metrics; 39% support input from the user; 37% have complex models; and just 6% involve multiple applications. Key associated themes include intelligent tutoring systems, learning analytics, and self-regulated learning. Compared with LADs, OLM research is more likely to be interactive (81% of papers compared with 31% for LADs), report evaluations (76% versus 59%), use assessment data (100% versus 37%), provide a comparison standard for students (52% versus 38%), but less likely to use behavioral metrics (33% against 75% for LADs). In OLM work, there was a heightened focus on learner control and access to their own data. Our analysis indicates that, despite some differences, there is indeed a large overlap between the two fields, with similar objectives and approaches being researched. The main differences include the use of assessment data, evaluation rigor, interaction, and comparison support. Given the strong overlap of both research fields, we believe that adopting lessons learned from OLM research can drive a next generation of LA tools in the fast growing LAK landscape.

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