Analytics for Learning Design: A Layered Framework and Tools

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Abstract
The field of *learning design* studies how to support teachers in devising suitable activities for their students to learn. The field of *learning analytics* explores how data about students' interactions can be used to increase the understanding of learning experiences. Despite its clear synergy, there is only limited and fragmented work exploring the active role that data analytics can play in supporting design for learning. This paper builds on previous research to propose a framework (AL4LD) that articulates three layers of data analytics – learning analytics, design analytics and community analytics - to support informed decision-making in learning design. Additionally, a set of tools and experiences are described to illustrate how the different data analytics perspectives proposed by the framework can support learning design processes.

Keywords
Learning Analytics, Learning Design, Framework, Tools

Introduction

The learning design field has produced representations, methodologies and computer tools to assist teachers in the creation of pedagogically-sound learning environments, for example by facilitating the mapping between activities and learning objectives, by providing patterns of good educational practices, and by supporting sharing and co-creation among teacher communities (Mor, Craft & Hernández-Leo, 2013). These contributions are transforming teaching and consolidating it as a design science (Laurillard, 2013). This paper addresses how data analytics can play a critical role in a new generation of tooling for evidence-based learning design (Rienties & Toetenel, 2016).

During recent years, analytics and data mining techniques have been used to extract actionable information from large quantities of data in an increasing variety of scientific fields. In the domain of learning technologies, the learning analytics field has undergone a fast expansion phase (Ferguson, 2012). Data-intensive applications are being considered for aiding in critical educational aspects such as students' retention, engagement or social interactions. Recent detailed analysis of the use of data in learning environments portrays an increasingly complex landscape influenced by multiple disciplines and in need of frameworks and guides to deploy educational initiatives effectively (Greller & Drachsler, 2012; Gašević, Dawson & Siemens, 2015).

The connection between learning analytics and learning design assumes the existence of comprehensive data capturing and analysis mechanisms at various levels to inform and influence the learning experience, the design process (or its ensuing refinement), and the community of educators creating these designs. The integration of learning analytics with learning design has been identified as important (Bos & Brand-Gruwel, 2016; Lockyer, Heathcote, & Dawson, 2013). However, there is limited and fragmented work exploring the use of data analytics to support learning design (Dyckhoff et al., 2013; Mor, Ferguson & Wasson, 2013; Bakharia et al., 2016; Sergis & Sampson, 2017). After a systematic literature review, Sergis & Sampson (2017) recently concluded that "*few teaching and learning analytics works have explicitly addressed the aspect of supporting teachers' reflection on the delivery of the educational design*". There are no models capturing the variety of connections that exist between learner/educator data, the design, co-design processes and the implementation of learning tasks.

In this paper we propose the *Analytics Layers for Learning Design* (AL4LD) framework. It captures the relations and interactions between educational data and learning designs in three layers: the learning experience, the learning design itself, and the community of educators. The framework builds on top of previous fragmented work to articulate these three differentiated but interdependent layers of data analytics to support and inform decision-making in learning design. This division can be derived from the data sources and purposes of the analytics and how they support learning design. The description of the framework is followed by a section describing research projects that have produced tools and experiences that illustrate the different facets of the framework in practice and showcase how the different data analytics perspectives, captured by the framework, can inform and enhance design for learning at different layers.

The "Analytics Layers for Learning Design" framework

Layers are constructs used to model complexity in multiple domains. Layered models are used to identify and logically segment different functions of a whole and to minimize the interactions (and information flow) across them. The AL4LD framework uses *layers* to define logical partitions associated with the *functions* that analytics can offer to support teachers as designers of learning experiences. This division into layers is also determined by the types of *data sources,* from which to obtain the data for the analytics methods (e.g., virtual learning environments, learning design tools and community environments for teachers); and the associated *data classes,* which indicate the data types or categories that can be reasonably obtained for each layer. The proposed layers are not bound to any particular learning/design technology implementation. Instead, the aim is to provide a characterization of the data sources, the functions of the analytics and data classes that are key for each layer and use them as guides for the deployment of technology that use analytics methods to effectively support the multiple dimensions of learning design.

The AL4LD framework includes three layers of analytics (see Figure 1 – bottom to top) to support awareness, sensemaking and reflection to address the following design questions:

- What are the effects of the learning designs on the actual learning experiences (Learning Analytics layer)?
- What are the design decisions and related aspects that characterize the learning designs (Design Analytics layer)?
- How educators (and related roles) co-design for learning (Community Analytics layer)?

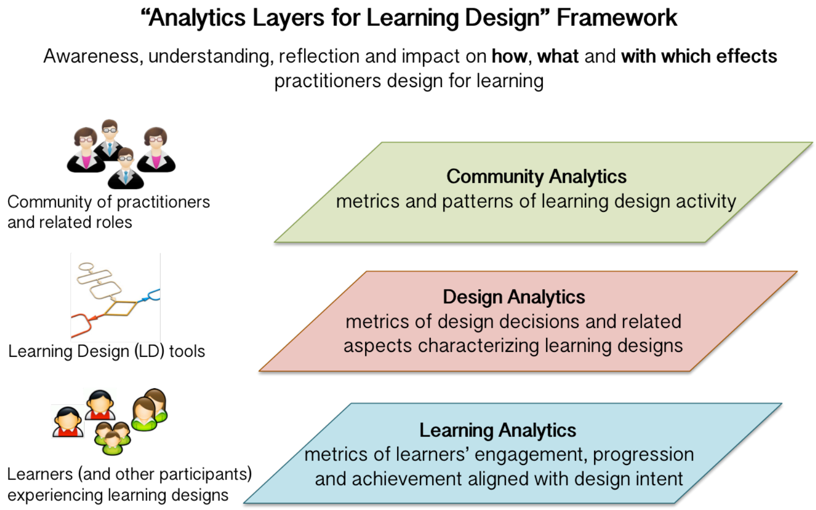


Figure 1. Graphical representation of the AL4LD framework

Learning Analytics layer

The Learning Analytics layer deals with the metrics of emergent engagement, progression, achievement, and satisfaction of learners while experiencing a learning design (Ferguson, 2012; Bakharia et al, 2016; Sergis & Sampson, 2017). Analytics in this layer can provide substantial evidence of design impact when deployed in a single or multiple learning situations. This evidence can be obtained as observed learner behaviors emerging from the implementation of the design, or from the actions of other involved participants (e.g., educators supporting the tasks). The data collected in this layer can enhance awareness about and support reflection on the effects of the learning designs and also help to identify design elements that need to be revised for future designs (see *functions* in Table 1). *Data sources* for this layer are derived from the learning environment where the design is implemented. The use of technology (learning management systems, software tools supporting specific activities, etc.) offers a wide range of possibilities for data collection. Additionally, data collection in physical spaces is also becoming feasible through the use of sensor-based technologies. Other institutional platforms, such as student information systems and surveys, can complement these sources with information about academic profiles, demographics, and students' satisfaction ratings. *Data classes* include the profiles of the participants, checkpoints, the process to implement of a learning design, performance, and satisfaction data (Greller & Drachsler, 2012; Dyckhoff et al., 2013; Lockyer, Heathocte & Dawson, 2013; Gašević, Dawson & Siemens, 2015; Bakharia et al., 2016; Bos & Brand-Gruwel, 2016; Rienties & Toetenel, 2016).

Learning analytics can be used to tackle questions about the impact of a learning design, such as: Is the support provided by educators in a task adequate for the learners? Is the average task completion time close to the expected value? Are the locations used by learners aligned with the needs of the task? Are the set of tools and resources suggested to complete the tasks actually used and perceived as satisfactory? Is (a portion of) the learning design leading to unsatisfactory performance? Is the design sufficiently engaging for non-native speakers?

Table 1: Learning analytics layer for learning design

Data classes:	Description:
	Data sources: Learners' and other stakeholders' actions, outcomes and satisfaction when experiencing a learning design in a learning environment. Institutional student information and evaluation (assessment and satisfaction) systems.
Profiles	Profile of learners and other participants (teachers, tutors…) experiencing a learning design, including demographic data, (e.g., gender, age, mother language) and academic data (e.g., academic level, courses completed) (Dyckhoff et al., 2013; Sergis & Sampson, 2017).
Checkpoints	Relevant access to resources and tools (e.g., view task description, signing up to a group for a collaborative assignment) or completion of tasks (e.g., submission of an assignment, answering a quiz); time and location when/where checkpoints occur (Lockyer, Heathcote, & Dawson, 2013; Bakharia et al, 2016; Sergis & Sampson, 2017).
Process	Presence and usage behavior within activities that learners and other participants do when completing a learning design (Shum & Ferguson, 2012; Lockyer et al, 2013; Bos & Brand-Gruwel, 2016; Rienties & Toetenel, 2016). It depends on the activity types (e.g., attempts and use of hints in gaming, notes in annotation activities, interactions in collaborative activities) (IMS, 2013; Bakharia et al, 2016; Sergis & Sampson, 2017); time and location when/where process actions occur (Melero et al., 2015).
Performance	Assessment-related data (e.g., grades from assignments, quizzes, exams, number of mistakes) (Ferguson, 2012; Dyckhoff et al, 2013; Gašević, Dawson & Siemens, 2015; Rienties & Toetenel, 2016; Sergis & Sampson, 2017).
Satisfaction	Satisfaction and preferences of learners and other participants (Dyckhoff et al, 2013).
	Functions: Enhance awareness and reflection about the impact of the learning design: understand the accumulated effects of a design with learners and other participants to help reflection about its actual impact. Learning redesign: identify learning design aspects to be revised.

Design Analytics layer

The Design Analytics layer is concerned with metrics of design decisions and aspects that characterize learning designs prior to their delivery. Several approaches have been proposed to represent and analyze learning designs (Mor, Craft & Hernández-Leo, 2013; Goodyear & Carvalho, 2014; Dillenbourg & Hong, 2008). Some of them are associated with particular pedagogies, because the representation is also proposed as a guide for the design process (Pozzi & Persico, 2013; Villasclaras et al., 2013). These representations also offer a means to express and categorize the properties of learning designs. Analytics about these properties can scaffold the design process by providing awareness and reflection on decisions made during the creation a learning design as well as the implications of future decisions (see *functions* in Table 2). Data collection (*data sources*) in this layer is greatly simplified when the design tools are software systems (Laurillard, 2013; Villasclaras et al., 2013). The quantifiable *data classes* depend on the data recorded and made available by the learning design tools, and on the design representation models used by these tools. The *data classes* proposed in this layer are based on their representativeness and easy mapping with current learning design representation models, and include: the design goals, the learning objectives, skills or competencies that educators intend for students to develop, the designed tasks, the social situation, the time dimension, the places and set of artifacts that support the realization of the tasks; and the resulting teacher and students workload. Values for each *data class* are influenced by the vocabulary provided by existing learning theories, frameworks and taxonomies (Dillenbourg & Hong, 2008; Laurillard, 2013; Sergis & Sampson, 2017).

The questions that can be addressed with design analytics include: What are the types of tasks considered in the learning design so far? Should I include a new type of task that I would like to propose to my students? Is the student load balanced across individual vs. group tasks? Will the resources and tools available have enough variety for students? Is the time estimated for the learning tasks reasonable or should I make adjustments to the design? Will the implementation of the design be sustainable from the perspective of the workload on educators?

Table 2: Design analytics layer for learning design

Data sources: Practitioners' and related stakeholders' actions determining elements and characteristics of a design within a learning design tool.

Data classes:	**Description**:
Goals	Aims of the design, including learning objectives, skills, competences, learning outcomes; usually framed using standard taxonomies (e.g., competence frameworks, learning objectives taxonomies) or local schemes (e.g., curriculum) (Laurillard, 2013; Villasclaras et al., 2013).
Task	Description of actions that may trigger learning. Actions can shape single tasks, where different classifications exist (e.g., derived from learning theories), or take more complex task structures, like sequences or flows (Laurillard, 2013; Villasclaras et al., 2013; Sergis & Sampson, 2017).
Social planes	Modes suggested to complete the task: individual, collaborative, collective (Dillenbourg & Hong, 2008).
Places and set	Physical context, digital and material spaces, tools and resources suggested to support the task (Goodyear & Carvalho, 2014).
Time	Expected length of time for students to carry out the tasks (Pozzi & Persico, 2013).
Teachers' workload	Time estimated for teachers to implement the task; time devoted to design the task (Laurillard, 2013).

Functions:
Enhance awareness and reflection about the properties of the learning design: monitor accumulated properties in a learning design to provoke reflection about the design decisions made.
Scaffolding of the learning design: identify potential implications for future design decisions .

Community Analytics layer

The Community Analytics layer deals with metrics and patterns of design activity within a community of teachers and related stakeholders. Educators are commonly involved in social processes of both dissemination and adoption of innovative teaching ideas. The notion of community can be considered in a general sense either as an educational center or a cross-institutional community where teachers and collaborators share and jointly contribute to devising educational designs (Hernández-Leo, 2011; Vourikari, Gilleran & Scimeca, 2011). This layer has the potential of backing and encouraging culture and organizational structures for collaboration, by enabling awareness and reflection about individual and collective design activity patterns and by triggering orientation and inspiration about how to improve the design practices (see *functions* in Table 3). Learning design communities can be supported by community information systems (Hernández-Leo et al., 2011) or by purpose-built physical design spaces (Thompson et al., 2013). These environments are ideal to provide the data (*data sources*) for learning design community analytics. Quantifiable *data classes* for this layer depend on what is available and feasible to track in a learning design community environment but may. include: the design tools being used, the types of designs created, the authors and other contributors involved in creating, commenting and annotating designs (with measurable structured information, e.g., tags), the history of versions of a design, and social ratings (see *data classes* in Table 3) (Vourikari, Gilleran & Scimeca 2011; Hernández-Leo et al., 2011, Thompson et al., 2013; Chacón et al., 2015). The learning design community data can be analyzed from the perspective of a member of the community, the whole community, or comparing both perspectives.

Analytics in this layer can serve to respond questions including: What tools should I explore based on how they are received by the community or on how frequently they are used by a reputed member? Which designs should I reuse because they are frequently used and revised by others? Which teachers are potential collaborators to work on designs for particular subject matters and pedagogies and are familiar with specific tools?

Table 3: Community analytics layer for learning design

Data sources: Practitioners' and other stakeholders' actions in a learning design community environment.	
Data classes:	**Description**:
Tools	Instruments and representations used by individuals and teams to create a learning design, degree and sequence of use; for a specific design or globally for all designs in the community (Thompson et al., 2013).
Labels	Types of designs by subject matter, pedagogical approach, targeted objectives/skills. Labels can take the form of tags or metadata compliant to existing global or local taxonomies (e.g., reference frameworks, curriculum) or emerging folksonomies (defined by the community) (Hernández-Leo et al., 2011).
Authors and co-contributors	Individuals editing, co-editing or commenting a design, degree and shape of participation and interaction. Designs started, co-created or commented by individual (Hernández-Leo et al., 2011; Vourikari, Gilleran & Scimeca, 2011).
Versioning	Learning designs created using or refining another design as starting point. Characterization of differences between different versions of the same learning design (Chacón et al., 2014).
Ratings	Social appraisal of a learning design within a community, typically in the form of a scale (Vourikari, Gilleran & Scimeca, 2011).
Functions: Enhance awareness and reflection about the learning design activity: monitor individual and collective learning design activity to help reflection about learning design activity patterns. Support orientation and inspiration for the learning design activity: identification of potentially interesting tools to be used in the design process learning design tools to explore, designs to reuse, teachers to collaborate.	

Interactions between layers

Although the layers implicitly define a categorization of data sources, classes and functions, there are interactions between layers that capture relevant synergies (Figure 2). Design Analytics can provide a framework for the alignment of design intent with the emerging learners' activity patterns, facilitating the interpretation of Learning Analytics. Also, if the learning analytics are aligned with the design intent, educators can consider them to improve the design in further design interactions.

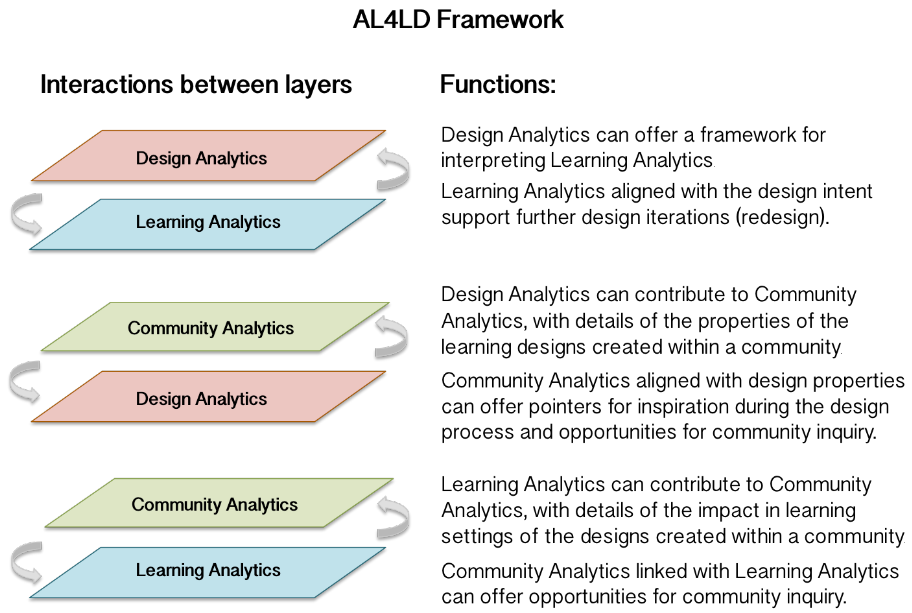


Figure 2. Interactions between AL4LD layers

The properties that characterize a design (Design Analytics) can serve as a basis for the Community Analytics layer to offer a deeper understanding and mutual inspiration about design practices in the context of a community. Learning Analytics for a design can also contribute to the Community Analytics layer by offering shared awareness of its effects when implemented in an actual learning setting (i.e. its impact on learners' engagement, progression and achievement). The relationship between the Learning and Design Analytics layers with the Community Layer enables moving from a focus on individual practice towards a social approach, providing awareness of learning design practice from multiple educators and opportunities for collaborative reflective teaching practice. Moreover, the interaction between layers can lead to opportunities for community inquiry (Mor, Ferguson & Wasson, 2015), in which several teachers can implement selected designs (or designs with particular properties) in their contexts, compare the resulting learning analytics, and aggregate the findings into a body of knowledge (to extract good practices, lessons learnt, factors affecting adoption, etc.).

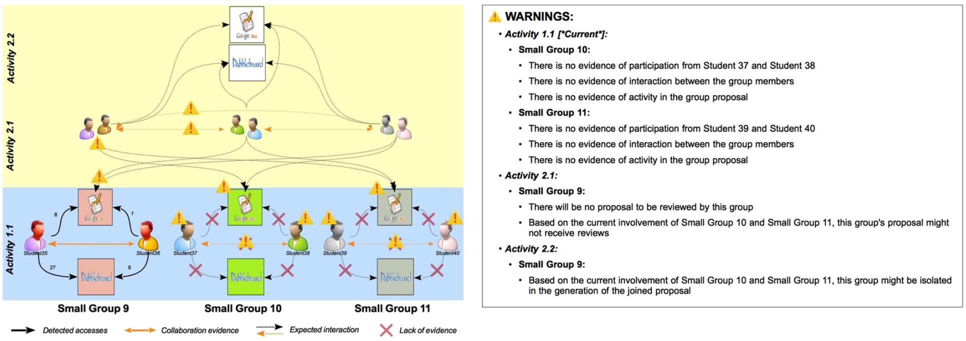
Tools and experiences

This section includes the description of four cases that highlight how the elements of the framework can be seen in practice within different tools and educational settings, and how the observed elements have implications for influencing educators in design decisions.

Case 1: GLIMPSE

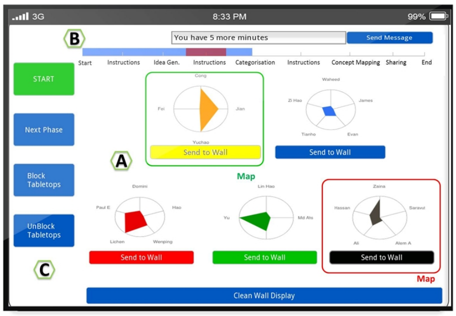
This case illustrates how two tools, GLUE!-CAS and GLIMPSE (Rodríguez-Triana et al., 2015), are integrated in the learning ecosystem to establish the bidirectional interactions between the Design and the Learning Analytics layers. GLUE!-CAS collects and integrates evidence from different enactment platforms (using as data sources, among others, virtual learning environments, web tools, attendance registers and students' feedback questionnaires). GLIMPSE compares this evidence with the teacher's design (using learning design authoring tools as data sources). Data gathered and analyzed include: *profiles* (students names, emails, IDs, etc.), *process* (e.g., number of views and editions in resources corresponding to specific activities of the learning design, attendance, submissions), *checkpoints* (warnings related to the usage of resources, etc.), and *performance* (e.g., comments inserted by teachers). These tools have been used in a Spanish university in authentic learning scenarios involving 365 students and 7 teachers in different subjects and courses. For example, in a Computer Networks course, students had to develop a chat application using data network protocols. In order to help them plan and anticipate problems for a subsequent programming assignment, two teachers designed a pyramid activity where students were expected to collaboratively elaborate and discuss a sequence diagram of their software design. Figure 3 (GLIMPSE) shows part of a monitoring report generated for the activity. The report is structured according to the learning design defined by the teachers (tasks, social planes, set of tools). In this case, learning analytics enabled the detection of: lack of participation and unused resources (e.g. in Small Groups 10 and 11 during the first activity), which hindered the desired pyramidal joining of groups in the subsequent activity. Apart from triggering the adaptation of the design to cope with the emerging problems during the learning activity, the analytics informed the reflection and the re-design. Design reflections supported by these analytics refer to *social planes* (e.g., revising strategies of student distribution in groups), *time* (e.g., identifying bottlenecks in case of eventualities), *set* of tools (e.g., detecting resources rarely used), and tasks (assessing the suitability of the collaborative patterns taking into account the risks of dropout). Later versions of this design were refined by allocating time between activities to allow intervention in case of eventualities. Also, the new strategy for group formation distributed students at risk to decrease the impact that dropout could have on the different social planes and on the sequence of tasks.

GLIMPSE



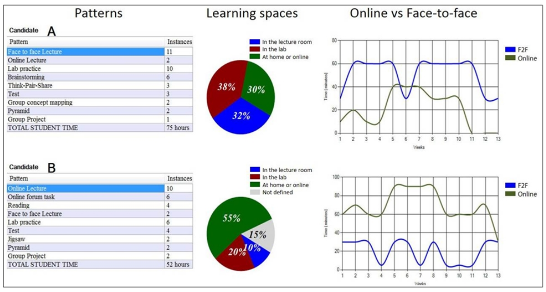
On the left, example of a report generated by GLIMPSE regarding the students' group performance. On the right, explanation of the warnings appearing in the report

MTClassroom

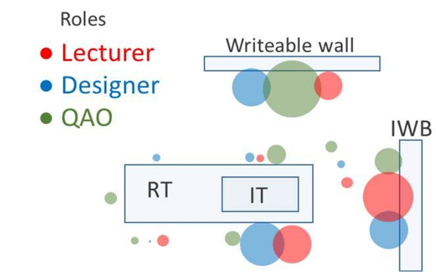


Left: The multi-surface MTClassroom composed of: 5 interactive tabletops, 3 public vertical displays and faculty's handheld dashboard. Right: The MTdashboard providing information about: a) each students-group task progress/performance, b) the progress of the runtime script and c) overtimed sub-tasks.

Educational Design Studio (EDS)

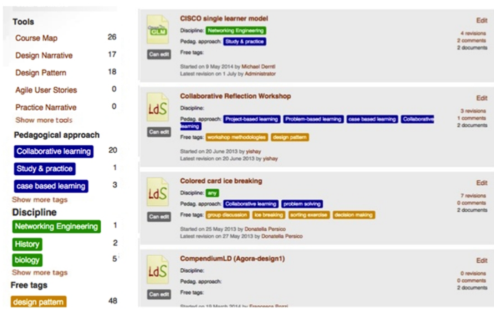


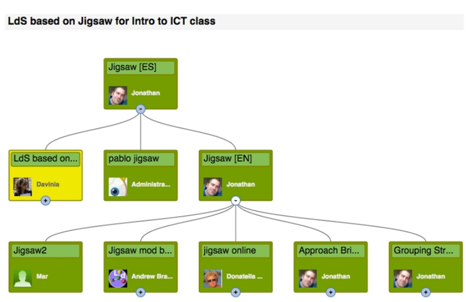
Design analytics visualization providing information about the patterns in each candidate designs (e.g. candidates A and B), the proportion of learning tasks in the learning spaces, and the distribution of online and face-to-face activities on a weekly basis.



Community analytics visualization about the space usage; the circles represent the time each user-role used the space: QAO=Quality Assurance Officer, RT= Regular table, IT=interactive tabletop, and IWB= Interactive whiteboard.

Integrated Learning Design Environment (ILDE)





On the left, design activity pattern of types of designs created (tools used, characterizing tags) within the community. On the right, family tree showing the evolution/versioning of a design.

Figure 3. Examples of tools illustrating the three Analytics Layers for Learning Design

Case 2: MTClassroom

This second case also highlights the interaction between the **Learning and the Design Analytics layers** and has been applied on a teacher's dashboard to be used in the classroom (Martinez-Maldonado, Clayphan, & Kay, 2015). The data classes used in this example corresponded to information about the *process* and the *performance* of students during the classroom sessions. The analytics tool was deployed in a multi-tabletop classroom -the MTClassroom- comprised of five interactive tabletops, each designed for face-to-face work in groups of up to five students (Figure 3, MTClassroom, left). This environment was used in an Australian university to conduct small-group activities for regular classes with more than 400 students of different subjects for 4 terms. In the design phase, teachers set explicit pedagogical intentions for the students work. In runtime, a handheld dashboard was provided to the teacher showing visual representations of Learning Analytics in real-time (Figure 3, MTClassroom, right). These representations included visualizations for each small-group working in the classroom, showing measures of participation and performance. At the same time, the dashboard provided real-time feedback to the teacher about how closely she was following the intended learning design. These visual representations included; i) the status of the learning tasks in terms of the time allocated in the design; and ii) an alarm indicating when a particular task was taking longer than planned. The analytics support allowed the teacher to be aware of the status of the execution of planned tasks in order to meet the learning goals and pedagogical objectives, and also to adapt the tasks and provide feedback accordingly to the emergent contingencies. Moreover, the analytics were also used for post-hoc analysis of the enactment to support the subject coordinator to reflect on the specific elements of the design that could be changed, reused or redesigned, based on classroom data.

Case 3: Educational Design Studio

The **Design Analytics** layer has been applied in an experimental Educational Design Studio (Martinez-Maldonado et al., 2017) located at The University of Sydney. This environment helps educators build rapid alternative course designs and make high level decisions on the pedagogical implications when modifying learning tasks. This space is equipped with wall projectors, an interactive whiteboard, a digital tabletop, writable walls, a design analytics dashboard, tablets and varied writing materials. The system allows teachers to use patterns as templates for students' tasks, learning spaces, or situations. Teachers can interact with the iconic representations of these patterns, with direct-touch input, to arrange them in a timeline or link learning tasks with particular learning spaces. The various displays allow designers to build multiple designs at the same time. Rather than using learners' data, the environment provides teachers with analytics about their designs. Figure 3 (EDS, left) shows a screenshot of the dashboard that conveys information about data classes corresponding to two comparable candidate course designs such as the *time*, *places* and *set, task, teacher/student workload, social planes*. The provided analytics support the teachers in three ways: 1) enhancing awareness of the broad view and the progress of their learning designs while building and editing individual tasks; 2) facilitating the rapid comparison of multiple designs (up to four at the same time) in order to adjust design decisions; and 3) supporting informed discussion of the learning designs at a high level.

The EDS also provides an example of **Community Analytics** in physical design spaces. Analytics can show how teachers and other stakeholders collaborate face-to-face while negotiating their varied roles and using a combination of tools and methods. This understanding can support reflection on good design practices, the use of tools, or the adequate distribution of roles that may inspire other practitioners. In this example, the data sources consisted of the actions performed by teachers and other stakeholders in the Design Studio. Specifically, analytics were focused on generating evidence about the degree, the sequencing and the ways designers used different design editors, the space and even furniture (*tools* data class) while designing. For example, Figure 3 (EDS, right), shows a visualization that served to analyze the use of the physical space by teachers as designers. This scenario also used the different design *versions* as another data class. Teachers were able to incorporate and re-configure learning design patterns into their own designs, serving as a way to obtain orientation and inspiration from other designers in the community.

Case 4: Integrated Learning Design Environment (ILDE)
ILDE provides several features that illustrate how the **Community Analytics layer** and its interactions with the **Learning and Design Analytics layers**, can support learning design (Hernández-Leo et al., 2014). ILDE is a community platform that integrates several learning design tools. These include templates for sketching and authoring tools to edit computationally represented designs for their automatic implementation in virtual learning environments. ILDE offers a collaborative space to (co)design, tag, share, explore, reuse and comment learning designs at different levels of granularity, pedagogies and phases of design, in diverse representations. The environment has been conceived to support delimited communities, such as educational centers and collaboration projects across centers and has been piloted in over ten communities (http://ilde.upf.edu/about). ILDE has been used, for example, to support teacher training in workshops and MOOCs, or to design integrated problem-based tasks co-created by teachers of diverse knowledge areas. These tasks are used in capstone courses where students apply the knowledge and skills acquired in previous courses in an integrated scenario. ILDE supports the orientation and awareness about the design activity happening in the community by making visible and available the data classes that refer to tools, labels, authors and co-contributors, and versions. Using these data classes, users can "browse" the designs shared in the community, Figure 3 (ILDE, left). In this context, analytics provide indicators about which tools are used in the community and the types of designs that are being created. If a design has been reused (duplicated and refined), the environment offers a "family tree" of the versions to facilitate understanding of its adoption and evolution, Figure 3 (ILDE, right). Each design is also documented with data showing the person that started the design, the number of received revisions and comments, and its tags. Design Analytics (provided by the integrated authoring tools) and Learning Analytics (coming from the learning environments in which designs have been deployed) contribute to Community Analytics with more detailed information about the designs and their impact. For example, in the case of the PyramidApp editor integrated in ILDE (Manathunga & Hernández-Leo, in press), design analytics contributes with data related to the levels of the pyramid pattern and the total time expected for a designed activity. The results from its enactment provide data related to the actual time consumed by the activity and the level of learners' engagement achieved in the discussions for each pyramid level. These interactions between layers help educators within a community to explore what others have designed and the impact of the designs, so as to make informed decisions when designing their own activities or when reusing those shared within the community. In another context in which ILDE-PyramidApp was used, educators were completing cycles of inquiry to collectively reflect about what configurations and tasks for pyramid activities can be useful in their context.

Conclusion

Data analytics is emerging as an area with the potential of improving several aspects of the learning experiences including their design. This paper presents the AL4LD framework that conceptualizes an extension of the role of analytics into the learning design space. Different tools and experiences illustrate the facets of the framework, showing that data-informed decision-making in learning design is possible and can be approached from three different angles, modeled in the framework as distinct, yet synergistic, layers. These layers provide a comprehensive and complementary view of the issues that need to be taken into account in order for learning designs to take full advantage of the use of the wide variety of data being collected in current educational environments.

The following lessons, derived from the analyzed cases, can be relevant for other scenarios in which data *analytics* are used to support *learning design*:

- The framework includes a comprehensive spectrum of relationships between data sources, classes and functions in the layers. Learning technology providers may consider some of these relations to effectively enable diverse data-driven scenarios in learning design.
- Pertinent data sources are highly dependent on the learning design scenario.
- Good practices for data-driven scenarios in learning design must include support for: a) evidence-based reflective redesign of learning activities through data from course enactment

(*learning analytics*); b) scaffolding for the design process through analyses of the pedagogical intentions reflected in the design (*design analytics*); c) inspiration and awareness of colleagues' design activity (*community analytics*).
- The interaction between learning design and learning analytic is bidirectional. Learning analytics outputs increase their meaningfulness when aligned with pedagogical intentions and learning designs can be strongly influenced by the data analytics available before or during the learning design activity.

In the future we envision a context in which the framework enables further inquiry and evolution of how the fields of learning design and the learning analytics can be fruitfully combined. It provides criteria for comparing and classifying proposals and an instrument for researchers and analytics providers to guide the creation of relevant analytics that can serve educators in their learning design processes.

Considering the three layers of the framework as a whole raises new questions and opportunities. For example, the connection of educational performance and satisfaction with particular learning design properties or to activity patterns in a design community requires considering elements of all three layers. Additionally, in many design environments, design and community aspects are predominantly sparse and qualitative and their quantification into analytics offers particular challenges that need to be addressed. The framework points to new potential approaches to tackle these challenges as illustrated by the given examples. Nonetheless, further research is needed to formulate educational analytics techniques that can further articulate the relationship between ill-structured design, design communities and useful analytics.

Statements on open data, ethics and conflict of interest

For each tool and experience data was collected according to the code of ethics of the corresponding university. There are no potential conflicts of interest in the work.

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