MDPI

Systematic Review

Model-Based Learning Analytics for a Partnership of Teachers and Intelligent Systems: A Bibliometric Systematic Review

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Abstract: This paper presents a bibliometric systematic review on model-based learning analytics (MbLA), which enable coupling between teachers and intelligent systems to support the learning process. This is achieved through systems that make their models of student learning and instruction transparent to teachers. We use bibliometric network analysis and topic modelling to explore the synergies between the related research groups and the main research topics considered in the 42 reviewed papers. Network analysis depicts an early stage community, made up of several research groups, mainly from the fields of learning analytics and intelligent tutoring systems, which have had little explicit and implicit collaboration but do share a common core literature. Th resulting topics from the topic modelling can be grouped into the ones related to teacher practices, such as awareness and reflection, learning orchestration, or assessment frameworks, and the ones related to the technology used to open up the models to teachers, such as dashboards or adaptive learning architectures. Moreover, results show that research in MbLA has taken an individualistic approach to student learning and instruction, neglecting social aspects and elements of collaborative learning. To advance research in MbLA, future research should focus on hybrid teacher–AI approaches that foster the partnership between teachers and technology to support the learning process, involve teachers in the development cycle from an early stage, and follow an interdisciplinary approach.

Keywords: model-based learning analytics; adaptive learning technology; intelligent tutoring systems; dashboards; bibliometric analysis; topic modelling

1. Introduction

The application of intelligent technologies (e.g., artificial intelligence, or AI) in domains where experts have to make professional decisions is currently an open research topic [1]. Some agreement already exists that intelligent systems, instead of replacing humans, could be better used to enhance experts' capabilities by automating parts of the tasks that they perform. In the context of Technology-Enhanced Learning (TEL), similar proposals are being advanced by research in "hybrid human–AI technologies" [2–4]. However, an open research question is how teachers and technology are working together in different learning environments to support student learning. While the traditional approach taken by intelligent tutoring systems (ITS) has been to focus on the technology that enables autonomous decisions, recent research in learning analytics (LA) has also tried to involve teachers in the decision loop, especially in cases wherein they are better suited to make decisions about students' learning [2,5].

Notwithstanding, there is a lack of a system-level perspective on how technology and teachers influence their respective decisions that aim to support the learning process. One

way of modelling this teacher–technology interplay would be to focus on the knowledge used by each of them, as well as on how this knowledge is exchanged among teachers and technology when supporting student learning practices. This approach is similar to the way in which, by supporting the practices of experts and novices, as well as their interactions, knowledge structures can mediate professional learning and knowledge creation in the workplace [6]. With the purpose of applying this idea in the dual context of teachers and technology, we could consider that there exists a tight coupling between the teacher cognition (i.e., the understanding that a teacher has of a student's learning process, and the knowledge behind their instructional decisions), and the way that the intelligent system operates (i.e., how it evaluates students' learning and knowledge, and how it chooses possible learning trajectories). For instance, an ITS might implement a hierarchical model of interrelated knowledge elements to diagnose the current student's knowledge and to later adapt the tasks that the student will have to perform. It is conceivable that a system and a teacher can influence each other, especially if we consider that teachers also apply a similar logic to think about the domain of teaching (e.g., by being guided by specific knowledge models). We refer to this situation whereby knowledge models are responsible for the coupling between teachers and intelligent learning systems as model-based learning analytics (MbLA). Additionally, MbLA is an attempt to respond to recent calls for more LA that is rooted in theory [7,8]. In this context, in addition to using theory to guide the analyses, MbLA would also require theory to be embedded into the LA solution as a computational model that enables autonomous decisions [9,10].

Realising MbLA is a highly complex and interdisciplinary endeavour. It requires tight collaboration across disciplinary boundaries. Learning scientists need to be involved to specify models of learning through which learning can be evidenced in the classroom. Computer and data scientists need to help to make sense of the abundance of learning traces that are available in the current digital systems. Experts on human–computer interaction (HCI) need to find ways to support human sensemaking with the results from the analyses. Finally, domain experts and educational practitioners need to be involved to validate the approaches. Managing this kind of interdisciplinarity is a general challenge in TEL [11], but it is even more of an issue in situations when a tight coupling needs to be created between the teacher's understanding of learning and the models used by intelligent systems. See [12] for an example of a coupling between an open model of a web tutoring system and teachers' expertise about their students and the related learning activities. In our previous work, we have conducted a systematic literature review on MbLA, guided by several qualitative analyses that aimed to identify the types of models that have been used, the context in which they have been used, and the benefits that their usage have had on teaching and learning practices [13]. Results from this previous research indicate that the lack of integrated interdisciplinary research may be a major roadblock in the realisation of MbLA. Specifically, we identified only 42 papers that used a model of teaching and learning and that also provided results of the automated analyses to teachers. Excluded papers (especially the ones that were manually excluded in the last round of the filtering process) were either lacking a model of teaching and learning (indicating a possible lack of collaboration or alignment with work from learning sciences) or did not include teachers in the loop (who are the main domain experts in this context).

The current paper aims to further explore the nature and dynamics inside the community of research that has managed to produce MbLA solutions. Our main goals are to *uncover elements at a community level that have enabled the implementation of successful MbLA solutions,* and to *identify potential constraints or research gaps that could trigger future research avenues*. A community of practice (such as the research community under investigation) consists of a social structure and a common knowledge (or epistemic) base. Thus, to understand the social structure of the community, we conducted several bibliometric analyses, while, to explore the main themes that have been studied in MbLA, we used topic-based analyses of the 42 papers previously identified. Concretely, we focused on *the structure of the research community*, guided by bibliometric network analyses about co-authoring,

co-citations, considered literature, and considered publishing venues. To discover *research topics that might be relevant to the implementation of MbLA* (and that we might have understated or overlooked in our previous analyses due to both their qualitative nature and the different research questions that guided them), we considered both explicit and implicit topics found in the 42 papers. We identified explicit topics through the network of the main keywords, as mentioned by the authors of the papers. Implicit topics were automatically identified by using Latent Dirichlet Allocation, a machine learning algorithm for topic modelling. Finally, we used Epistemic Network Analysis [7] to visualise the relations between the identified latent topics and the models of teaching and learning used in the systems presented in the papers under review (discussed in detail in Section 2). Results from these analyses enabled us to propose a set of guidelines that could help the LA community to move forward in an attempt to address hybrid settings in which teachers collaborate with intelligent systems in education.

The rest of the paper is structured as follows: Section 2 presents the related work; Section 3 describes the methodology followed for the bibliometric systematic review, the guiding research questions, and the data analysis methods; Section 4 presents the main findings; Section 5 discusses the implications from the results, gives an outlook of future research, and considers the limitations of this study; Section 6 concludes the paper.

2. Related Literature Reviews

Several literature reviews exist that have focused on the use of intelligent learning systems by teachers. These reviews can be grouped into LA- and ITS-related. LA-related reviews have mainly focused on the interactions of teachers and dashboards. For instance, a review on monitoring for awareness and reflection in blended learning concluded that there had been little focus on teacher practices, as well as on explaining the theoretical models behind the LA solutions [14]. In a similar fashion, a review on LA dashboards found that while teachers have been the main targeted stakeholders, there has been little focus on understanding the underlying models to explain students' learning behaviour [15]. A more recent review on teachers' interaction with AI applications concluded that while AI has the potential to help teachers to make instructional and assessment decisions, current implementations usually employ data from a single source, which might be insufficient to model the complexity of the learning process or to guide effective learning interventions [16].

ITS-related reviews have mainly focused on opening learning models up to teachers. For instance, existing reviews on open learner models call for multi-dimensional models of learners that can provide learning experiences tailored to the needs of individual learners [17,18], as well as for further research exploring in depth how teachers use the models [19]. A systematic review on open learner models and LA dashboards, which focused on the synergies between the two fields, concluded that learners that had access to their models demonstrated increased agency about their data, as well as awareness about their knowledge and needs [20]. These results emphasise that it is important to enable teachers and students to provide their own complementary input to LA processes.

In conclusion, MbLA solutions where knowledge models enable an interplay between teachers and intelligent systems are in their infancy. The feedback that is provided to teachers is mainly based on mirroring information, often without a strong theoretical framing, and thus providing little attainability. At the same time, there is a need for solutions that enable second-order adaptation, in which LA systems partially offload teachers' scaffolding and decision making, by helping teachers to understand the learning processes of individual students, which could lead to better instructional decisions [5]. In our previous work, we intended to contribute to the research on the interaction between teachers and models of teaching and learning used by intelligent systems by conducting a systematic review on MbLA. Concretely, we focused on the types of models that have been used, the context in which they have been used, and the benefits that their usage have had for teaching and learning practices [13]. We identified that the models used to enable a teacher–system coupling could be clustered into five groups.

- **Domain models** that provide a model of the domain of instruction (e.g., computational thinking), the relation between the learning tasks, and the knowledge needed to solve each task. See, for instance, an example of a teacher dashboard that displays the correlation between student responses, questions, and course resources [21].
- **Learner models** that provide a representation of the knowledge of a student in time. For instance, predictive systems have been widely guided by learner models. For example, Ref. [22] used machine learning guided by students' course activity to identify students at risk of not submitting the next assignment.
- **Instructional models** that include rules on how to adapt the instruction based on the domain model and the current knowledge of a student. See [23] for an example of a system that supports the regulation of learning by providing cognitive and behavioural feedback to teachers and learners.
- **Collaborative models** that model how collaborative learning should be conducted (e.g., through a collaborative learning script that is computational and open to teachers, such as in [24]).
- **Social models** that include information about the social structure of a group of students (see, for instance, [25]).

Most of the 42 papers under review used a combination of domain and learner models, suggesting that instructional decisions were usually left to teachers [13]. In the current paper, we complement the previous qualitative analyses with quantitative analyses that explore the research community that has produced the MbLA solutions, by focusing on its structure and the main research topics that have been considered. We will further make use of the models discussed above in our analyses when modelling the associations between them and the latent topics discovered in the papers under review.

3. Methodology

In this section, we first describe the bibliometric systematic review process. Next, we present the research questions that derive from our goal of understanding the dynamics inside the community that has implemented MbLA. This is followed by the data analysis methods used to respond to them.

3.1. Bibliometric Systematic Review Process

We followed the guidelines for conducting a systematic review proposed by Kitchenham and Charters [26]. Concretely, we started by defining several search queries that included keywords related to the following:

1. Research fields inquiring about learning models designed to be transparent to teachers (i.e., open learner models and LA);
2. Socio-technical contexts where MbLA have been applied (e.g., intelligent tutors or adaptive learning);
3. The targeted stakeholders (e.g., teachers, instructors).

Next, we applied the queries (on 21 December 2020) in seven databases, all pertinent to research in TEL, as shown in Figure 1. To identify relevant grey literature (e.g., project deliverables), we also included the first 100 results from Google Scholar. We compared the output for each query in terms of the total number of papers returned and if the results included papers that we had previously identified as relevant for this research. The selected query that returned a total of 4408 papers was (*"learning analytics"* OR *"open learner model*"*) AND (*"intelligent tutor*"* OR *"adaptive learning"* OR *"tutoring system*"* OR *"educational recommender"* OR *"personali*ed learning"* OR *"dashboard*"*) AND (*"teacher*"* OR *"practitioner*"* OR *"instructor*"*).

In continuation, we automatically filtered the resulting pool of papers for duplicates, obtaining 3590 unique documents. To identify papers in which our keywords played a pertinent role, as well as to standardise the process (as different databases have different filtering criteria), we automatically filtered the papers by applying the search query only to the main parts (i.e., title, abstract, and keywords), obtaining 276 papers. Next, we manually screened the remaining papers to identify cases where models were designed to be transparent to teachers. Ten reviewers (all researchers in TEL) manually checked the papers in two stages. During the first one, two randomly assigned reviewers separately checked the abstract (and, if needed, the full text) of each paper to identify if it was written in English and within the scope of the review, resulting in 53 papers. In the second stage, we used a second random assignment during which two reviewers separately checked the entire content of each paper to identify if it met the following criteria:

1. It includes empirical work or uses case scenarios involving a model designed to be transparent to teachers;
2. It presents an implemented and pedagogically grounded technological solution;
3. Teachers are part of the target group of the proposed system/intervention in the paper;
4. It describes the transparent model;
5. The technological solution includes a computational model (i.e., autonomously used by a system), which is also interpretable by teachers (i.e., uses a meaningful pedagogical/psychological model of student learning).

Cases of disagreement during the manual screening phases were discussed among all the reviewers until reaching an agreement. The entire process of automatic and manual filtering resulted in a pool of 42 selected papers and is illustrated in Figure 1.
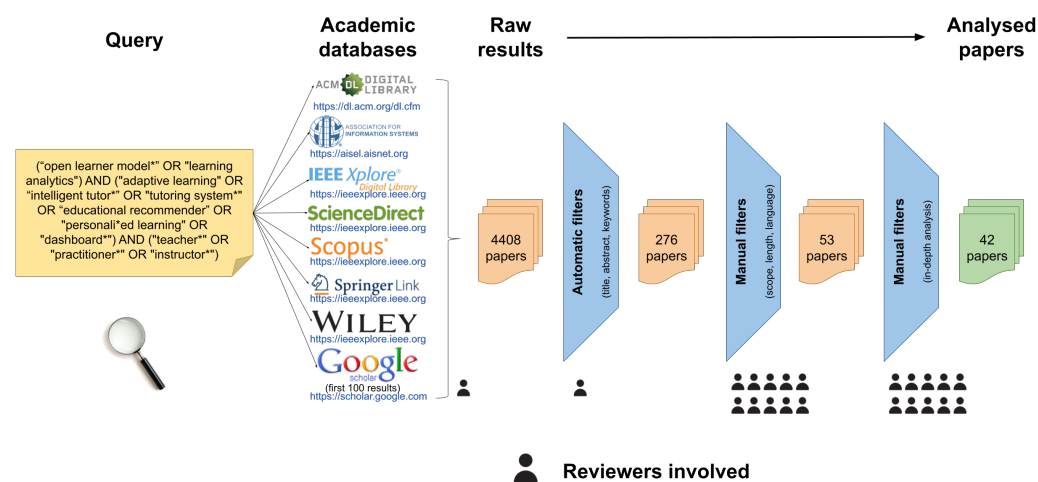

Figure 1. Stages of the bibliometric systematic review.

3.2. Data Analysis Methods

The methodology of the in-depth manual screening of the papers and the corresponding results are reported in [13]. In the current paper, we report on the following research questions (RQs) that derive from our goals (discussed in Section 1):

- **RQ1.** What are the synergies of the research community that has inquired about MbLA?
- **RQ2.** What are the main research topics that have been considered?

We further divided each RQ into themes (T) and, when necessary, into informative questions (IQ), as shown in Figure 2. To respond to each T/IQ, we conducted the following analyses.

1. **Social Network Analyses** (with red in Figure 2), which are methods used to map and analyse the connections between individuals or groups in a given network [27]. We used them in RQ1 to check the synergy between the authors of the papers under review, in terms of (a) *co-authoring* (T1.1); (b) *bibliographic coupling* (T1.2), where we explored the network of *co-citations among the authors* of the papers under review in IQ1.2.1, the *similarity of the papers based on the co-cited literature* in IQ1.2.2, and the network of the *main co-cited authors* in IQ1.2.3; (c) *publishing venues* (T1.3). We also used network analysis in RQ2 to identify explicit research topics through the (d) network of *co-occurrence of keywords* (IQ2.1.1). We used Vosviewer https://www.vosviewer.com (accessed on 1 April 2023) to create the network visualisations. We applied fractional counting to allow for a more accurate representation of the strength of the relationship between the elements being visualised (such as papers, authors, etc.), as suggested by [27]. For instance, in the case of co-citations, this method weights the co-citation relationships between the papers, dividing the count of each citation by the total number of citations in the paper.

2. **Latent Dirichlet Allocation (LDA)** (with purple in Figure 2), a generative statistical model used to discover the most important topics in our dataset of textual documents and to determine which documents belong to which topics. LDA considers that each document includes a small number of topics, each represented by the likelihood of containing specific words from a predetermined vocabulary [28]. We used LDA in RQ2 to *automatically explore the latent topics* found in the 42 papers under review (IQ2.1.2). We used as input the textual content of the papers, excluding authors' details and bibliographies. LDA requires the specification of the number of topics to be discovered as input. In our case, the number of topics was not known beforehand and we used two metrics proposed by [29,30] to determine the optimal number of topics. In our study, the application of these metrics led to the conclusion that 5 was the optimal number of topics (see Figure A1 in Appendix B.1). To interpret the topics, two of the authors of this paper manually checked the most salient terms per topic (further discussed in Section 4, as well as in Figure A2 in Appendix B.2) and the content of the papers that were principally connected to each topic.

3. **Epistemic Network Analysis (ENA)** (with green in Figure 2), usually applied to visually represent the connections between different coding schemes, mainly in discourse analysis, but also beyond [7]. In our context, we considered each paper as a conversation between the authors and the research community. We used ENA in T2.2 to *explore the connection between the topics identified using LDA* (see Section 4 for a description of each topic) and the types of models used by the technological systems that were proposed in the 42 papers under review to generate the teacher feedback (discussed previously in Section 2). Furthermore, to better visualise the connections between models, topics, and the types of systems proposed in the papers, we created and subtracted two ENA networks, one based on papers where the primary role of adapting the learning process was played by the proposed intelligent system, and the other based on papers where teachers were the primary agents of adaptation (further discussed in Section 4). We implemented LDA and ENA in R, using the topicmodels package https://cran.r-project.org/web/packages/topicmodels/index.html (accessed on 1 April 2023). In the SNA and ENA figures, the sizes of the nodes and ties correspond, respectively, to the importance of a node (e.g., a paper) and the strength of a connection.
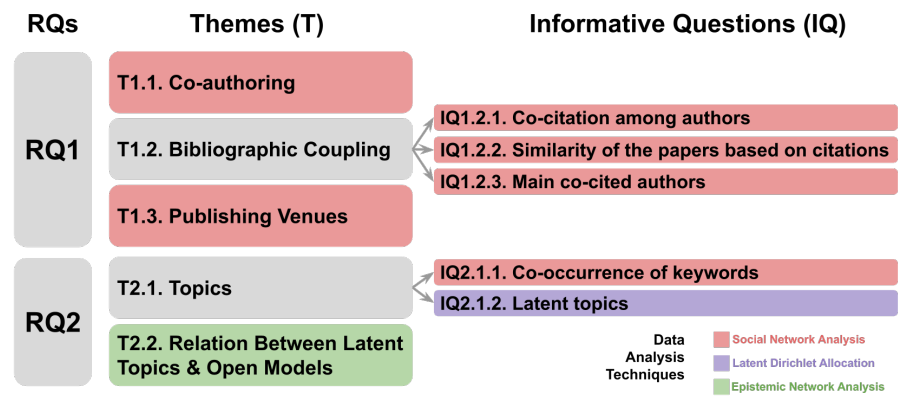
Figure 2. Research questions (RQ), topics (T), informative questions (IT), and data analysis techniques (represented by the colours).

4. Results

This section presents the results organised along the RQs, Ts, and IQs. For a general overview, from the 42 papers under review, 16 (38%) were journals, 23 (55%) were conferences, and 3 (7%) were workshop papers. While we did not restrict the search in time, the resulting papers were published between 2004 and 2021. Table A1 in Appendix A includes the full list of papers under review.

4.1. The Synergies Inside the Research Community (RQ1)

T.1. Co-authorship. The co-authoring network shows several disconnected research groups that have independently inquired about MbLA (represented in colours in Figure 3). We might deduce from this network that although in its infancy, the interest in MbLA is already broad in TEL, contrary to a network that would only have had a small number of interconnected authors.

Figure 3. Network of the co-authorship of the papers under review.

T.1.2. **Bibliographic coupling.** Apart from explicit collaborations between the authors (i.e., co-authoring), we also looked at networks that provided insights about potential implicit alignments among the papers under review. For instance, regarding *IQ1.2.1. Co-citation among the authors*, as we can notice in Figure 4, only a small number of authors have referenced each other, and they are usually the ones who tend to have co-authored together. This might suggest that the different research groups that have inquired about MbLA need to be more aware of each others' work.

Figure 4. Co-citation among authors of the papers under review, showing only the 21 authors that appear connected. The relatedness among the authors is specified based on the number of times they cite each other.

Concerning *IQ1.2.2. Similarity of the papers based on citations that they share*, as can be seen in Figure 5, most of the papers under review appear connected, suggesting that they share at least a core common literature. Further, in Figure 5, we can notice three main clusters. After checking the related papers, the cluster represented with green contained mainly ITS papers, where the main role of adapting and supporting the learning process was played by the system (using a pedagogical/psychological model). In these papers, teachers were also involved, usually by having access to the logic used by the model, but, in specific cases, they could even overwrite the decisions taken by the system (see, for instance, [31]). Papers with red came mainly from the field of LA. In these cases, the analyses of students' data were guided by a pedagogical/psychological model of student learning, but teachers had to take the appropriate decision about how to intervene. The blue cluster in the middle corresponds to papers that describe cases where both teachers and intelligent systems work in tandem to support the learning process. As an example, Ref. [32] proposed a teacher dashboard that had to be used together with an ITS, aiming to help teachers to design and later orchestrate learning activities that involved the ITS.
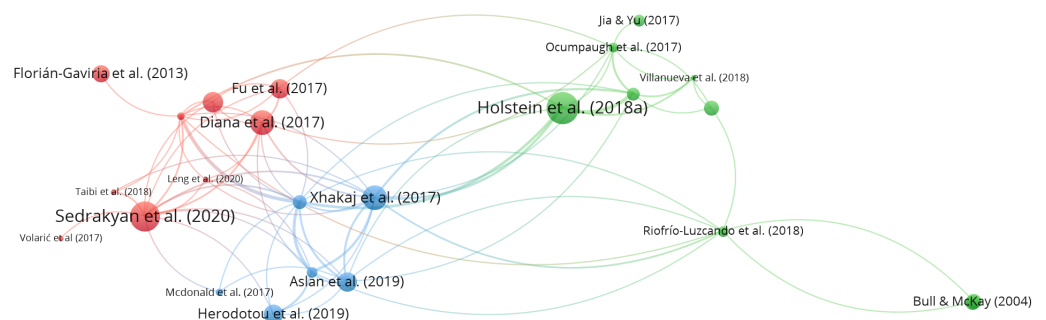

Figure 5. Similarity of the papers based on the body of citations that they share, showing 36 papers (out of 42) that appear connected. Colours represent papers mainly related to ITS (green), LA (red), or both of them (blue).

IQ1.2.3. Main co-cited authors helped us to further explore who the main authors in the identified common core literature are. While still interconnected, the authors cited can again be clustered into the ones mainly cited by LA (with red and blue in Figure 6) and ITS papers (with green in Figure 6). The red cluster includes authors that have a stronger focus on collaborative learning, while the blue cluster includes authors that have focused

on supporting aspects that are more individualistic (e.g., self-regulated or personalised learning).
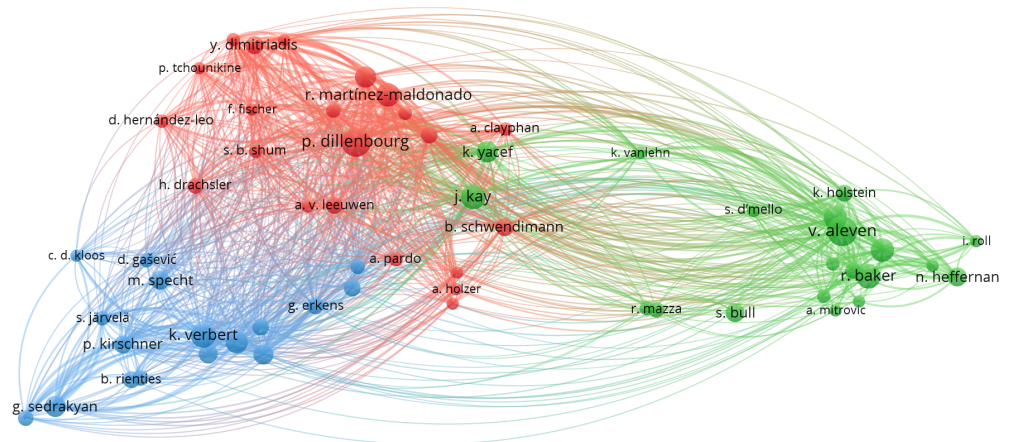

Figure 6. Main co-cited authors, as found in the references of the papers under review. With green, on the right side, authors connected mostly with ITS. With red and blue, on the left, authors connected mostly with LA research. The red cluster includes authors related to collaborative learning, while the blue cluster includes authors that have focused on individualistic aspects (e.g., self-regulated learning).

Publishing venues (T1.3). A similar picture appears when considering the main publishing venues that are co-cited in the papers under review. We can again notice two distinguished clusters of venues cited mainly by LA and ITS papers, represented, respectively, with red and green in Figure 7. While the extremes of this figure show mainly the community-oriented venues that have been targeted, there also exist common channels where these communities meet, such as the Learning Analytics and Knowledge (LAK) conference.
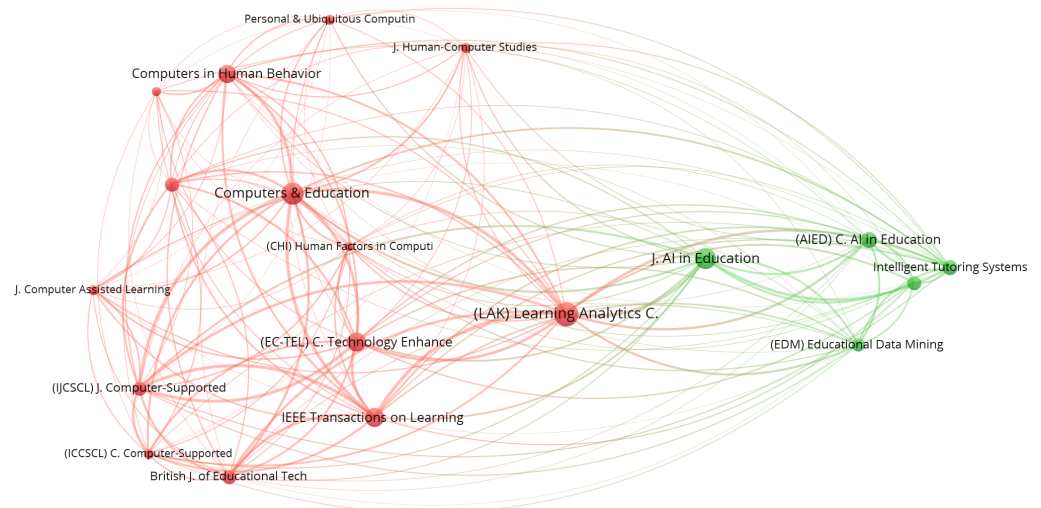

Figure 7. The main publishing venues co-cited by the papers under review. With green, venues targeted by the ITS community; with red, the ones targeted by LA.

4.2. Main Research Topics (RQ2)

Topics (T2.1). We checked both explicit and implicit topics found in the papers under review, represented, respectively, by the keywords that the authors explicitly used in their papers, and the latent topics resulting from LDA. Apropos *IQ2.1.1 The co-occurrence of keywords*, apart from the obvious nodes (e.g., LA, ITS, adaptive learning, etc.), the emphasis

seems to have been on several specific settings (e.g., game-based learning or blended learning), as well as on specific student practices and skills (e.g., digital competences, academic performance, college attendance, or coding). Dashboards constituted an important element of the technological context that made the models available to teachers (see Figure 8). Interestingly, few keywords explicitly referred to teacher practices, despite them being one of the main targeted stakeholders in the solutions proposed in the papers under review.
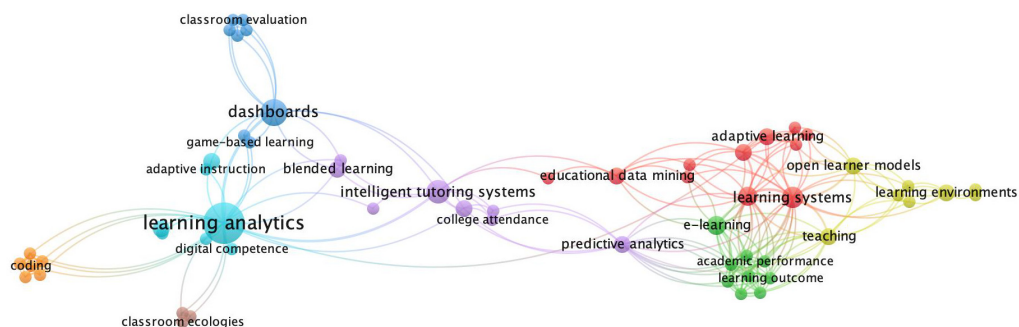

Figure 8. Network of the most common keywords explicitly co-used in the papers under review.

Regarding *IQ3.4.2 Latent topics found in the papers*, Table 1 shows the five topics resulting from the LDA, two illustrative examples from the papers that were mainly connected to each of these topics, ten of the most salient terms per topic, and the number of papers per topic. See Figure A2 in Appendix B.2 and the online version of this table https://bit.ly/MbLALDA (accessed on 1 April 2023) for a visualisation of the most salient terms per topic and a short description of each paper connected to a topic.

Differently from the network of keywords, here, we may notice two topics that are connected to teacher practices, namely *Learning Orchestration* and *Awareness and Reflection*. These two topics, together with *Dashboards*, corroborate the results from our qualitative analyses, where we identified that dashboards were the main tool used to provide information from the open learner models to teachers, and that the main purpose of feeding back data to teachers has been to support pedagogical adaptions (e.g., by supporting teachers to provide personal guidance to students, or to improve their learning designs) [13]. Interestingly, LDA also highlighted the importance of two topics that went unnoticed in our qualitative analyses. The topic *Adaptive Learning Architectures* represents the technical infrastructure that supported the MbLA solutions proposed in the papers. For instance, Ref. [33] presents an architecture that supports the assessment of competence-based learning in blended learning environments, intended to be used to enable teachers to better adapt their learning designs to students' needs. Another related example included a system that integrated feedback from students, parents, and teachers into the open model of a specific student [12]. Apart from the technical infrastructure, MbLA need to be rooted in learning theory, which is represented by the topic *Assessment Frameworks*. The most common types of assessment frameworks were competence frameworks that guided the assessment of student knowledge. These were usually predefined and implemented in the design of the intelligent system (see the examples in Table 1), but there were also cases whereby teachers could change it or implement their own assessment framework (see, for instance, [34]). See Table A1 in Appendix A for the full list of papers under review and their corresponding latent topics.

Table 1. LDA topics with illustrative examples from the pool of papers under review, the ten most salient terms per topic, the number of papers per topic, and the number of papers that included each type of model.

LDA Topic	Examples from the Papers	Ten Most Salient Terms	No. Papers	Models
Awareness and Reflection	Ref. [35] proposed a system that can capture the behaviour of students in the classroom when learning programming and that consequently helps teachers to improve their learning materials. Ref. [21] presented a system that analyses students' written responses in order to provide insights into student conceptions and that can inform teacher actions.	teachers, students, learning, classroom, goals, engagement, individual, course, dashboard, needs.	9	• Domain (8) • Learner (4) • Instructional (2) • Social (2)
Dashboards	Ref. [36] presented a dashboard that provides adaptive support for collaborative argumentation in a face-to-face context. Ref. [23] introduced a dashboard that helps teachers to provide feedback to students on how to improve their learning behaviour and cognitive processes, guided by analytics informed by a process-oriented feedback model.	students, teachers, visualisations, learning, dashboard, data, assessment, time, errors, analysis.	6	• Learner (4) • Domain (2) • Instructional (1) • Collaborative (1)
Adaptive Learning Architectures	Ref. [33] presents an architecture that supports the assessment of competence-based learning in blended learning environments, intended to be used to enable teachers to better adapt their learning designs to students' needs. Ref. [12] proposed a system that integrated feedback from students, parents, and teachers into the open model of a specific student.	data, learning, tutor, architecture, sources, system, assessment, model, information, context.	10	• Learner (10) • Domain (7) • Instructional (2)
Learning Orchestration	Ref. [37] presented the design and evaluation of a teacher orchestration dashboard to enhance collaboration in the classroom. Ref. [32] explored how an ITS dashboard affects teachers' decision making when orchestrating.	teachers, students, design, context, data, goals, classroom, dashboard, process, collaborative.	8	• Learner (6) • Domain (4) • Collaborative (3) • Instructional (2)
Assessment Frameworks	Ref. [38] presented an implementation of a competency assessment framework in university settings, called SCALA. Ref. [39] proposed an assessment framework for serious games that informs teachers on the competences acquired by learners.	learning, students, dashboard, competences, tutor, analysis, level, time, errors, task.	9	• Learner (7) • Domain (4) • Social (1) • Collaborative (1)

T2.2. Relations between the latent topics and the models used to provide the feedback to teachers. Table 1, under the column 'Models', shows the different types of models connected to each LDA topic and the number of papers where each model was used. We also used ENA to visualise the relations between the latent topics mentioned in IQ2.1.2 and the five main types of models that we identified in our previous qualitative analyses. See Section 2 for an explanation of each model group and Table A1 in Appendix A for the full list of papers under review and their corresponding models. Regarding the two-dimensional space of Figure 9, the horizontal and vertical lines seem to place the more technology-oriented topics (e.g., Adaptive Learning Architectures) and the more teacher-oriented ones (e.g., Awareness and Reflection) on opposite sides. One might think of the models, generally placed in the middle of the visualisation, as the links between the two sides. Furthermore, as we can see in Figure 9 and in Table 1, there appears to be a stronger connection between domain models (but also learner models) and topics such as Awareness and Reflection or Learning Orchestration. This suggests that teacher practices in the papers under review were mainly guided by models of the domain of instruction, as well as, to a lesser extent, by models representing the knowledge of the students. On the other hand, automatic decisions taken by the system (represented by topics such as Adaptive Learning Architectures or Assessment Frameworks) were mainly based on students' current knowledge (i.e., learner models). In general, MbLA have been mainly based on learner, domain, and instructional models. While this has been a known trend in intelligent systems [40], as these models capture the essence of instructional decisions, it is interesting that there was no connection between the Adaptive Learning Architectures topic and social or collaborative models. These results highlight that the current MbLA systems have taken a rather individualistic view of student learning and instruction, while neglecting aspects that also make learning a social process. Indeed, it is visible in Table 1 and Figure 9 that collaborative and social models (which were underrepresented in our pool of papers) have weak ties regardless of the topic.

In our previous work, we classified the papers under review into two groups: those where the proposed systems played the primary role in adapting the learning process, and those where the teachers were the primary agents of adaptation (see Table A1 in Appendix A for more details). When building ENA, we created and subtracted two different networks based on these two groups of papers (respectively, with red and blue in Figure 9). It is unsurprising that the network of papers focused on system-guided learning displayed a higher level of interconnectedness between topics related to Adaptive Learning Architectures and Assessment Frameworks, or models such as domain and social models (evidenced by stronger red connections in the subtracted network in Figure 9). On the other hand, the network of papers focused on teacher-guided learning showed stronger connections between most of the models, as well as topics such as Dashboards or Awareness and Reflection (with blue in Figure 9).
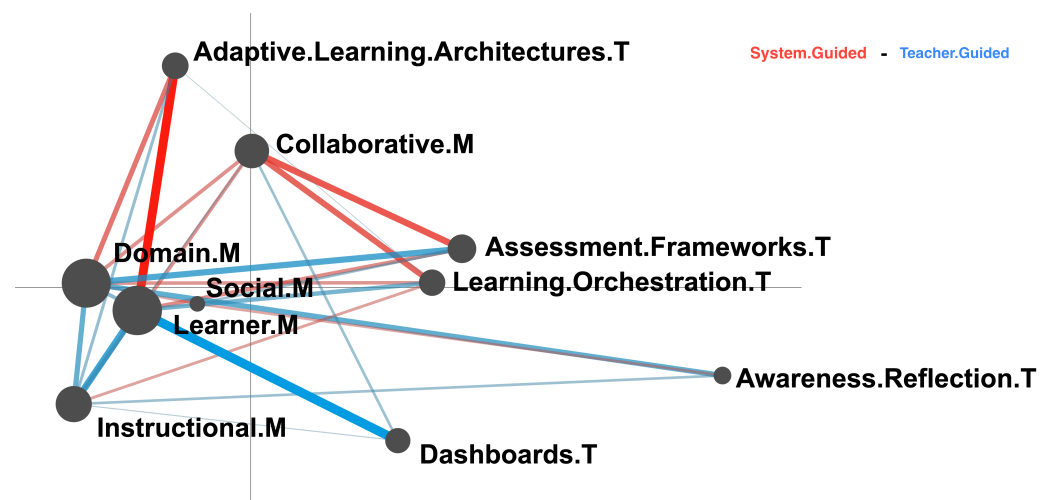

Figure 9. ENA visualisation of the relations between the different models used to provide feedback to teachers and the latent topics. The visualisation is a result of the study of two networks based, respectively, on papers focused on teacher-guided and system-guided learning.

5. Discussion

Regarding RQ1 *(The synergies inside the community investigating MbLA)*, we identified several research groups that have inquired about MbLA. These groups have had little explicit and implicit interactions among them in this context, as seen from the disconnected co-authoring network in Figure 3, and the fact that only a core group of authors have co-cited each other, as shown in Figure 4. We also noted that LA and ITS are two specific fields in the broader context of TEL that can be considered as the main advocates of MbLA. Indeed, these two fields share a common body of literature in this context, which could be considered as a core literature in MbLA (as seen with the networks of the main co-cited authors in Figure 4, and the similarity of the papers based on their citations in Figure 5). Successful MbLA implementation will require further explicit alignment from these two fields. On the one hand, LA provides good practices on how LA-guided systems can inform and enhance teaching and learning practices [14,35,41–43]. On the other hand, ITS brings examples of how a system can adapt a learning activity to students' needs and the role that a teacher can play in this process [5,32,44]. Clearly, both communities are complementary and would benefit from further explicit alignment in the future with respect to research on MbLA. In the short term, common venues might serve as a starting point, where future workshops around this topic might be organised.

Concerning RQ2 *(Main research topics)*, our results showed that the body of research on MbLA has mainly focused on technological solutions that target teachers' awareness and reflection about the learning process, as well as enabling them to intervene (i.e., in relation to learning orchestration). This result confirms the ones from our qualitative analyses that

showed that our set of papers had a stronger focus on guidance, as opposed to mirroring, which had been the main focus in previous LA reviews (see, for instance, [14,15]). Not surprisingly, dashboards have been the main tool used to open the learner models up to teachers both in ITS and LA (as seen by the network of keywords in Figure 8 and the latent topics in Table 1). All together, the topics that we identified in our analyses could be considered as the basic prerequisites that make MbLA possible, rather than from a technical point of view (i.e., through system architectures and dashboards, which are guided by specific pedagogical frameworks), or by targeting the main teaching practices (i.e., related to design and orchestration). Nevertheless, future research should take a step further and improve the partnership between teachers and intelligent systems to support the learning process [2,3,5]. On the one hand, this means that future research could focus on systems that not only allow teachers to modify their models (such as in [31], where teachers had the option to overwrite the decisions of the system), but that are also able to improve over time by learning from the continuous teacher input. This second type of teacher–system interaction was missing in our pool of papers. On the other hand, teachers would also benefit from systems that move beyond transparency, such as by assisting teacher decision making by providing guidance. For instance, a starting point could be the use of AI systems that support teachers when designing and orchestrating a learning activity (such as in [43], where the system provides feedback to teachers about the learning design that they are creating in real time). It is worth mentioning that the implementation of AI-supported systems comes with related risks. For instance, datasets that include biased data could cause distortion in the decisions or suggestions made by the system. Moreover, the most powerful AI models are non-transparent black-box models, the decision making of which is unknown. Therefore, the future systems that we are advocating for should focus not only on training AI systems based on diverse and representative data, but also on the implementation of interpretable algorithms whenever possible. Recent advancements in machine learning that help to create black-box models more interpretable might also be useful in this context [45]. Moreover, it is necessary to consider distortion in the decisions made by the system based on a possible bias found in the dataset used to train it.

In our pool of papers, domain, learner, and instructional models predominated. Domain models have mainly guided teacher reflection practices, while a combination of learner, domain, and instructional models have been used to guide the adaptive learning decisions taken by intelligent systems (as seen in Figure 9). This suggests that current MbLA systems have taken an individualistic approach to student learning and instruction, while neglecting aspects that make learning a social process. Indeed, to enable a successful teacher–AI partnership, MbLA systems should take a step further and also include elements from social and collaborative models.

Helping teachers to adopt and use MbLA systems in a meaningful way would improve the support that they provide to students, by offering better and more personalised feedback or supporting students' self-regulated learning, among others [31,46–48]. For the successful adoption of MbLA in teaching practices, it is essential to consider that teachers already struggle to adopt new technological and pedagogical practices, due to the challenge of learning the required new skills, as well as teachers' already heavy workloads [49]. To facilitate this adoption, future research should explore the pedagogical aspects of implementing MbLA in different learning contexts. Moreover, training is one of the common approaches used to support teachers' professional development. While teacher training could promote the adoption of MbLA, it is expensive and its effects are limited in time [45]. Therefore, future research should also focus on systems that include sufficient intelligent guidance that would not only require less training but that will also be perceived as useful by teachers. To accomplish this aim, teachers (together with learners) should be an essential part of the development process from an early stage, such as through the implementation of a participatory design approach, as suggested by recent initiatives on human-centred LA [24,49,50]. Only a few of the papers under review took a similar approach, as also shown by the lack of related topics in our analyses. A good example related to MbLA

is provided by [32], which followed a participatory design approach to design a teacher dashboard intended to be used with an ITS.

Limitations of this study are related to the systematic review methodology and the methods used for the analyses. Potentially relevant keywords that we may have not included in our query might have obscured relevant work. To minimise this effect, we experimented with different queries before choosing one (see Section 3). Related relevant research might have been published since the time that we compiled our list of papers under review. We might have also missed relevant work published in other databases, or in languages other than English, which was one of our inclusion criteria. The small number of papers under review (42) is a limitation for LDA. Nevertheless, even with a small number of documents, LDA can still provide useful insights about the latent topics found in the papers under review in systematic reviews [51]. Although the nature of this study was mainly quantitative, when necessary, we also performed manual qualitative analyses. For instance, LDA included a subjective interpretation, which we tried to diminish by involving two researchers in the process and by discussing the results among all the co-authors.

6. Conclusions

We started this paper by emphasising that MbLA call for a challenging interdisciplinary approach that does not only require input from different fields (i.e., learning sciences, computer sciences, HCI, and domain experts), but one which additionally needs to create a tight coupling between teachers' understanding of learning and models implemented in intelligent systems. Results from our bibliometric review revealed that research on MbLA is still in its early stage, with few examples that were rooted in interdisciplinary approaches (such as through the application of participatory design studies that integrate the input from stakeholders from different fields). Nevertheless, our review provides a pool of existing good practices on how to achieve the mentioned coupling of teachers and intelligent systems to support the learning process, through the multiple system architectures, guiding assessment frameworks, or dashboards.

The focus on guiding teachers in the papers under review is indeed a step in the right direction, as opposed to simply mirroring. The next step, which would truly enable a teacher–technology partnership to support learning practices, would be to focus on systems that provide higher-order guidance to teachers (e.g., through AI), and that also improve their model of learning and instruction over time (i.e., by learning from the continuous teacher input). To achieve this goal, future research in MbLA should not only take an individualistic approach to student learning and instruction, as seen in our results, but should also consider aspects of their social nature (e.g., social structures or patterns of collaborative learning).

Appendix A

Table A1. List of papers under review, with the corresponding types of models used in the systems that they proposed, the main LDA topics, and whether the learning activity was mainly teacher- vs. system-guided.

Paper	Models	Main LDA Topic	Teacher vs. System Guidance
Abdi et al. [52]	Learner, Domain	Adaptive Learning Architectures	Teacher
Al-Jadaa et al. [12]	Learner, Domain	Adaptive Learning Architectures	System
Aleven et al. [53]	Learner, Domain	Learning Orchestration	Teacher
Amarasinghe et al. [37]	Instructional, Collaborative	Learning Orchestration	System
Aslan et al. [54]	Learner, Collaborative	Learning Orchestration	Teacher
Balaban et al. [55]	Learner	Assessment Frameworks	System
Boulanger et al. [56]	Learner	Dashboards	Teacher
Bull and McKay [31]	Learner, Domain	Adaptive Learning Architectures	System
Calvo-Morata et al. [39]	Collaborative	Assessment Frameworks	System
de Leng and Pawelka [57]	Domain	Dashboards	Teacher
Diana et al. [25]	Domain, Social	Awareness and Reflection	System
Ebner and Schön [58]	Learner, Domain	Assessment Frameworks	Teacher
Florian-Gaviria et al. [59]	Learner	Assessment Frameworks	System
Fouh et al. [60]	Domain	Awareness and Reflection	Teacher
Fu et al. [61]	Domain	Awareness and Reflection	Teacher
Guenaga et al. [38]	Learner, Domain	Assessment Frameworks	Teacher
Han et al. [36]	Collaborative	Dashboards	Teacher
Hardebolle et al. [35]	Domain	Awareness and Reflection	Teacher
Herodotou et al. [22]	Learner	Learning Orchestration	Teacher
Holstein et al. [44]	Learner, Domain, Instructional	Learning Orchestration	Teacher
Holstein et al. [62]	Learner	Adaptive Learning Architectures	Teacher
Jia and Yu [63]	Learner	Adaptive Learning Architectures	System
Johnson et al. [34]	Learner	Assessment Frameworks	Teacher
Kickmeier-Rust and Albert [64]	Learner, Domain	Assessment Frameworks	Teacher
Lazarinis & Retalis [65]	Learner, Domain, Instructional	Adaptive Learning Architectures	Teacher
Martinez-Maldonado [41]	Domain, Collaborative	Learning Orchestration	System
McDonald et al. [21]	Domain	Awareness and Reflection	Teacher
Molenaar and Knoop-van Campen [66]	Learner, Domain	Learning Orchestration	Teacher
Montebello [67]	Learner	Adaptive Learning Architectures	Teacher
Ocumpaugh et al. [68]	Learner	Adaptive Learning Architectures	Teacher
Pérez-Marín and Pascual-Nieto [69]	Learner, Domain	Awareness and Reflection	System
Riofrío-Luzcando et al. [70]	Learner, Domain	Assessment Frameworks	Teacher
Rudzewitz et al. [71]	Learner, Domain, Instructional	Awareness and Reflection	Teacher
Ruiz-Calleja et al. [72]	Social	Assessment Frameworks	Teacher

Table A1. *Cont.*

| Paper	Models	Main LDA Topic	Teacher vs. System Guidance
Sedrakyan et al. [23]	Learner, Domain, Instructional	Dashboards	Teacher
Taibi et al. [73]	Learner, Domain, Social	Awareness and Reflection	Teacher
Villamañe et al. [33]	Learner, Domain	Adaptive Learning Architectures	System
Villanueva et al. [74]	Learner, Domain, Instructional	Adaptive Learning Architectures	Teacher
Volarić and Ljubić [75]	Learner, Domain	Dashboards	Teacher
Xhakaj et al. [32]	Learner, Domain	Learning Orchestration	System
Yoo and Jin [76]	Learner	Dashboards	Teacher
Zhu and Wang [77]	Learner, Instructional	Awareness and Reflection	Teacher

Appendix B
Appendix B.1
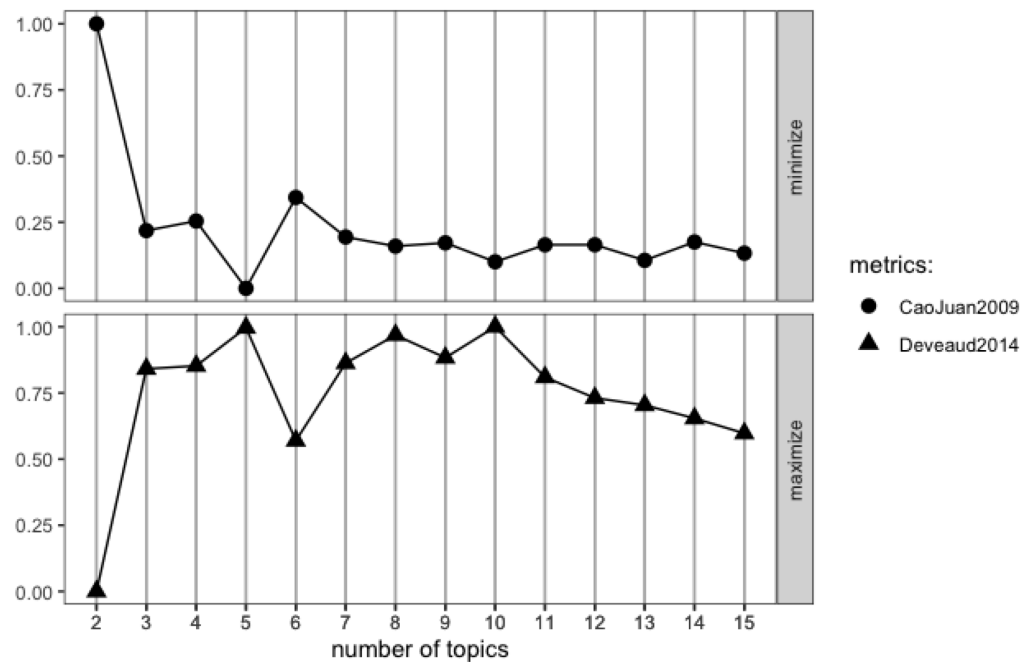
Figure A1. Results from two metrics proposed by [29,30] to determine the optimal number of topics, which guided us to choose five as the most appropriate number.
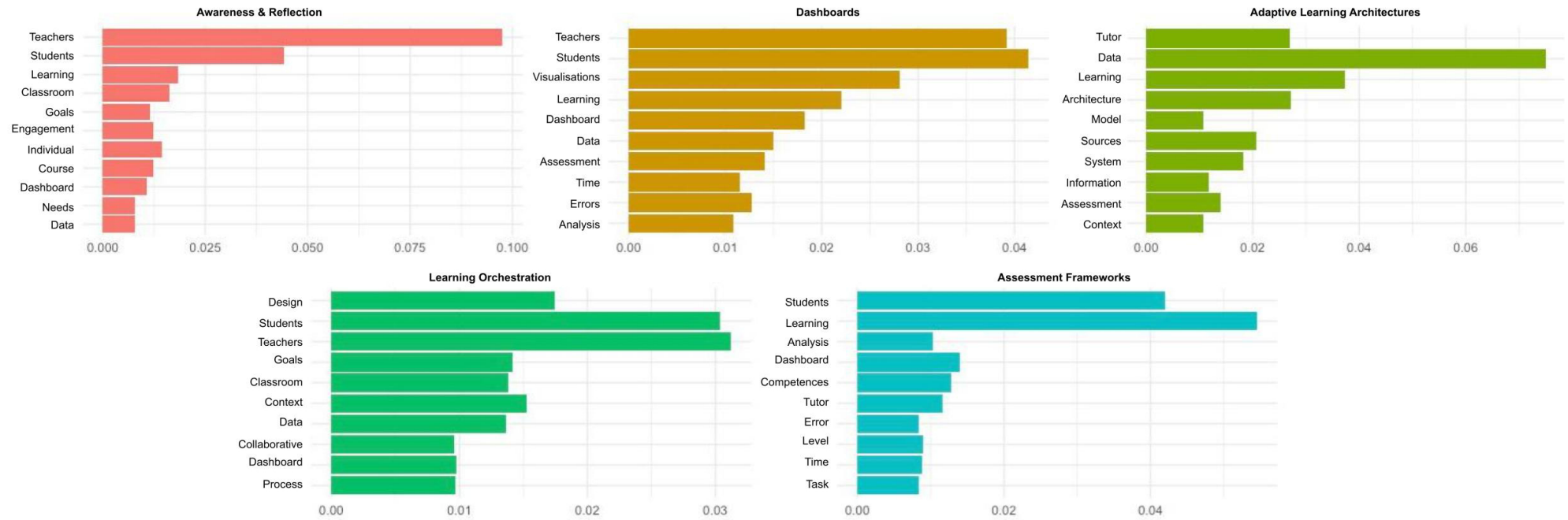
Appendix B.2

Figure A2. Most salient terms for each topic resulting from the LDA.

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