

# Analytics for Learning Design: An overview of existing proposals

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TALLINN UNIVERSITY

# Goals

1. **Raise your awareness** about how analytics can help learning design
2. **Illustrate** these synergies with existing studies using analytics for learning design
3. **Share** take away messages
4. **Discuss** these ideas with you

# Definitions

**Learning  
Design**

Assist practitioners in the **creation** of pedagogically-sound learning environments

(Mor, Craft, & Hernández-Leo, 2013)

**Learning  
Analytics**

**Understand and optimize** learning and the environments in which it occurs

SoLAR – Society for Learning Analytics: <http://solaresearch.org/about>

**Teaching  
Analytics**

Support teachers' dynamic diagnostic **decision-making**

(Vatrapu, 2012)

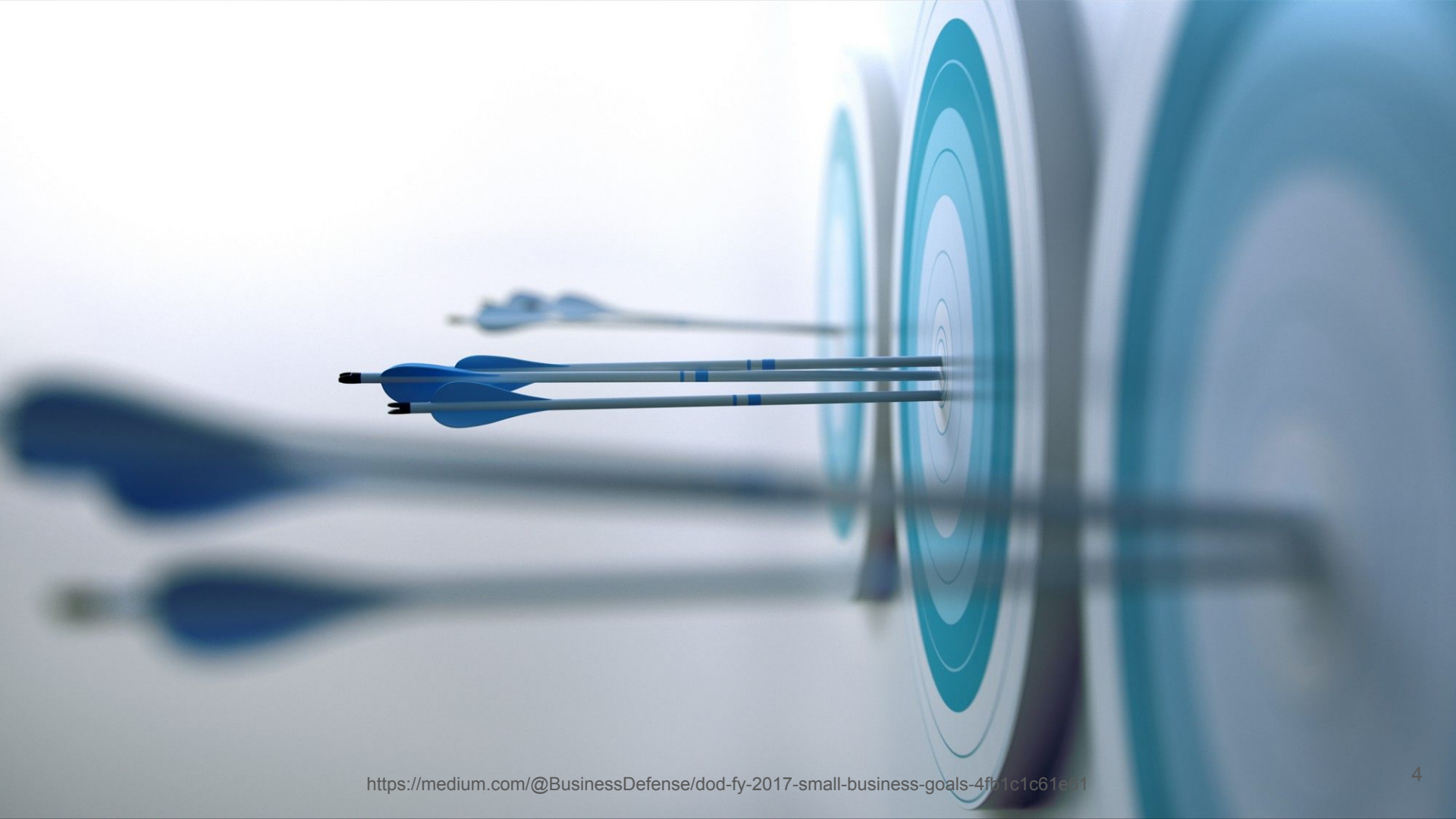
**Academic  
Analytics**

Evaluate and analyse organisational data for **reporting and decision making**

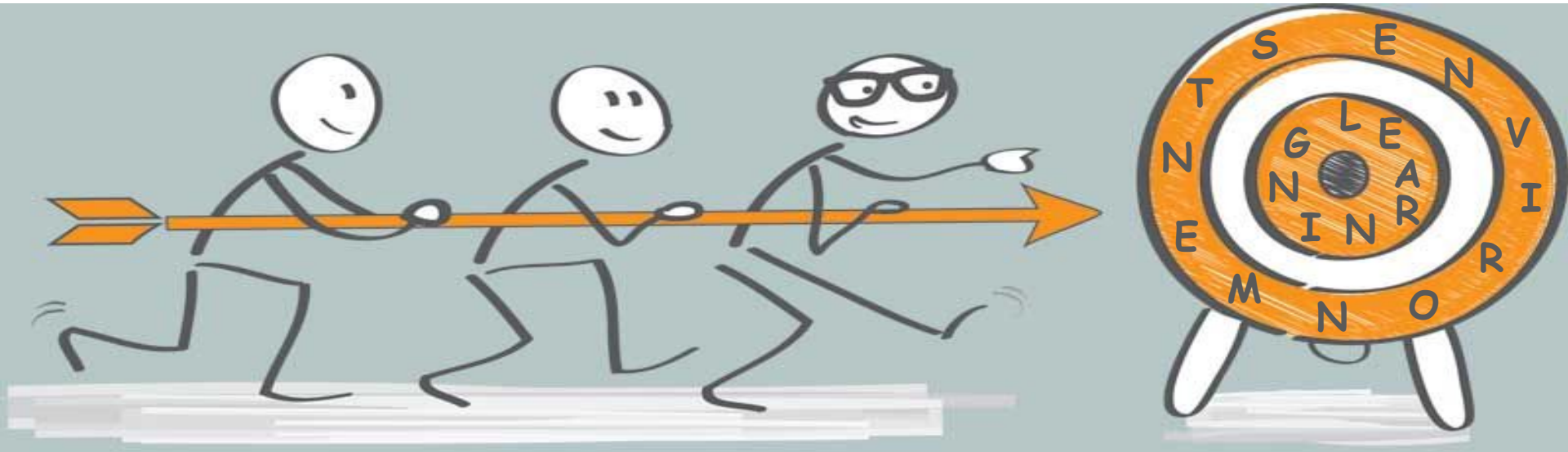
(Campbell & Oblinger, 2007)

...

...



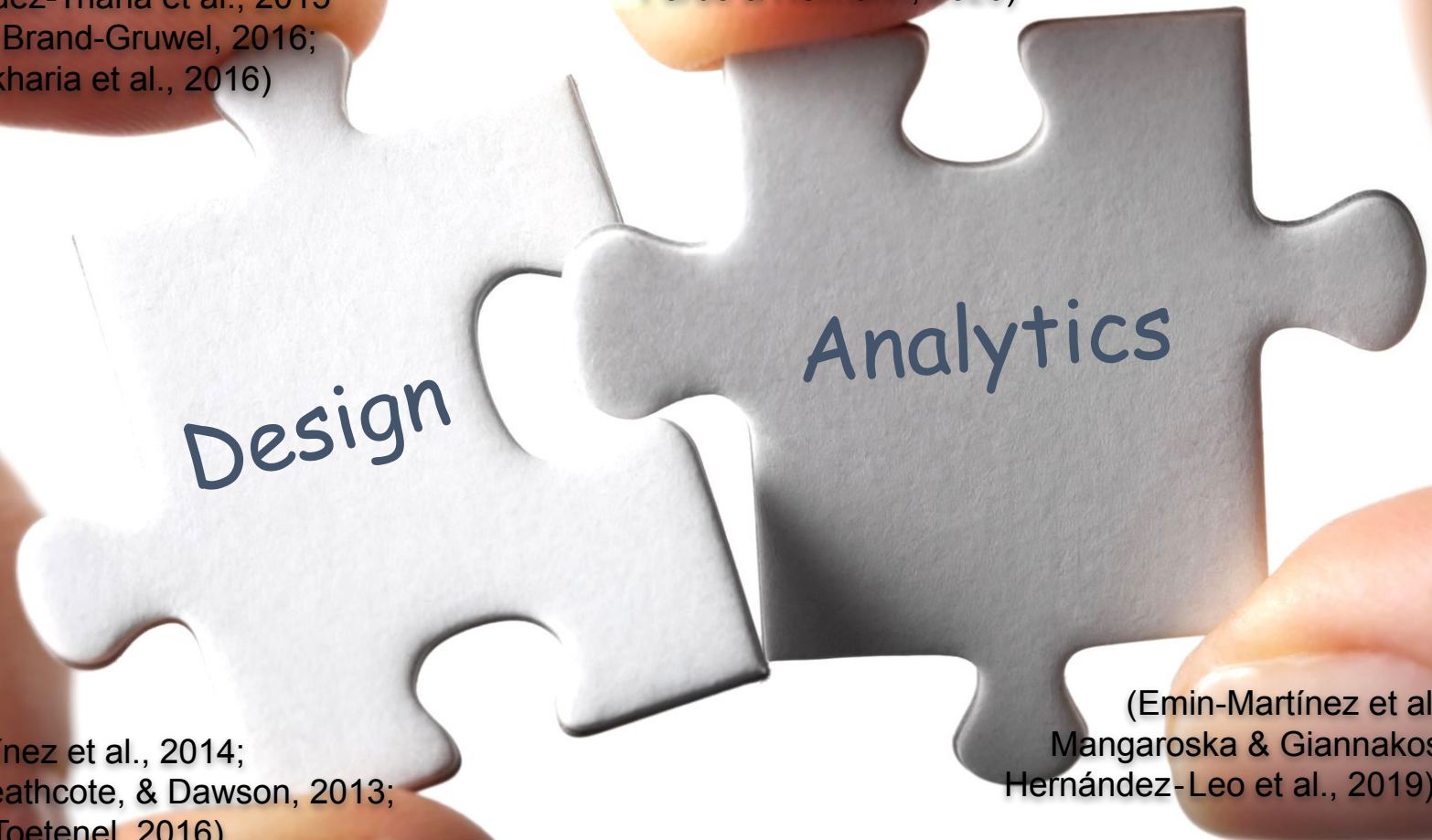
# Lack of alignment



<http://www.cb-counselling.com.au/your-goals.htm>

(Lockyer, Heathcote, & Dawson, 2013;  
Mor, Ferguson & Wasson, 2015;  
Rodríguez-Triana et al., 2015  
Bos & Brand-Gruwel, 2016;  
Bakharia et al., 2016)

(Lockyer & Dawson, 2011;  
Shen et al., 2020;  
Pardo & Reimann, 2020)



(Emin-Martínez et al., 2014;  
Lockyer, Heathcote, & Dawson, 2013;  
Rienties & Toetenel, 2016)

(Emin-Martínez et al., 2014;  
Mangaroska & Giannakos, 2018;  
Hernández-Leo et al., 2019)

# Challenges

## Learning Design

- What are the effects?
- What are the characteristics?
- How practitioners co-design for learning?

(Hernández-Leo et al., 2019)

## Analytics

- Compatibility with the **contextual constraints**
  - Compatibility with the **user practice**
  - **Ethical** and **privacy** issues
  - **Data literacy**
  - **Actionability**
- 
- **Added value** (costs vs benefits)

(Prieto et al., 2019)

# Synergies: Design for Analytics

## Learning Design

- What are the effects?
- What are the characteristics?
- How practitioners co-design for learning?

(Hernández-Leo et al., 2019)

## Analytics

- Compatibility with the **contextual constraints**
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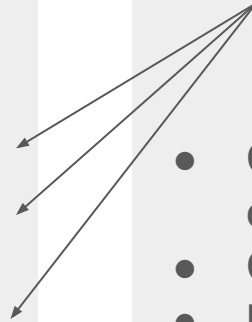


# Synergies: Analytics for Learning Design

## Learning Design

- What are the effects?
- What are the characteristics?
- How practitioners co-design for learning?

(Hernández-Leo et al., 2019)



## Analytics

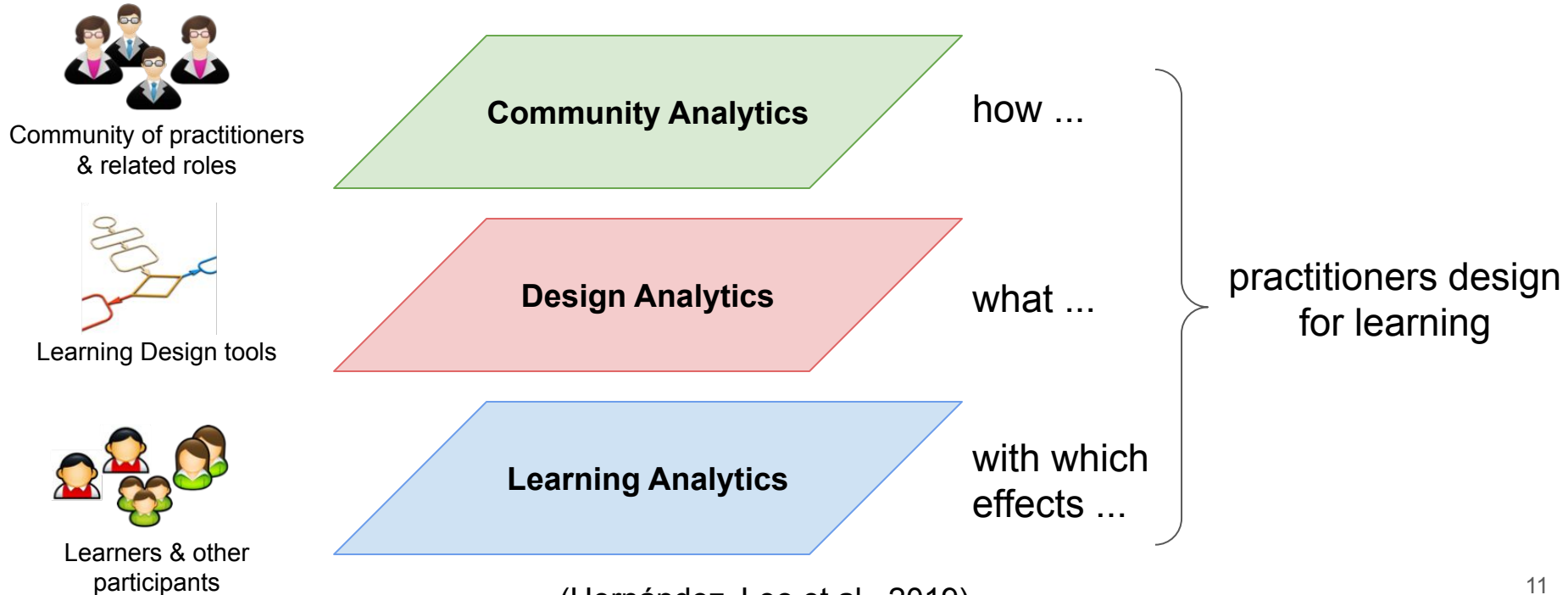
- Compatibility with the **contextual constraints**
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  - **Data literacy**
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- **Added value** (costs vs benefits)

(Prieto et al., 2019)

# Analytics Layers for Learning Design (AL4LD)

# Analytics Layers for Learning Design Framework (AL4LD)

**Goal:** to support awareness, sensemaking and reflection on ...



(Hernández-Leo et al., 2019)

# Analytics Layers for Learning Design Framework (AL4LD)

	<b>Data sources</b>	<b>Data classes</b>	<b>Metrics</b>	<b>Functions</b>
<b>Community Analytics</b>	LD communities platforms	Tools, labels, authors, versioning & ratings	Metrics and patterns of individual and collective LD activity	<ul style="list-style-type: none"><li>- Enhance awareness and reflection about the LD activity patterns</li><li>- Support orientation and inspiration for the learning design activity</li></ul>
<b>Design Analytics</b>	LD (digital) tools	Goals, tasks, social planes, places and set, time & teachers' workload	Design decisions and related aspects characterizing LDs	<ul style="list-style-type: none"><li>- Enhance awareness and reflection about the LD properties, provoking reflection</li><li>- Identify implications for future LD decisions</li></ul>
<b>Learning Analytics</b>	Learning environment (LMS, learning tools, sensors, information systems, ...) + surveys	Profile, checkpoints, process, performance & satisfaction	Engagement, progression, achievement and satisfaction	<ul style="list-style-type: none"><li>- Enhance awareness and reflection about the LD impact</li><li>- Learning redesign</li></ul>

(Hernández-Leo et al., 2019)

# Learning Analytics

Community Analytics

Design Analytics

Learning Analytics

Computers in Human Behavior 60 (2016) 333–341



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Computers in Human Behavior

journal homepage: [www.elsevier.com/locate/comphumbeh](http://www.elsevier.com/locate/comphumbeh)



Full length article

The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules



Bart Rienties\*, Lisette Toetenei\*\*

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## ARTICLE INFO

### Article history:

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### Keywords:

Learning design

Learning analytics

Academic retention

Learner satisfaction

Virtual learning environment

## ABSTRACT

Pedagogically informed designs of learning are increasingly of interest to researchers in blended and online learning, as learning design is shown to have an impact on student behaviour and outcomes. Although learning design is widely studied, often these studies are individual courses or programmes and few empirical studies have connected learning designs of a substantial number of courses with learning behaviour. In this study we linked 151 modules and 111,256 students with students' behaviour (<400 million minutes of online behaviour), satisfaction and performance at the Open University UK using multiple regression models. Our findings strongly indicate the importance of learning design in predicting and understanding Virtual Learning Environment behaviour and performance of students in blended and online environments. In line with proponents of social learning theories, our primary predictor for academic retention was the time learners spent on communication activities, controlling for various institutional and disciplinary factors. Where possible, appropriate and well designed communication tasks that align with the learning objectives of the course may be a way forward to enhance academic retention.

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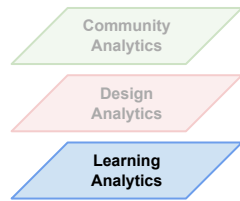
**RQ:** To what extent LD decisions made by teachers predict VLE engagement, satisfaction and academic performance?

**Contribution:** Regression analyses linking LDs of 151 modules and 111,000 students

**Technological context:** Institutional VLE at OU UK

## Findings:

- LD has strong impact on behaviour, satisfaction, and performance.
- Primary predictor for academic retention was communication activities.



# Learning Analytics

	Type of activity	Example
Assimilative	Attending to information	Read, Watch, Listen, Think about, Access.
Finding and handling information	Searching for and processing information	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather.
Communication	Discussing module related content with at least one other person (student or tutor)	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe.
Productive	Actively constructing an artefact	Create, Build, Make, Design, Construct, Contribute, Complete,.
Experiential	Applying learning in a real-world setting	Practice, Apply, Mimic, Experience, Explore, Investigate,.
Interactive/adaptive	Applying learning in a simulated setting	Explore, Experiment, Trial, Improve, Model, Simulate.
Assessment	All forms of assessment (summative, formative and self assessment)	Write, Present, Report, Demonstrate, Critique.

**RQ:** To what extent LD decisions made by teachers predict VLE engagement, satisfaction and academic performance?

**Contribution:** Regression analyses *linking* LDs of 151 modules and engagement, satisfaction and retention from >111 K students

**Technological context:** Moodle (Institutional VLE at OU UK)

## Findings:

- The importance of LD in predicting and understanding VLE behaviour and performance
- LD has strong impact on behaviour, satisfaction, and performance.
- Primary predictor for academic retention was communication activities.

# Analytics Layers for Learning Design Framework (AL4LD)

	<b>Data sources</b>	<b>Data classes</b>	<b>Metrics</b>	<b>Functions</b>
<b>Community Analytics</b>	LD communities platforms	Tools, labels, authors, versioning & ratings	Metrics and patterns of individual and collective LD activity	<ul style="list-style-type: none"><li>- Enhance awareness and reflection about the LD activity patterns</li><li>- Support orientation and inspiration for the learning design activity</li></ul>
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# Design Analytics

Community  
Analytics

Design  
Analytics

Learning  
Analytics

International Journal of Artificial Intelligence in Education  
<https://doi.org/10.1007/s40593-021-00253-3>

ARTICLE



## Knowledge-Based Design Analytics for Authoring Courses with Smart Learning Content

Laia Albó<sup>1</sup> · Jordan Barria-Pineda<sup>2</sup> · Peter Brusilovsky<sup>2</sup> · Davinia Hernández-Leo<sup>1</sup>

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### Abstract

Over the last 10 years, learning analytics have provided educators with both dashboards and tools to understand student behaviors within specific technological environments. However, there is a lack of work to support educators in making data-informed design decisions when designing a blended course and planning appropriate learning activities. In this paper, we introduce knowledge-based design analytics that uncover facets of the learning activities that are being created. A knowledge-based visualization is integrated into edCrumble, a (blended) learning design authoring tool. This new approach is explored in the context of a higher education programming course, where instructors design labs and home practice sessions with online smart learning content on a weekly basis. We performed a within-subjects user study to compare the use of the design tool both with and without visualization. We studied the differences in terms of cognitive load, controllability, confidence and ease of choice, design outcomes, and user actions within the system to compare both conditions with the objective of evaluating the impact of using design analytics during the decision-making phase of course design. Our results indicate that the use of a knowledge-based visualization allows the teachers to reduce the cognitive load (especially in terms of mental demand) and that it facilitates the choice of the most appropriate activities without affecting the overall design time. In conclusion, the use of knowledge-based design analytics improves the overall learning design quality and helps teachers avoid committing design errors.

**Keywords** Design analytics · Blended learning · Concept-level visualization · Knowledge-based analytics · Authoring tool · Learning design · Smart learning content

**RQ:** What is the value of knowledge-based design analytics during the design process?

**Contribution:** Knowledge-based design analytics visualization

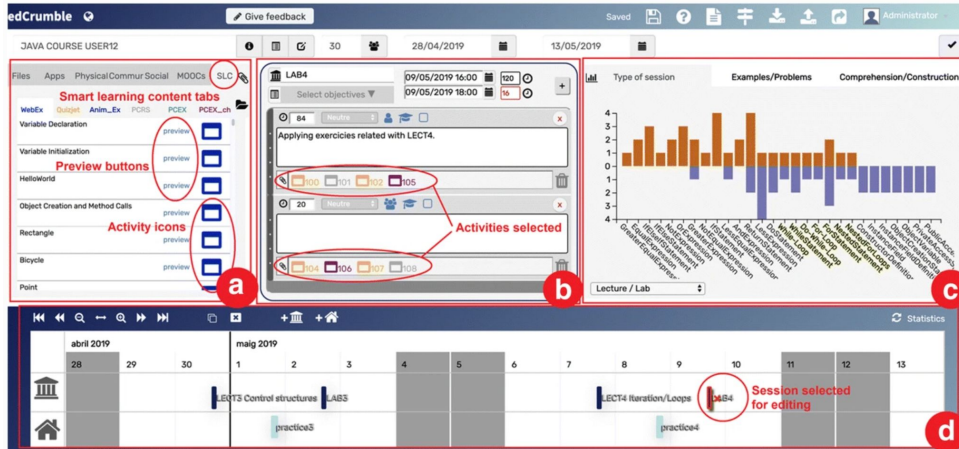
**Technological context:** [edCrumble](#)

**Findings:** The use of a knowledge-based visualization allows ...

- the teachers to reduce the cognitive load
- facilitates the choice of the most appropriate activities without affecting the overall design time
- improves the overall LD quality
- helps teachers avoid design errors



# Design Analytics



**RQ:** What is the value of knowledge-based design analytics during the design process?

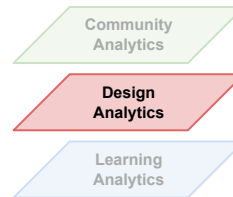
**Contribution:** Knowledge-based design analytics visualization

**Technological context:** [edCrumble](#)

**Findings:** The use of a knowledge-based visualization allows ...

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- helps teachers avoid design errors

# Design Analytics



Education Tech Research Dev (2021) 69:417–444  
<https://doi.org/10.1007/s11423-020-09904-z>



FEATURED PAPER



## Understanding teacher design practices for digital inquiry-based science learning: the case of Go-Lab

Ton de Jong<sup>1</sup> · Denis Gillet<sup>2</sup> · María Jesús Rodríguez-Triana<sup>3</sup> · Tasos Hovardas<sup>4</sup> · Diana Dikke<sup>5</sup> · Rosa Doran<sup>6</sup> · Olga Dziabenko<sup>7</sup> · Jens Koslowsky<sup>8</sup> · Miikka Korventausta<sup>9</sup> · Effie Law<sup>10</sup> · Margus Pedaste<sup>11</sup> · Evita Tasiopoulou<sup>12</sup> · Gérard Vidal<sup>13</sup> · Zacharias C. Zacharia<sup>4</sup>

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### Abstract

Designing and implementing online or digital learning material is a demanding task for teachers. This is even more the case when this material is used for more engaged forms of learning, such as inquiry learning. In this article, we give an informed account of Go-Lab, an ecosystem that supports teachers in creating Inquiry Learning Spaces (ILSs). These ILSs are built around STEM-related online laboratories. Within the Go-Lab ecosystem, teachers can combine these online laboratories with multimedia material and learning apps, which are small applications that support learners in their inquiry learning process. The Go-Lab ecosystem offers teachers ready-made structures, such as a standard inquiry cycle, alternative scenarios or complete ILSs that can be used as they are, but it also allows teachers to configure these structures to create personalized ILSs. For this article, we analyzed data on the design process and structure of 2414 ILSs that were (co)created by teachers and that our usage data suggest have been used in classrooms. Our data show that teachers prefer to start their design from empty templates instead of more domain-related elements, that the makeup of the design team (a single teacher, a group of collaborating teachers, or a mix of teachers and project members) influences key design process characteristics such as time spent designing the ILS and number of actions involved, that the characteristics of the resulting ILSs also depend on the type of design team and that ILSs that are openly shared (i.e., published in a public repository) have different characteristics than those that are kept private.

### RQs:

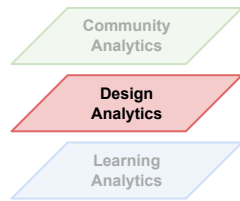
- What is the starting point for the design (reusing existing materials vs from scratch)?
- What are the the virtues and dynamics of the collaborative design process?
- What is the objective of the design (use them in the classroom and/or share them with their colleagues)?

**Contribution:** Analysis of 2414 designs implemented in the classroom

**Technological context:** [Go-Lab](#) ([Graasp.eu](#))

### Findings:

- Teachers prefer to start their design from empty templates instead of more domain-related elements
- Cocreation influences key design process characteristics such as time spent in the LD and number of actions involved
- The (structural) characteristics of the resulting LD also depend on the type of design team (individual, teachers, teachers & experts)
- Public LDs have different characteristics vs. private ones.



# Design Analytics

**Table 2** Average or median values for design effort per ILS (co)creation category for implemented ILSs

	Single teacher ( <i>n</i> = 1234 ILSs)	Group of teachers ( <i>n</i> = 490 ILSs)	Teacher(s) & project member(s) ( <i>n</i> = 690 ILSs)	Kruskal– Wallis <i>H</i>
Authors (median)	1	3	4	–
Design time (average min)	251	329	433	122.72***
Design actions (average number)	977	1125	1399	124.14***
Active authors (design time > 10 min; median)	1	1.5	2	–
Design time (average min for active authors > 10 min)	248	323	430	108.72***
Design actions (average number for active authors > 10 min)	936	1085	1339	103.05***

Note: \*\*\*  $p < .001$

## RQs:

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**Contribution:** Analysis of 2414 designs implemented in the classroom

**Technological context:** [Go-Lab](https://go-lab.com/) ([Graasp.eu](https://graasp.eu/))

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# Design Analytics

Community Analytics

Design Analytics

Learning Analytics

ORIGINAL ARTICLE

WILEY Journal of Computer Assisted Learning

## Multimodal teaching analytics: Automated extraction of orchestration graphs from wearable sensor data

L.P. Prieto<sup>1</sup>  | K. Sharma<sup>2</sup> | Ł. Kidzinski<sup>3</sup> | M.J. Rodríguez-Triana<sup>1,4</sup>  | P. Dillenbourg<sup>2</sup>

<sup>1</sup>Tallinn University, Estonia

<sup>2</sup>École Polytechnique Fédérale de Lausanne, Switzerland

<sup>3</sup>Stanford University, CA, USA

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### Correspondence

Luis P. Prieto, Tallinn University, Estonia.  
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### Funding information

Horizon 2020 Framework Programme, Grant/Award Number: 731685; European Union's Horizon 2020 research and innovation programme, Grant/Award Number: No. 669074; Marie Curie Fellowship (7th European Community Framework Programme), Grant/Award Number: MIOCTI, FP7-PEOPLE-2012-IEF project no. 327384; US National Institute of Health, Grant/Award Number: U54EB020405

### Abstract

The pedagogical modelling of everyday classroom practice is an interesting kind of evidence, both for educational research and teachers' own professional development. This paper explores the usage of wearable sensors and machine learning techniques to automatically extract orchestration graphs (teaching activities and their social plane over time) on a dataset of 12 classroom sessions enacted by two different teachers in different classroom settings. The dataset included mobile eye-tracking as well as audiovisual and accelerometry data from sensors worn by the teacher. We evaluated both time-independent and time-aware models, achieving median F1 scores of about 0.7–0.8 on leave-one-session-out k-fold cross-validation. Although these results show the feasibility of this approach, they also highlight the need for larger datasets, recorded in a wider variety of classroom settings, to provide automated tagging of classroom practice that can be used in everyday practice across multiple teachers.

### KEYWORDS

activity detection, eye-tracking, multimodal learning analytics, sensors, teaching analytics

### RQs:

- How effective can be a model trained/tuned for a single teacher?
- What are the most informative data sources and features when building this kind of models?

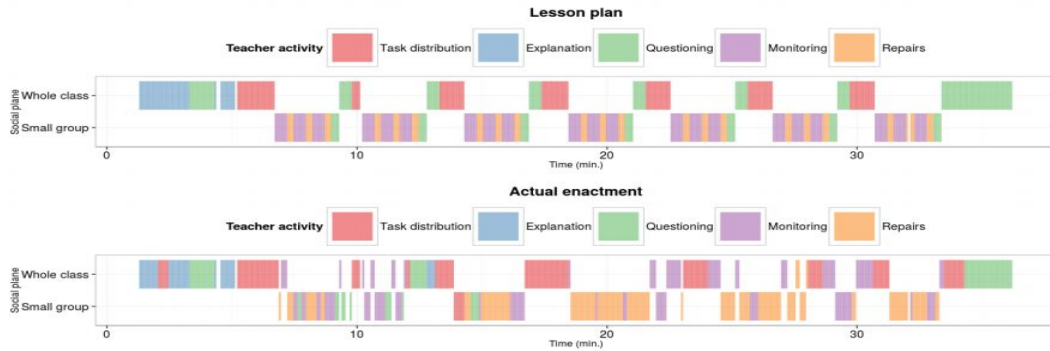
**Contribution:** Automated extraction of orchestration graphs from wearable sensor data (gaze, video, audio, accelerometer)

**Technological context:** Wearable sensors (eye-tracking glasses + a smartphone)

### Findings:

- ML models can be successfully trained with such multimodal sensor data.
- Less costly data sources (such as audio or accelerometer) are already quite effective.

# Design Analytics



## RQs:

- How effective can be a model trained/tuned for a single teacher?
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**Contribution:** Automated extraction of orchestration graphs from wearable sensor data (gaze, video, audio, accelerometer)

**Technological context:** Wearable sensors (eye-tracking glasses + a smartphone)

## Findings:

- ML models can be successfully trained with such multimodal sensor data.
- Less costly data sources (such as audio or accelerometer) are already quite effective.
- An LD  $\neq$  the classroom enactment of that LD

# Analytics Layers for Learning Design Framework (AL4LD)

	<b>Data sources</b>	<b>Data classes</b>	<b>Metrics</b>	<b>Functions</b>
<b>Community Analytics</b>	LD communities platforms	Tools, labels, authors, versioning & ratings	Metrics and patterns of individual and collective LD activity	<ul style="list-style-type: none"><li>- Enhance awareness and reflection about the LD activity patterns</li><li>- Support orientation and inspiration for the learning design activity</li></ul>
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# Community Analytics

Computers in Human Behavior 85 (2018) 255–270



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Computers in Human Behavior

journal homepage: [www.elsevier.com/locate/comphumbeh](http://www.elsevier.com/locate/comphumbeh)



Community Analytics

Design Analytics

Learning Analytics

Supporting awareness in communities of learning design practice

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### Keywords:

Learning design  
Activity theory  
Communities of practice  
Awareness  
Community analytics  
Dashboards

## ABSTRACT

The field of learning design has extensively studied the use of technology for the authoring of learning activities. However, the social dimension of the learning design process is still underexplored. In this paper, we investigate communities of teachers who used a social learning design platform (ILDE). We seek to understand how community awareness facilitates the learning design activity of teachers in different educational contexts. Following a design-based research methodology, we developed a community awareness dashboard (inILDE) based on the Cultural Historical Activity Theory (CHAT) framework. The dashboard displays the activity of teachers in ILDE, such as their interactions with learning designs, other members, and with supporting learning design tools. Evaluations of the inILDE dashboard were carried out in four educational communities – two secondary schools, a master programme for pre-service teachers, and in a Massive Open Online Course (MOOC) for teachers. The dashboard was perceived to be useful in summarizing the activity of the community and in identifying content and members' roles. Further, the use of the dashboard increased participants' interactions such as profile views and teachers showed a willingness to build on the contributions of others. As conclusions of the study, we propose five design principles for supporting awareness in learning design communities, namely community context, practice-related insights, visualizations and representations, tasks and community interests.

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**RQ:** How does community awareness facilitate the learning design activity of teachers?

**Contribution:** community awareness dashboard

**Technological context:** [ILDE](https://www.elsevier.com/locate/ilde)

**Findings:** The dashboard ...

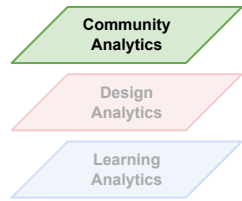
- was useful in *summarizing* the activity of the community and in *identifying* content and members' roles.
- increased participants' *interactions*







# Community Analytics



International Journal of Computer-Supported Collaborative Learning (2020) 15:445–467  
<https://doi.org/10.1007/s11412-020-09331-5>



## Social practices in teacher knowledge creation and innovation adoption: a large-scale study in an online instructional design community for inquiry learning

María Jesús Rodríguez-Triana<sup>1</sup> • Luis P. Prieto<sup>1</sup> • Tobias Ley<sup>1</sup> • Ton de Jong<sup>2</sup> • Denis Gillet<sup>3</sup>

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### Abstract

Social practices are assumed to play an important role in the evolution of new teaching and learning methods. Teachers internalize knowledge developed in their communities through interactions with peers and experts while solving problems or co-creating materials. However, these social practices and their influence on teachers' adoption of new pedagogical practices are notoriously hard to study, given their implicit and informal nature. In this paper, we apply the Knowledge Appropriation Model (KAM) to trace how different social practices relate to the implementation of pedagogical innovations in the classroom, through the analysis of more than 40,000 learning designs created within Graasp, an online authoring tool to support inquiry-based learning, used by more than 35,000 teachers. Our results show how different practices of knowledge appropriation, maturation and scaffolding seem to be related, to a varying degree, to teachers' increased classroom implementation of learning designs. Our study also provides insights into how we can use traces from digital co-creation platforms to better understand the social dimension of professional learning, knowledge creation and the adoption of new practices.

**RQ:** how do social practices relate to the implementation of pedagogical innovations in the classroom?

**Contribution:** Analysis of > 40,000 LDs & > 35,000 teachers

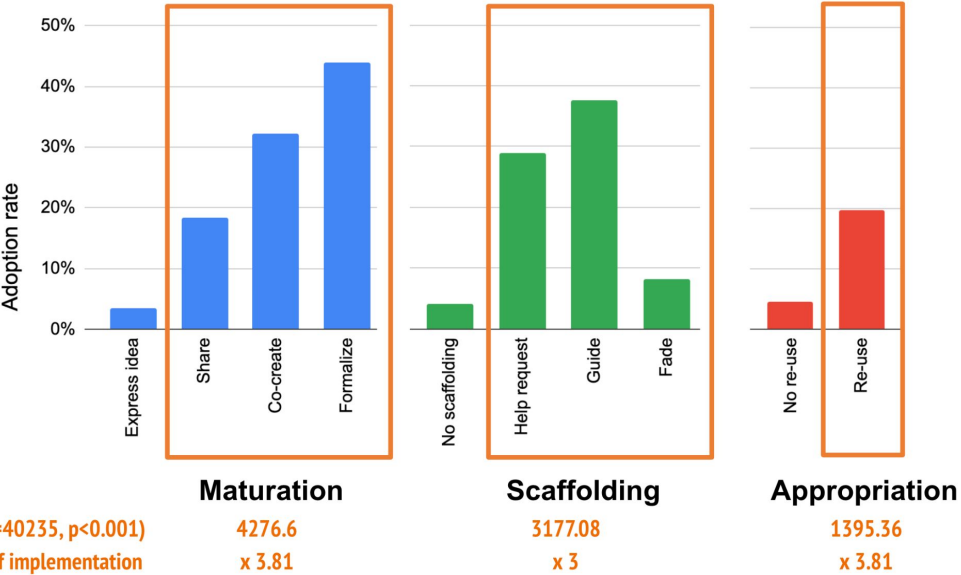
**Technological context:** [Go-Lab](#) ([Graasp.eu](#))

### Findings:

- The higher the social practices, the higher the adoption

(Rodríguez-Triana et al., 2020)

# Community Analytics



**RQ:** how do social practices relate to the implementation of pedagogical innovations in the classroom?

**Contribution:** Analysis of > 40,000 LDs & > 35,000 teachers

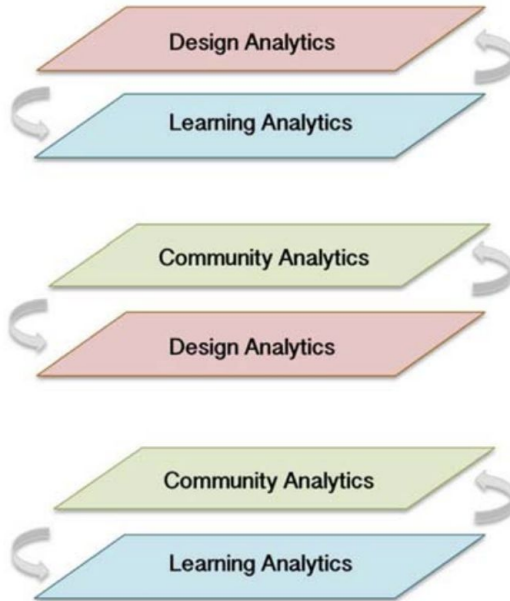
**Technological context:** [Go-Lab](https://go-lab.org) ([Graasp.eu](https://graasp.eu))

**Findings:**

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# Analytics Layers for Learning Design Framework (AL4LD)

## Interactions between layers



## Functions:

Design Analytics can offer a framework for interpreting Learning Analytics  
Learning Analytics aligned with the design intent support further design iterations (redesign).

Design Analytics can contribute to Community Analytics, with details of the properties of the learning designs created within a community.  
Community Analytics aligned with design properties can offer pointers for inspiration during the design process and opportunities for community inquiry.

Learning Analytics can contribute to Community Analytics, with details of the impact in learning settings of the designs created within a community.  
Community Analytics linked with Learning Analytics can offer opportunities for community inquiry.

# Take away messages

- **For practitioners:**
  - Analytics can help you in your practice, not only to monitor and assess your students ;)
- **For teacher trainers:**
  - Analytics can help you in your practice (e.g, identify weaknesses/strengths in teaching) → future trainings
- **For TEL providers:**
  - Few solutions are currently available for final users :( → startup/product ideas!
- **For SOLAR researchers (especially PhD students):**
  - There is A LOT OF ROOM for supporting LD stakeholders:
    - How educators (and related roles) design for learning? → *Community analytics*
    - What are the design decisions and related aspects that characterize the LDs? → *Design analytics*
    - What are the effects of the LDs on the actual learning experiences? → *Learning analytics*
  - We should bring those stakeholders in the loop
- **For TEL researchers:**
  - Analytics could help us understand the pedagogical adoption of TEL innovations!

## Wrap up

1. **Raise your awareness** about how analytics can help learning design → A4LD Framework
2. **Illustrate** these synergies → existing studies using analytics for learning design
3. **Share** take away messages
4. **Discuss** these ideas with you

*Thanks for your attention!*

*Comments, questions?*

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