The Open University

@DrBartRienties

Professor of Learning Analytics

A review of five years of implementation and research in aligning learning design with learning analytics at the Open University UK

ASCILITE SIG LA Webinar
20 September 2017

ASCILITE
SHAPING THE FUTURE OF TERTIARY EDUCATION

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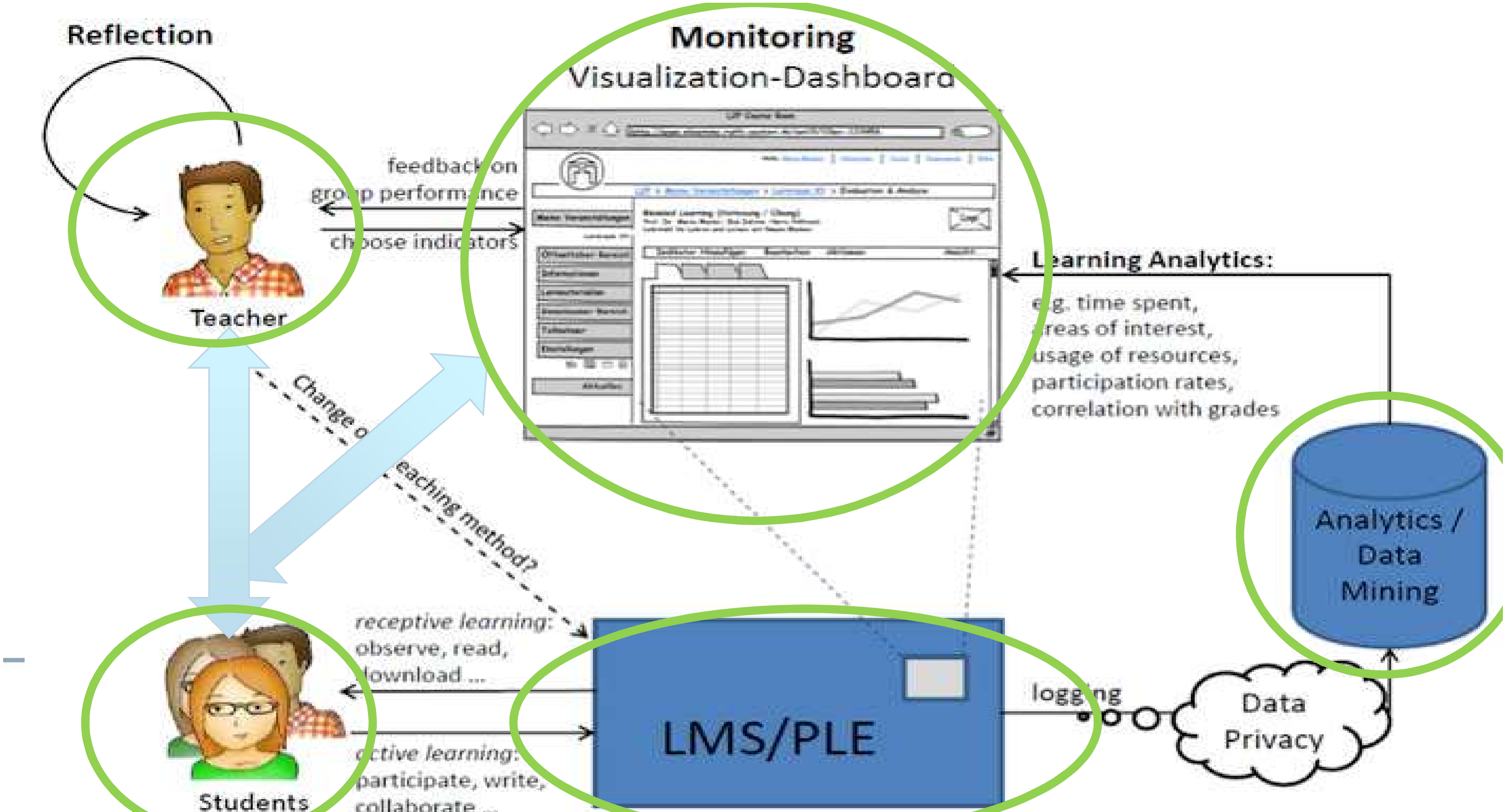
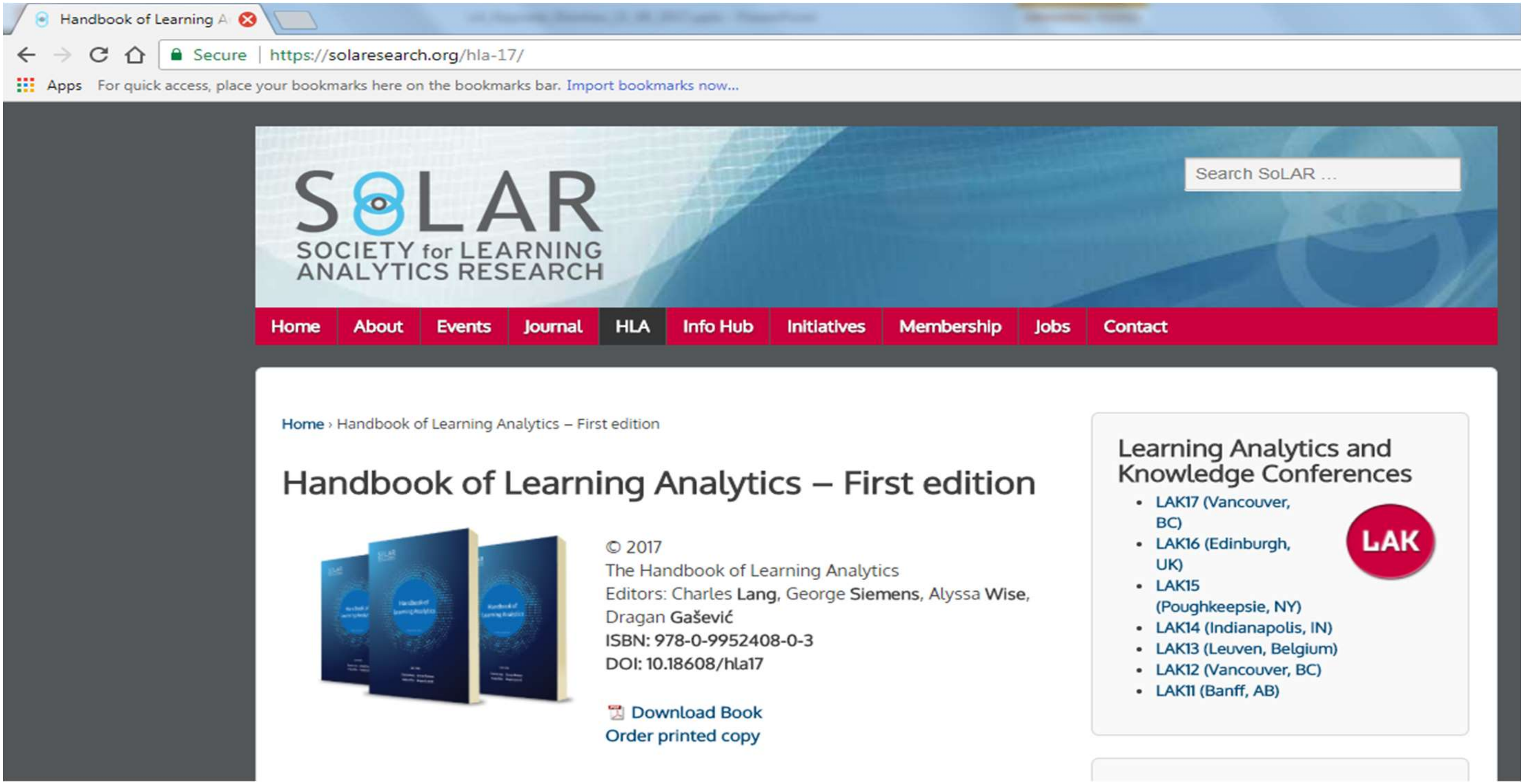
A special thanks to Avinash Boroowa, Shi-Min Chua, Simon Cross, Doug Clow, Chris Edwards, Rebecca Ferguson, Mark Gaved, Christothea Herodotou, Martin Hlosta, Wayne Holmes, Garron Hillaire, Simon Knight, Nai Li, Vicky Marsh, Kevin Mayles, Jenna Mittelmeier, Vicky Murphy, Quan Nguygen, Tom Olney, Lynda Prescott, John Richardson, Jekaterina Rogaten, Matt Schencks, Mike Sharples, Dirk Tempelaar, Belinda Tynan, Lisette Toetenel, Thomas Ullmann, Denise Whitelock, Zdenek Zdrahal, and others…



Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and Implementation of a Learning Analytics Toolkit for Teachers. *Journal of Educational Technology & Society, 15*(3), 58-76.



https://solaresearch.org/hla-17/

LAK 18

The 8th International

Learning Analytics & Knowledge Conference

SMC Conference & Function Centre, Sydney, NSW, Australia

March 5–9, 2018

hosted by THE UNIVERSITY OF SYDNEY

SOLAR SOCIETY for LEARNING ANALYTICS RESEARCH

Deadline (papers): 2nd October 2017

HOME ABOUT

1. Increased availability of learning data
2. Increased availability of learner data
3. Increased ubiquitous presence of technology
4. Formal and informal learning increasingly blurred
5. Increased interest of non-educationalists to understand learning (Educational Data Mining, 4profit companies)
6. Personalisation and flexibility as standard

The power of learning analytics: is there still a need for educational research?

1. How can learning analytics empower teachers?
2. How can learning analytics empower students?
3. How to join us…

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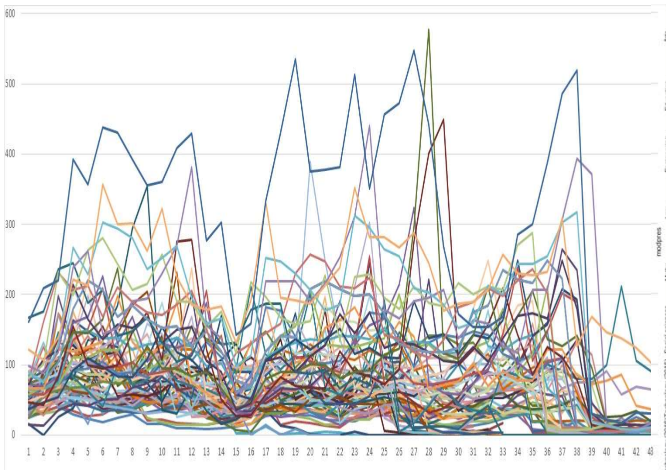
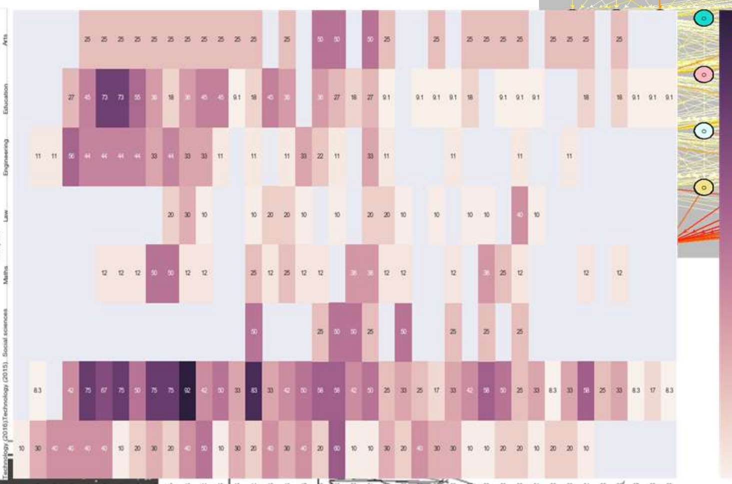
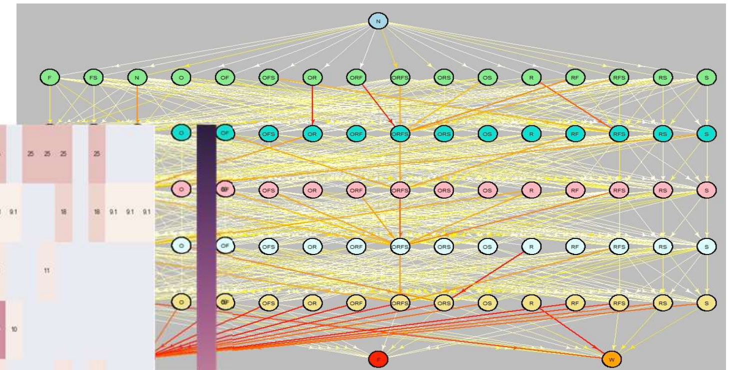
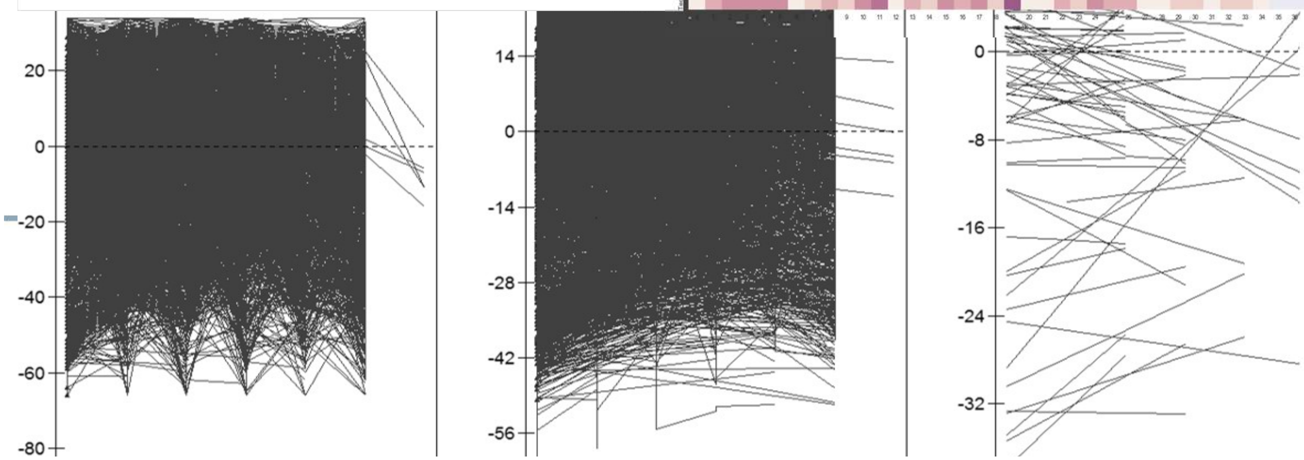
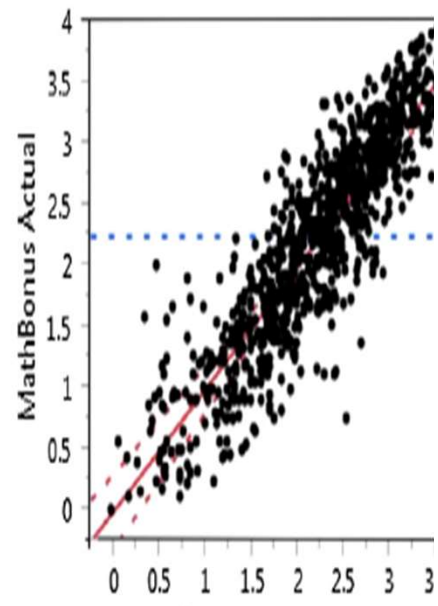
Big Data is messy!!!











Learning Design is described as “a methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies” (Conole, 2012).

Open University Learning Design Initiative (OULDI)

	Assimilative	Finding and handling information	Communication	Productive	Experiential	Interactive/ Adaptive	Assessment
Type of activity	Attending to information	Searching for and processing information	Discussing module related content with at least one other person (student or tutor)	Actively constructing an artefact	Applying learning in a real-world setting	Applying learning in a simulated setting	All forms of assessment, whether continuous, end of module, or formative (assessment for learning)
Examples of activity	Read, Watch, Listen, Think about, Access, Observe, Review, Study	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather, Order, Classify, Select, Assess, Manipulate	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe, Question	Create, Build, Make, Design, Construct, Contribute, Complete, Produce, Write, Draw, Refine, Compose, Synthesise, Remix	Practice, Apply, Mimic, Experience, Explore, Investigate, Perform, Engage	Explore, Experiment, Trial, Improve, Model, Simulate	Write, Present, Report, Demonstrate, Critique

Conole, G. (2012). *Designing for Learning in an Open World*. Dordrecht: Springer.

Rienties, B., Toetenel, L., (2016). The impact of learning design on student behaviour, satisfaction and performance: a cross-institutional comparison across 151 modules. *Computers in Human Behavior*, 60 (2016), 333-341

Edit module - Learning D

learning-design.open.ac.uk/module/176/edit

Apps For quick access, place your bookmarks here on the bookmarks bar. Import bookmarks now...

Module Summary | Learning Outcomes | Activity Planner | Workload Tool | Module Map | Design Log | Evaluation

Hours spent undertaking each type of activity

Design stages

Initial | Specification (REP03) | Draft (D2) | Final

Copy and replace: Initial → Specification | Specification → Draft | Draft → Final

Workload tool → Initial | Workload tool → Specification | Workload tool → Draft | Workload tool → Final

Total hours: Avg: 12.16, StDv: 6.28 Hide guides

Week	Assimilative	Finding and handling information	Communication	Productive	Experiential	Interactive / Adaptive	Assessment	Total hours
Week 1	10	1.5	1	0.6	0	0	0.2	13.30
Week 2	6.1	0	0.5	0.6	2	0	6.2	15.40
Week 3	6.1	0	0	2.2	2.85	0	3.5	14.65
Week 4	0	0	0	0	0	0	0	0
Week 5	5.8	0	0	0	19.1	0	10.9	35.85
Week 6	13.5	0	0	3.55	4.3	0	1.8	23.15
Week 7	7.25	0.4	0	1	0.7	0	3.3	12.65
Week 8	5.79	0	0	0	0	0	9.3	15.09
Week 9	10.5	0	0	3	0.1	0	2.5	16.16
Week 10	6.31	0	0.5	0.35	0.7	0	2.65	10.51
Week 11	7.46	4	0	2.1	0	0	3.2	16.76
Week 12	5.69	0	0	1.3	0.35	0.5	1.8	9.64
Week 13	7.43	0.65	0	2.8	0.6	0	1.6	13.08

Merging big data sets

- Learning design data (>300 modules mapped)
- VLE data
    - >140 modules aggregated individual data weekly
    - >37 modules individual fine-grained data daily
- Student feedback data (>140)
- Academic Performance (>140)
- Predictive analytics data (>40)

- Data sets merged and cleaned
    - 111,256 students undertook these modules

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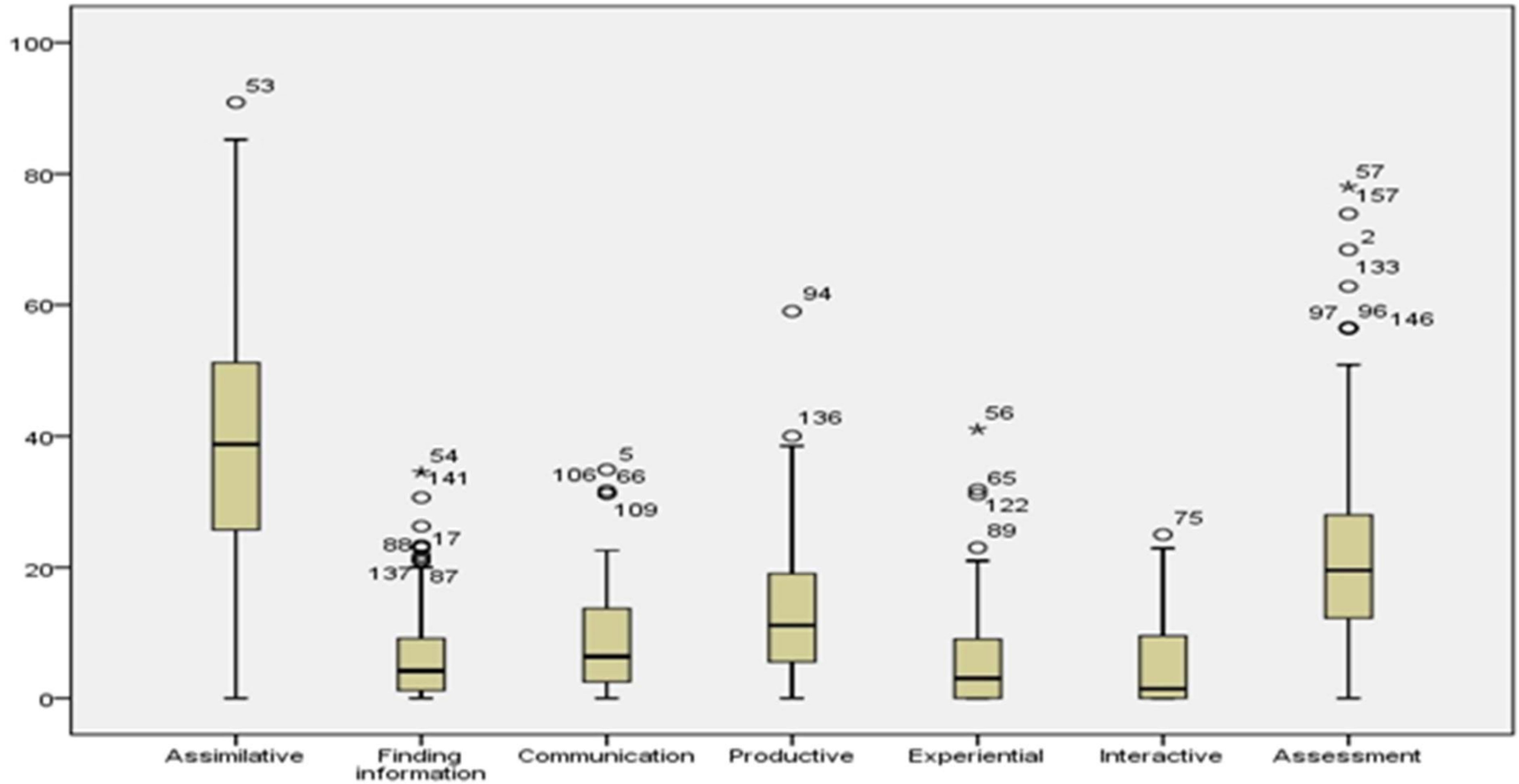
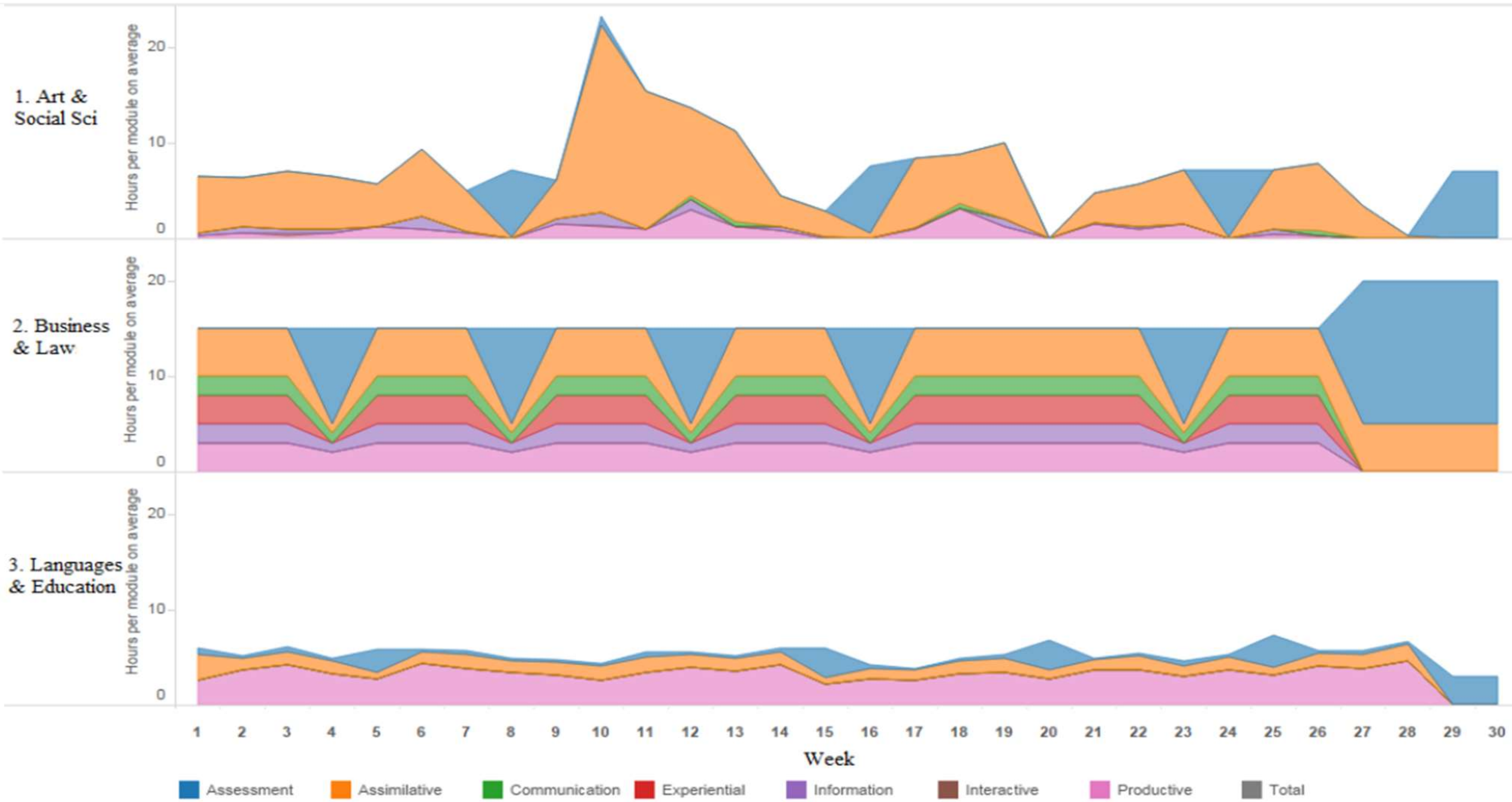
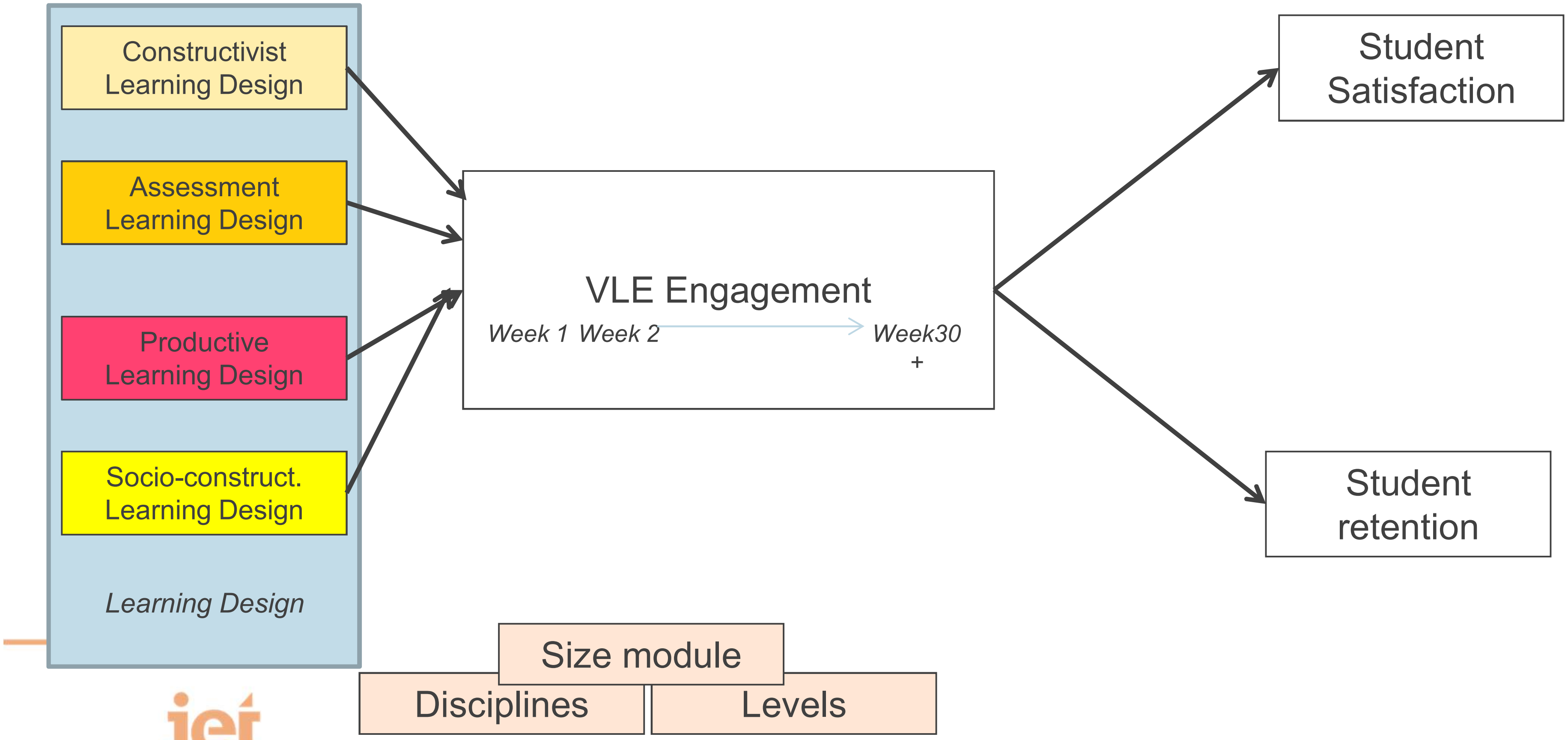


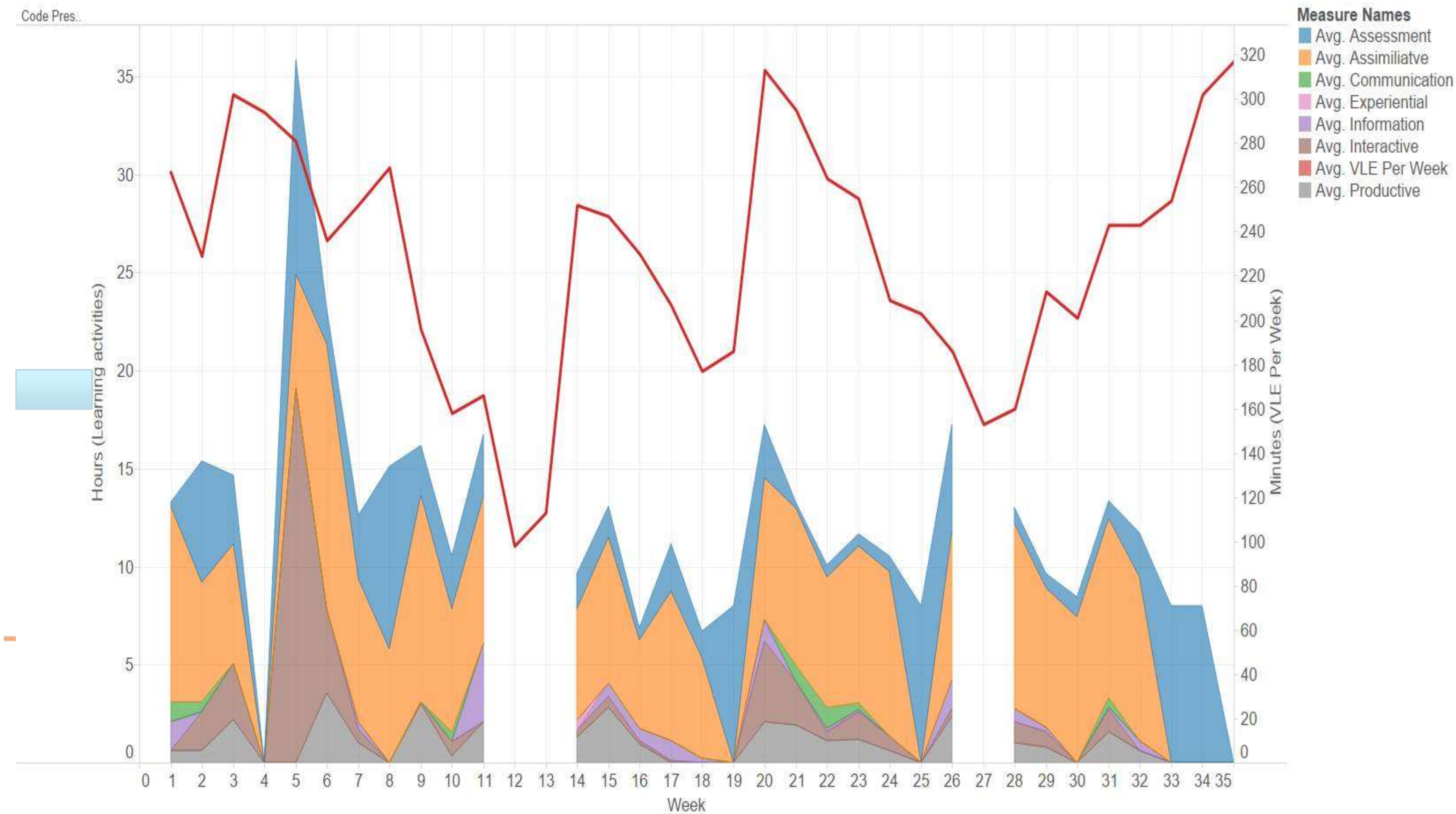
Toetenel, L., Rienties, B. (2016). Analysing 157 Learning Designs using Learning Analytic approaches as a means to evaluate the impact of pedagogical decision-making. *British Journal of Educational Technology, 47*(5), 981–992.



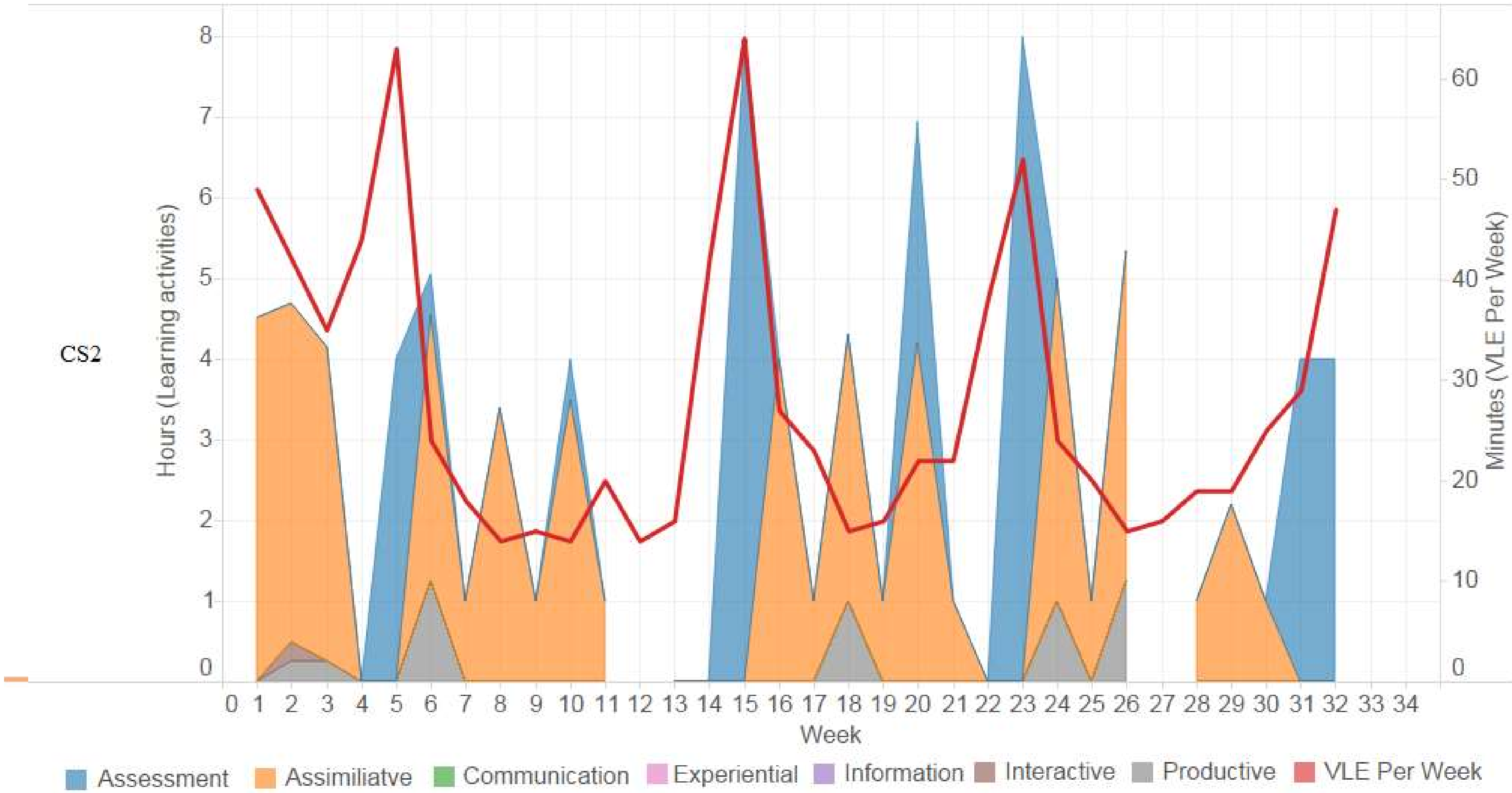
Nguyen, Q., Rienties, B., & Toetenel, L. (2017). Unravelling the dynamics of instructional practice: a longitudinal study on learning design and VLE activities. Paper presented at the *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, Vancouver, British Columbia, Canada, pp. 168-177



Rienties, B., Toetenel, L., Bryan, A. (2015). “Scaling up” learning design: impact of learning design activities on LMS behavior and performance. Learning Analytics Knowledge conference.

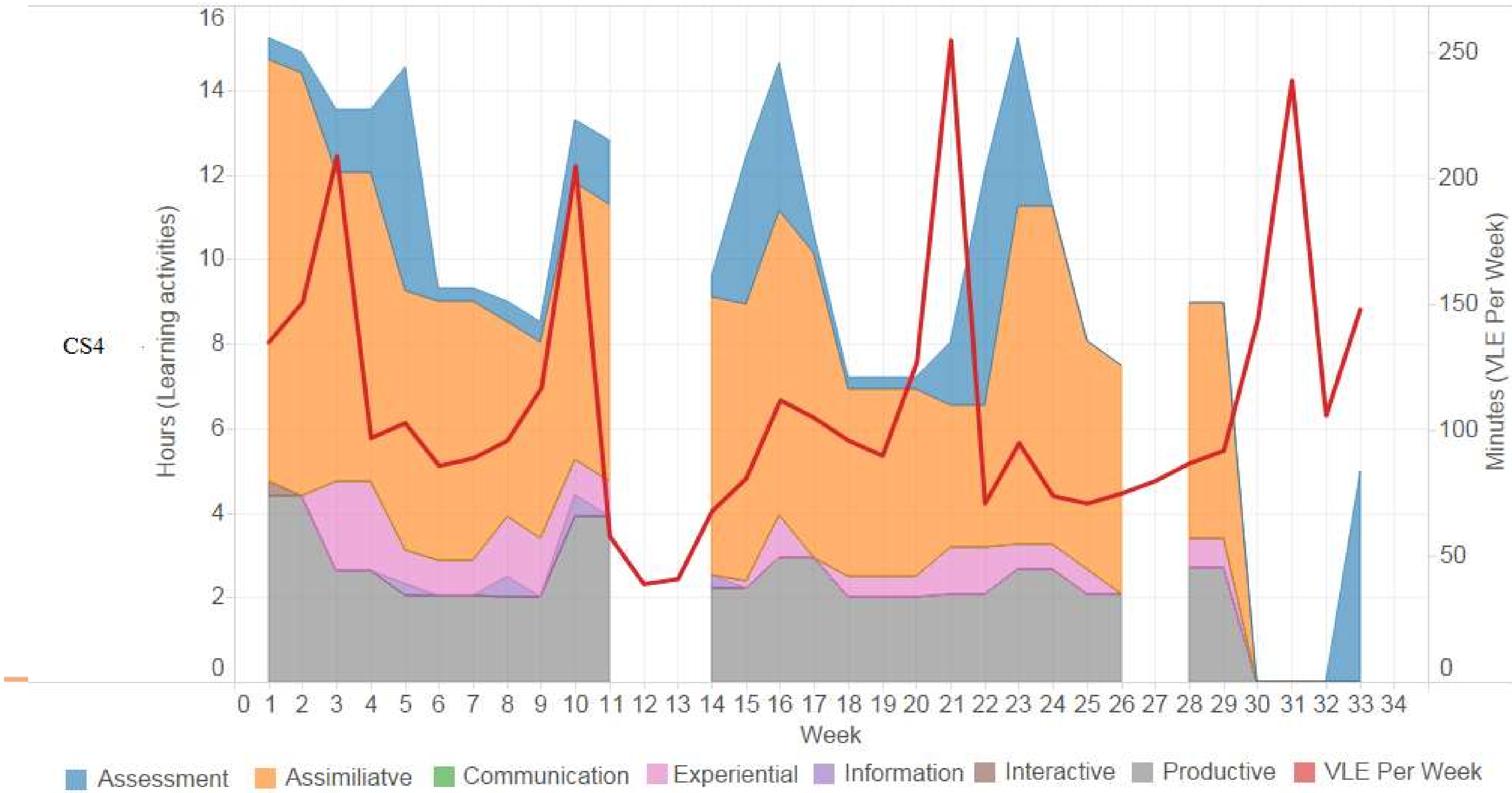

Code Pres..
Measure Names
Avg. Assessment
Avg. Assimiliatve
Avg. Communication
Avg. Experiential
Avg. Information
Avg. Interactive
Avg. VLE Per Week
Avg. Productive
Hours (Learning activities)
Minutes (VLE Per Week)
Week
0 5 10 15 20 25 30 35
0 20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35

CS2



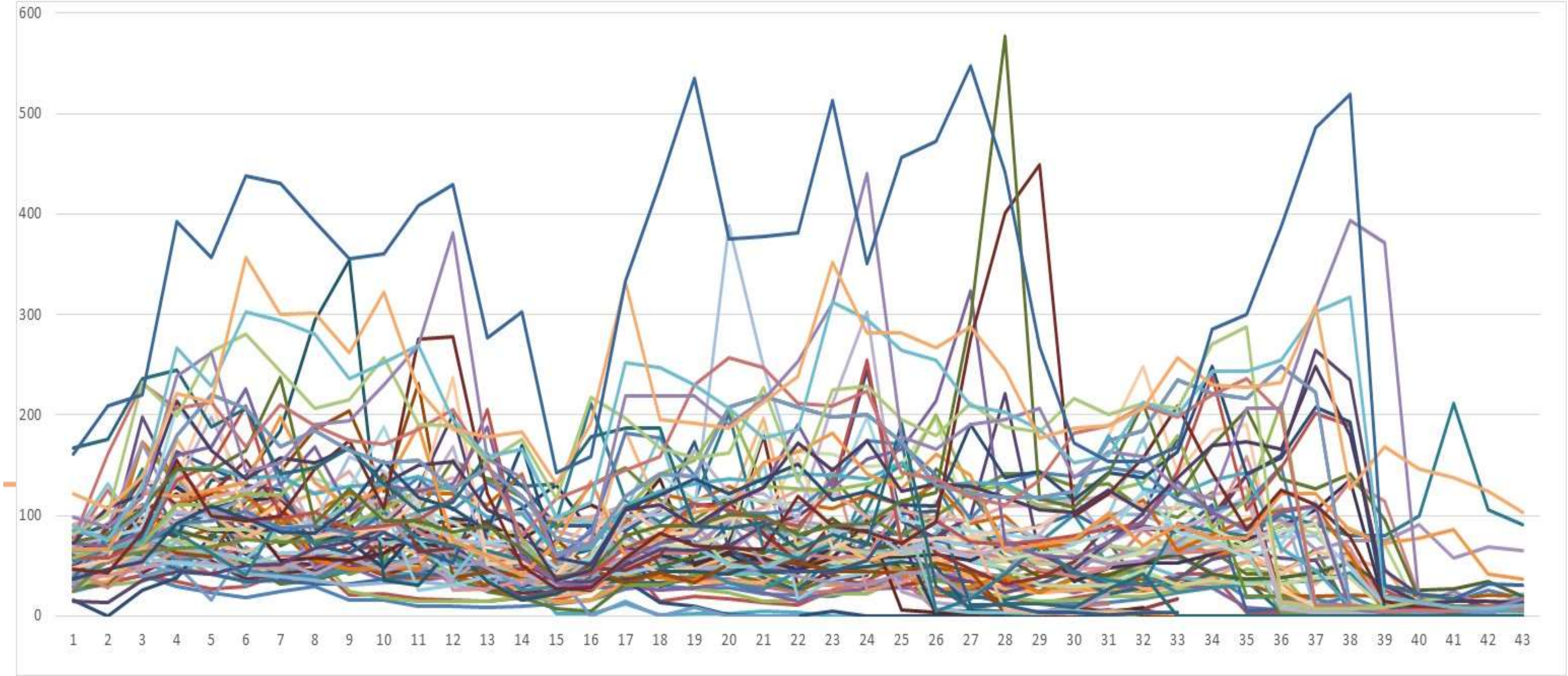
Nguyen, Q., Rienties, B., Toetenel, L., Ferguson, R., Whitelock, D. (2017). Examining the designs of computer-based assessment and its impact on student engagement, satisfaction, and pass rates. *Computers in Human Behavior*. DOI: 10.1016/j.chb.2017.03.028.

CS4

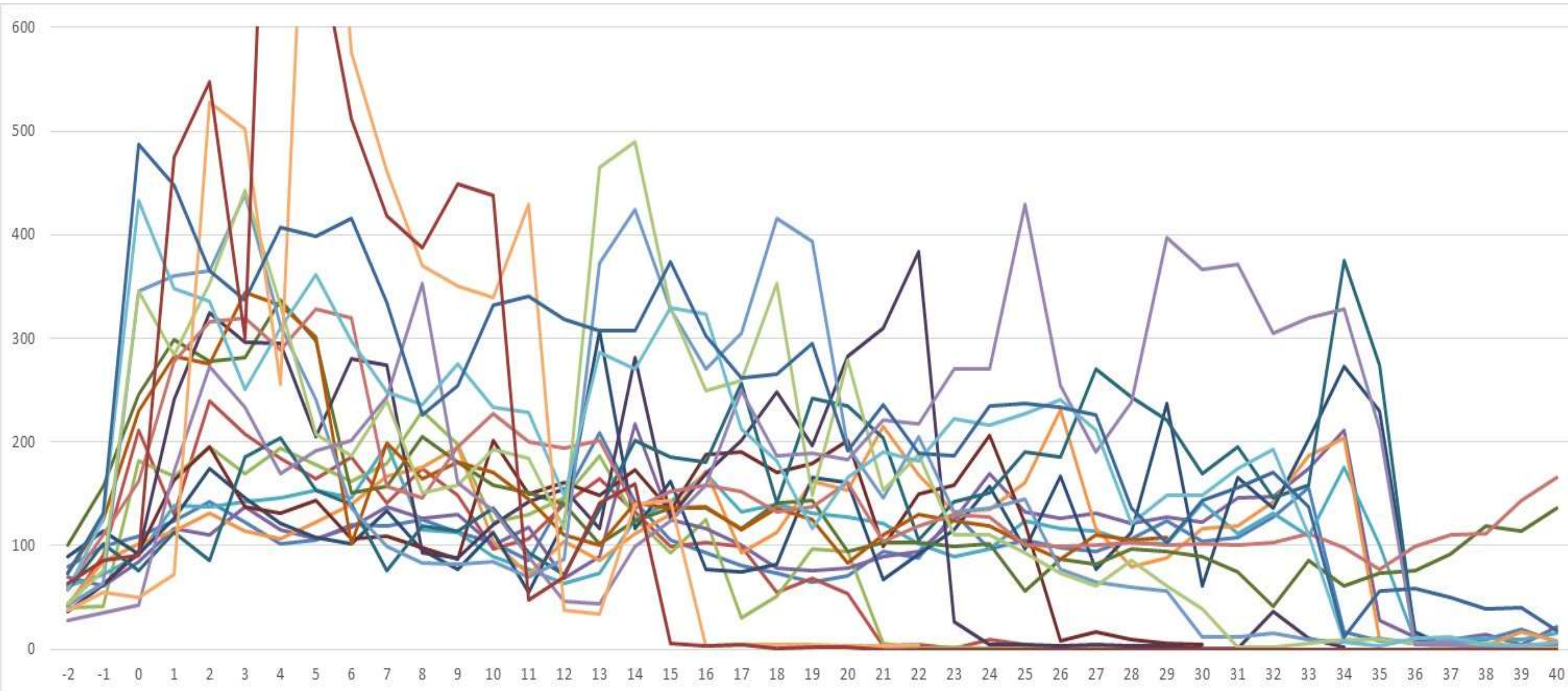


Nguyen, Q., Rienties, B., Toetenel, L., Ferguson, R., Whitelock, D. (2017). Examining the designs of computer-based assessment and its impact on student engagement, satisfaction, and pass rates. *Computers in Human Behavior*. DOI: 10.1016/j.chb.2017.03.028.

Cluster 1 Constructive (n=73)



Cluster 4 Social Constructivist (n=20)



	Model 1	Model 2	Model 3
Level0	-.279**	-.291**	-.116
Level1	-.341*	-.352*	-.067
Level2	.221*	.229*	.275**
Level3	.128	.130	.139
Year of implementation	.048	.049	.090
Faculty 1	-.205*	-.211*	-.196*
Faculty 2	-.022	-.020	-.228**
Faculty 3	-.206*	-.210*	-.308**
Faculty other	.216	.214	.024
Size of module	.210*	.209*	.242**
Learner satisfaction (SEAM)		-.040	.103
Finding information			.147
Communication			.393**
Productive			.135
Experiential			.353**
Interactive			-.081
Assessment			.076
R-sq adj	18%	18%	40%

n = 140, * p < .05, ** p < .01

Table 3 Regression model of LMS engagement predicted by institutional, satisfaction and learning design analytics

- Level of study predict VLE engagement
- Faculties have different VLE engagement
- Learning design (communication & experiential) predict VLE engagement (with 22% unique variance explained)

Rienties, B., Toetenel, L., (2016). The impact of learning design on student behaviour, satisfaction and performance: a cross-institutional comparison across 151 modules. *Computers in Human Behavior*, 60 (2016), 333-341

Table 6

Fixed effect model of VLE engagement per visit predicted by learning design activities.

DV = VLE per visit	Unstandardized coefficients			
Models	(1)	(2)	(3)	(4)
	OLS	FE_week	FE_module	FE_module_week
Assessment	0.46** (0.07)	0.48** (0.08)	0.02 (0.05)	0.05 (0.05)
Information	0.13 (0.35)	0.20 (0.35)	−0.29 (0.22)	−0.21 (0.21)
Communication	2.76** (0.35)	2.78** (0.35)	0.96** (0.24)	1.06** (0.23)
Productive	0.46** (0.15)	0.46** (0.15)	−0.17 (0.11)	−0.16 (0.11)
Experiential	1.04* (0.51)	1.09* (0.51)	0.52 (0.33)	0.60 (0.32)
Interactive	0.79** (0.30)	0.72* (0.30)	−0.34 (0.20)	−0.39 (0.20)
Constant	20.56** (0.39)	24.15** (1.37)	21.00** (0.91)	24.66** (1.18)
Observations	1088	1088	1088	1088
Adjusted R-squared	0.08	0.10	0.67	0.69

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$ Baseline: assimilative.

- VLE engagement per module significantly predicted by Communication
- VLE engagement per week significantly predicted by Communication (with 69% unique variance explained)

Nguyen, Q., Rienties, B., Toetenel, L., Ferguson, R., Whitelock, D. (2017). Examining the designs of computer-based assessment and its impact on student engagement, satisfaction, and pass rates. *Computers in Human Behavior*. DOI: 10.1016/j.chb.2017.03.028.

	Model 1	Model 2	Model 3
Level0	.284**	.304**	.351**
Level1	.259	.243	.265
Level2	-.211	-.197	-.212
Level3	-.035	-.029	-.018
Year of implementation	.028	-.071	-.059
Faculty 1	.149	.188	.213*
Faculty 2	-.039	.029	.045
Faculty 3	.090	.188	.236*
Faculty other	.046	.077	.051
Size of module	.016	-.049	-.071
Finding information		-.270**	-.294**
Communication		.005	.050
Productive		-.243**	-.274**
Experiential		-.111	-.105
Interactive		.173*	.221*
Assessment		-.208*	-.221*
LMS engagement			.117
R-sq adj	20%	30%	31%

n = 150 (Model 1-2), 140 (Model 3), * p < .05, ** p < .01

Table 4 Regression model of learner satisfaction predicted by institutional and learning design analytics

- Level of study predict satisfaction
- Learning design (finding info, productive, assessment) negatively predict satisfaction
- Interactive learning design positively predicts satisfaction
- VLE engagement and satisfaction unrelated

Rienties, B., Toetenel, L., (2016). The impact of learning design on student behaviour, satisfaction and performance: a cross-institutional comparison across 151 modules. *Computers in Human Behavior*, 60 (2016), 333-341

	Model 1	Model 2	Model 3
Level0	-.142	-.147	.005
Level1	-.227	-.236	.017
Level2	-.134	-.170	-.004
Level3	.059	-.059	.215
Year of implementation	-.191**	-.152*	-.151*
Faculty 1	.355**	.374**	.360**
Faculty 2	-.033	-.032	-.189*
Faculty 3	.095	.113	.069
Faculty other	.129	.156	.034
Size of module	-.298**	-.285**	-.239**
Learner satisfaction (SEAM)		-.082	-.058
LMS Engagement		-.070	-.190*
Finding information			-.154
Communication			.500**
Productive			.133
Experiential			.008
Interactive			-.049
Assessment			.063
R-sq adj	30%	30%	36%

n = 150 (Model 1-2), 140 (Model 3), * p < .05, ** p < .01

Table 5 Regression model of learning performance predicted by institutional, satisfaction and learning design analytics

- Size of module and discipline predict completion
- Satisfaction unrelated to completion
- Learning design (communication) predicts completion

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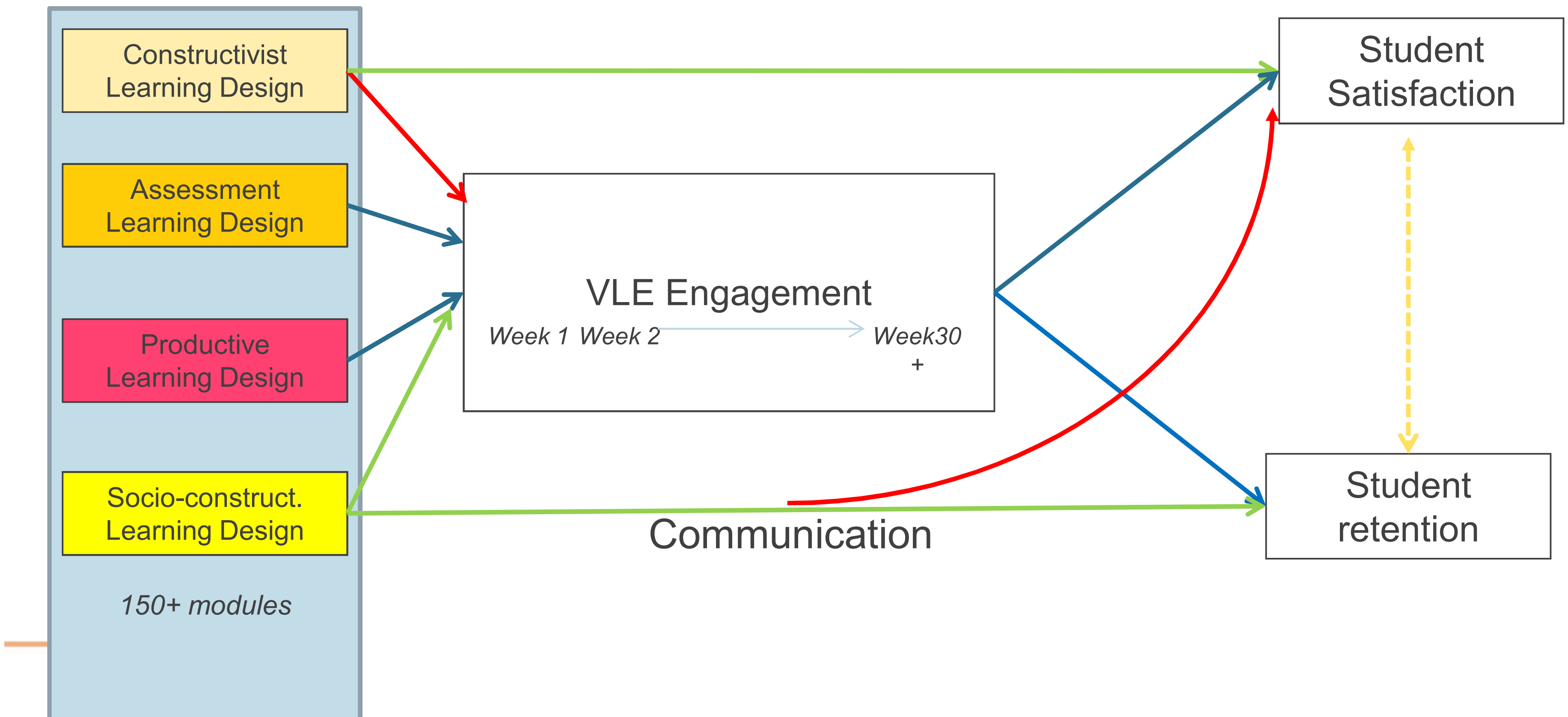

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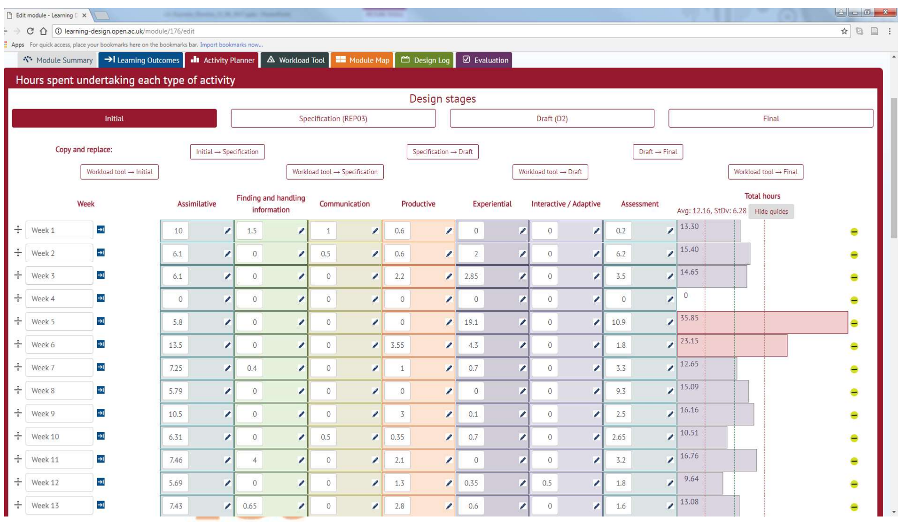
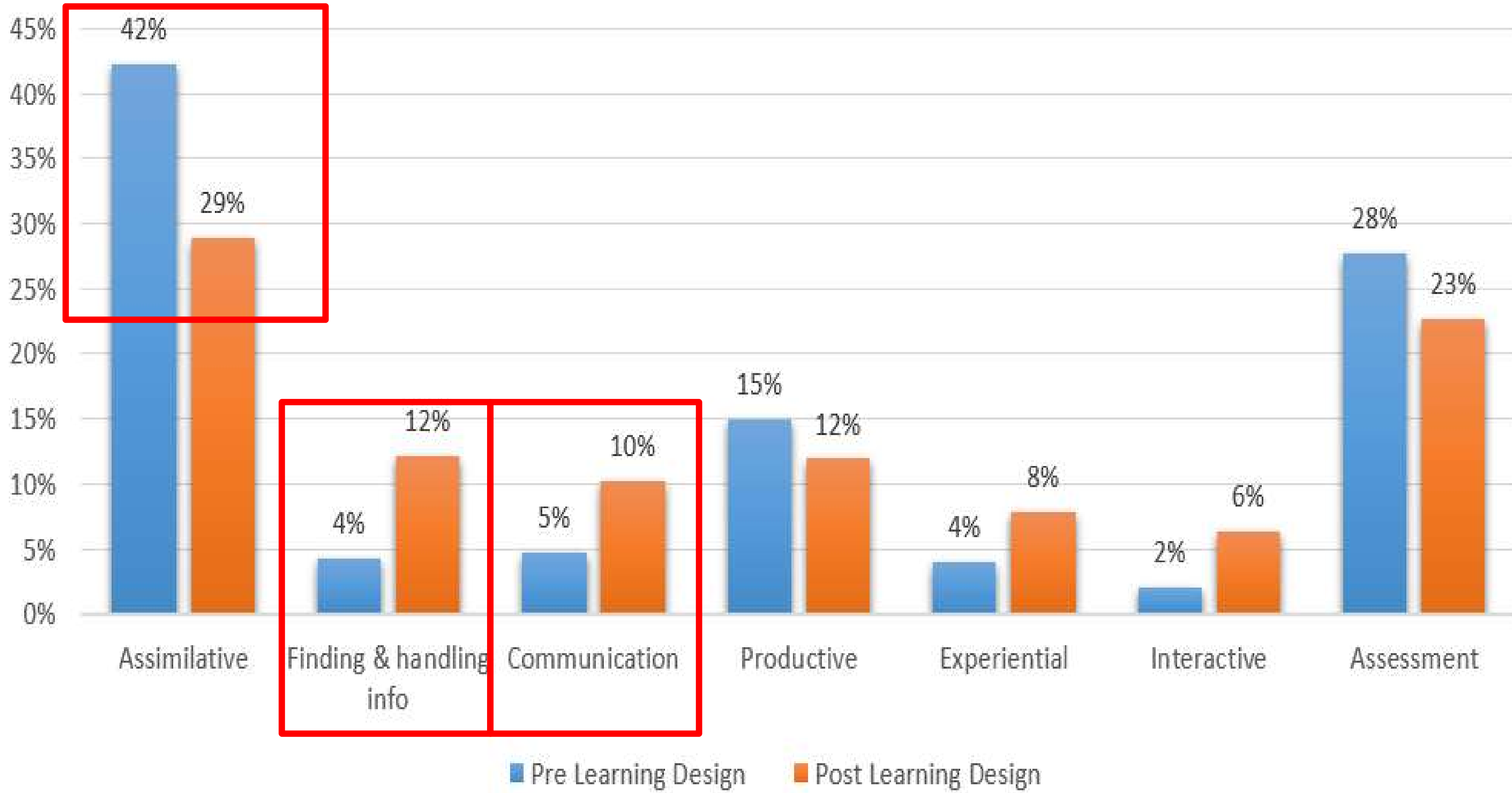
So what happens when you give learning design visualisations to teachers?

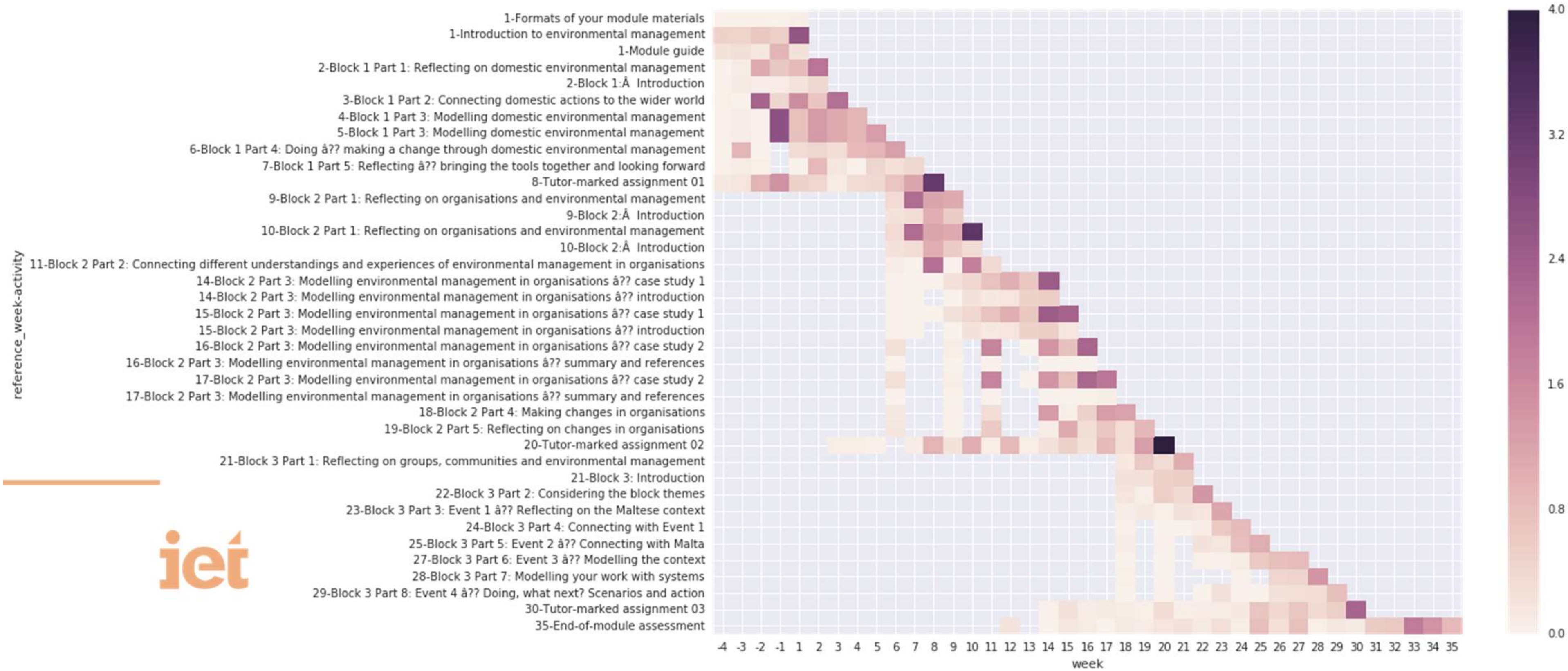


Toetenel, L., Rienties, B. (2016) Learning Design – creative design to visualise learning activities. *Open Learning: The Journal of Open and Distance Learning,* 31(3), 233-244.

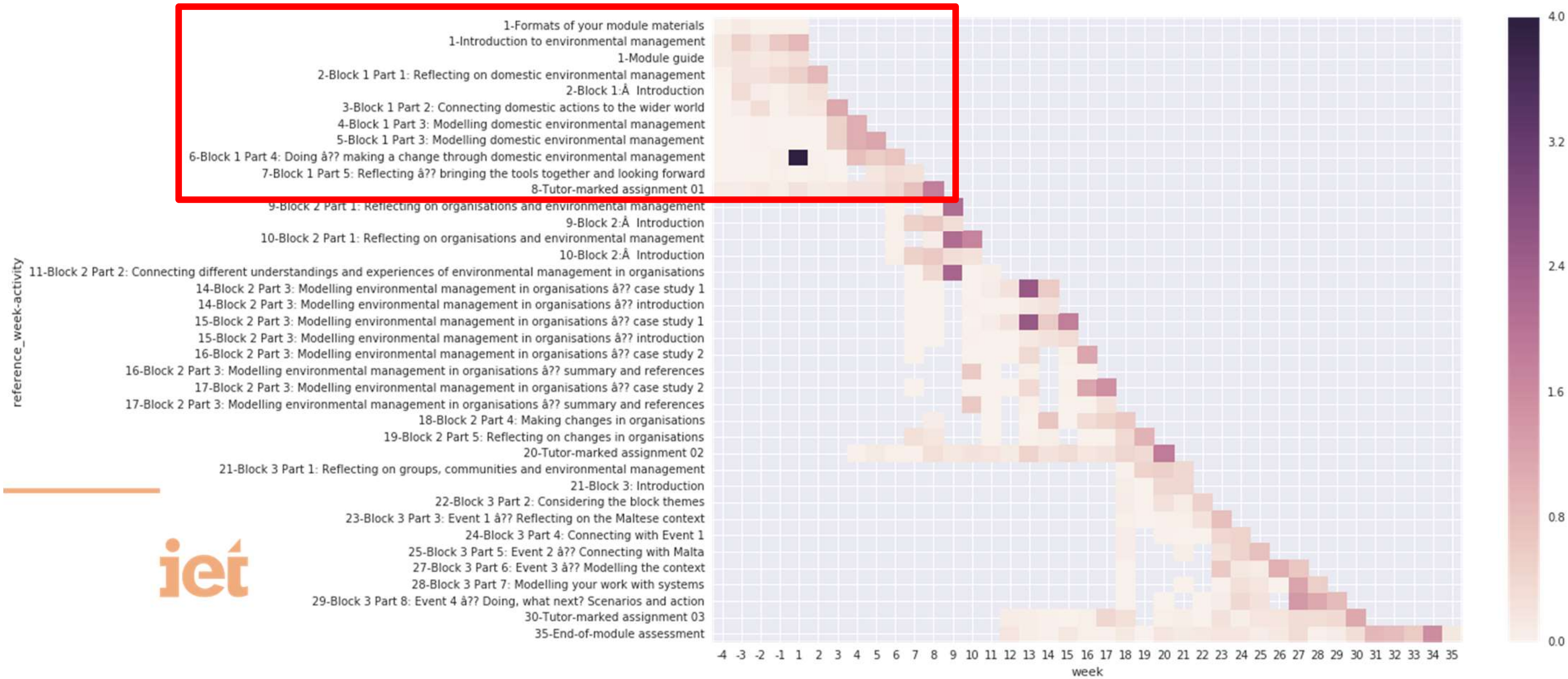


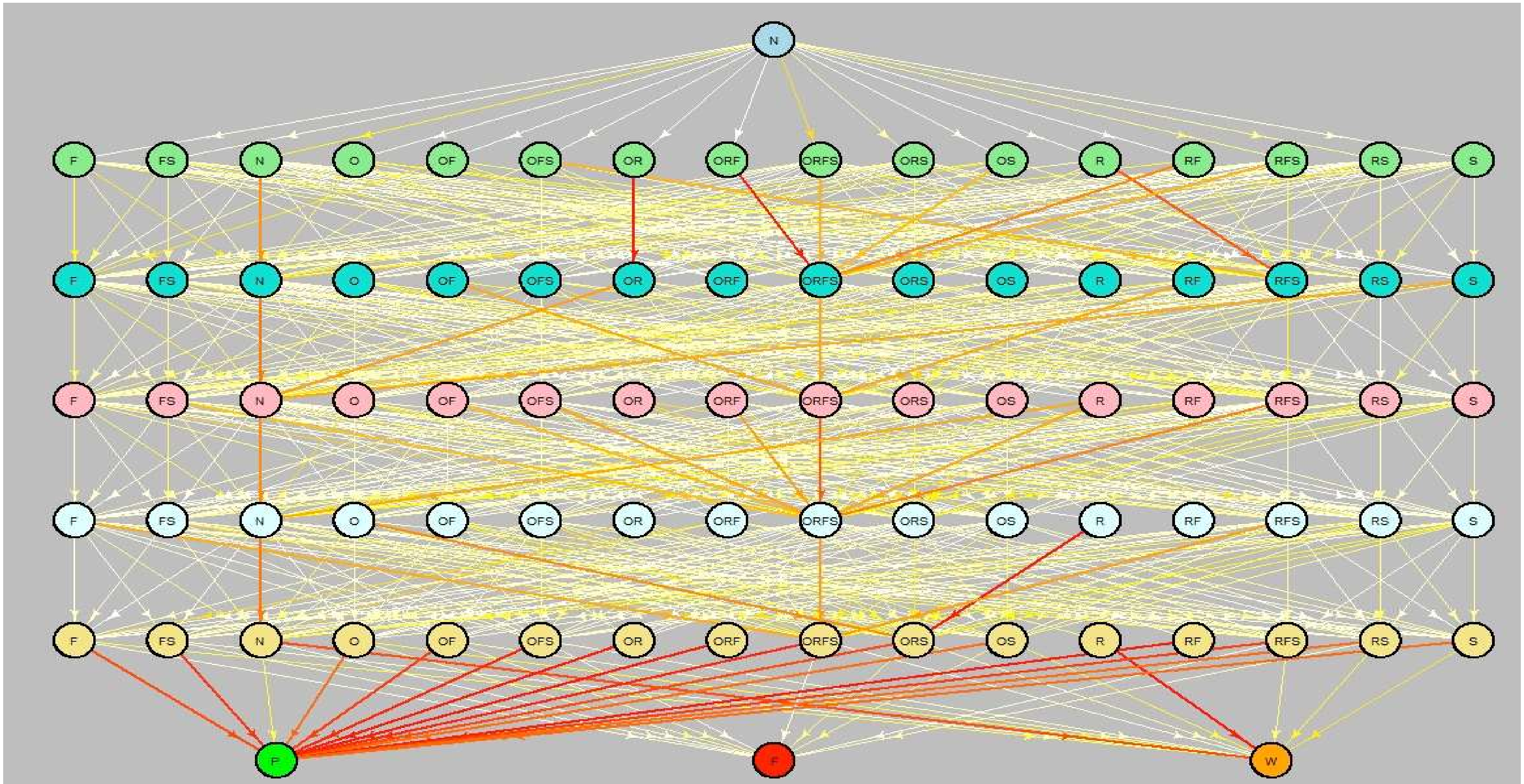
Toetenel, L., Rienties, B. (2016) Learning Design – creative design to visualise learning activities. *Open Learning: The Journal of Open and Distance Learning,* 31(3), 233-244.

“Excellent” students

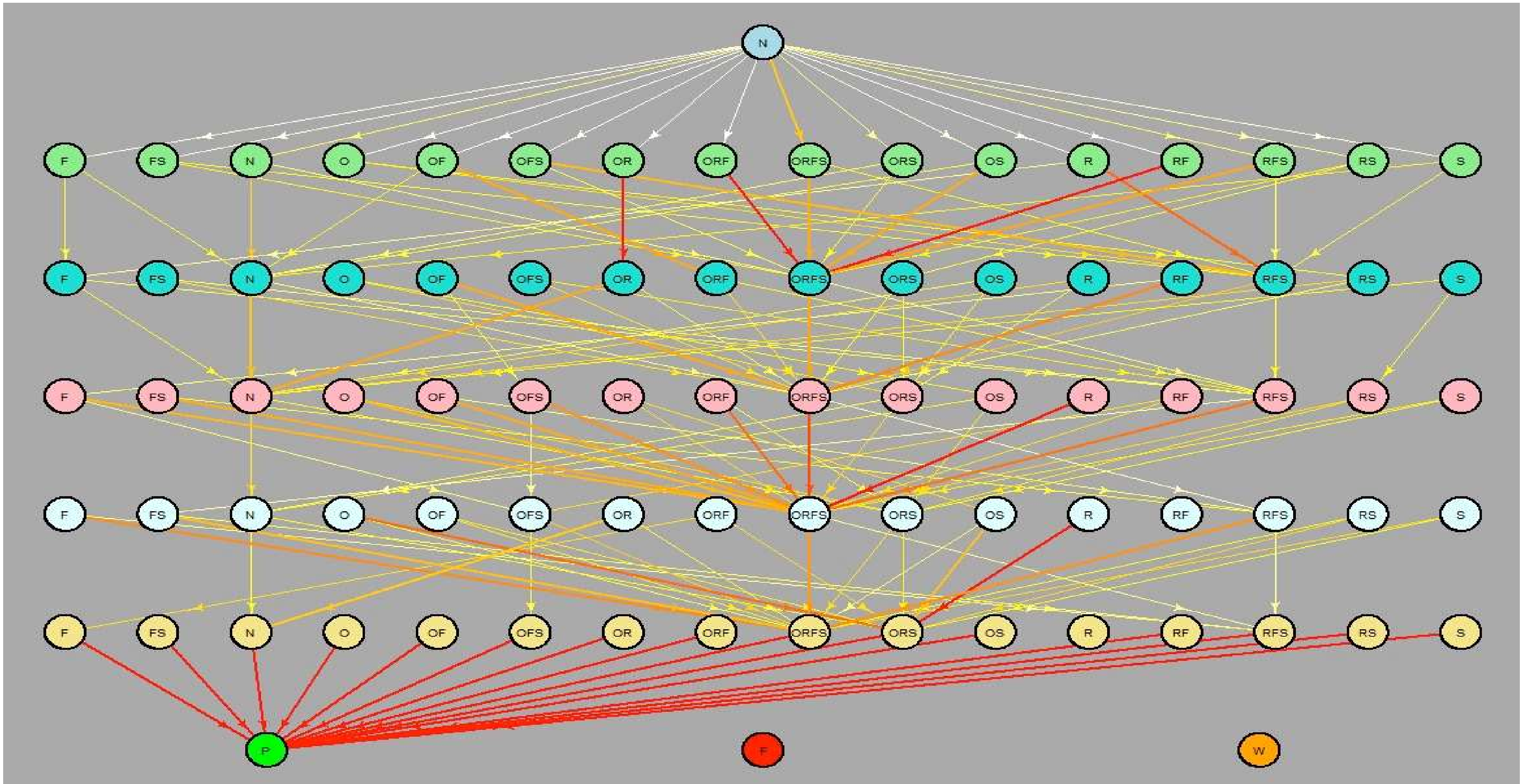


“Failing” students





Hlosta, M., Herrmannova, D., Zdrahal, Z., & Wolff, A. (2015). OU Analyse: analysing at-risk students at The Open University. Learning Analytics Review, 1-16.



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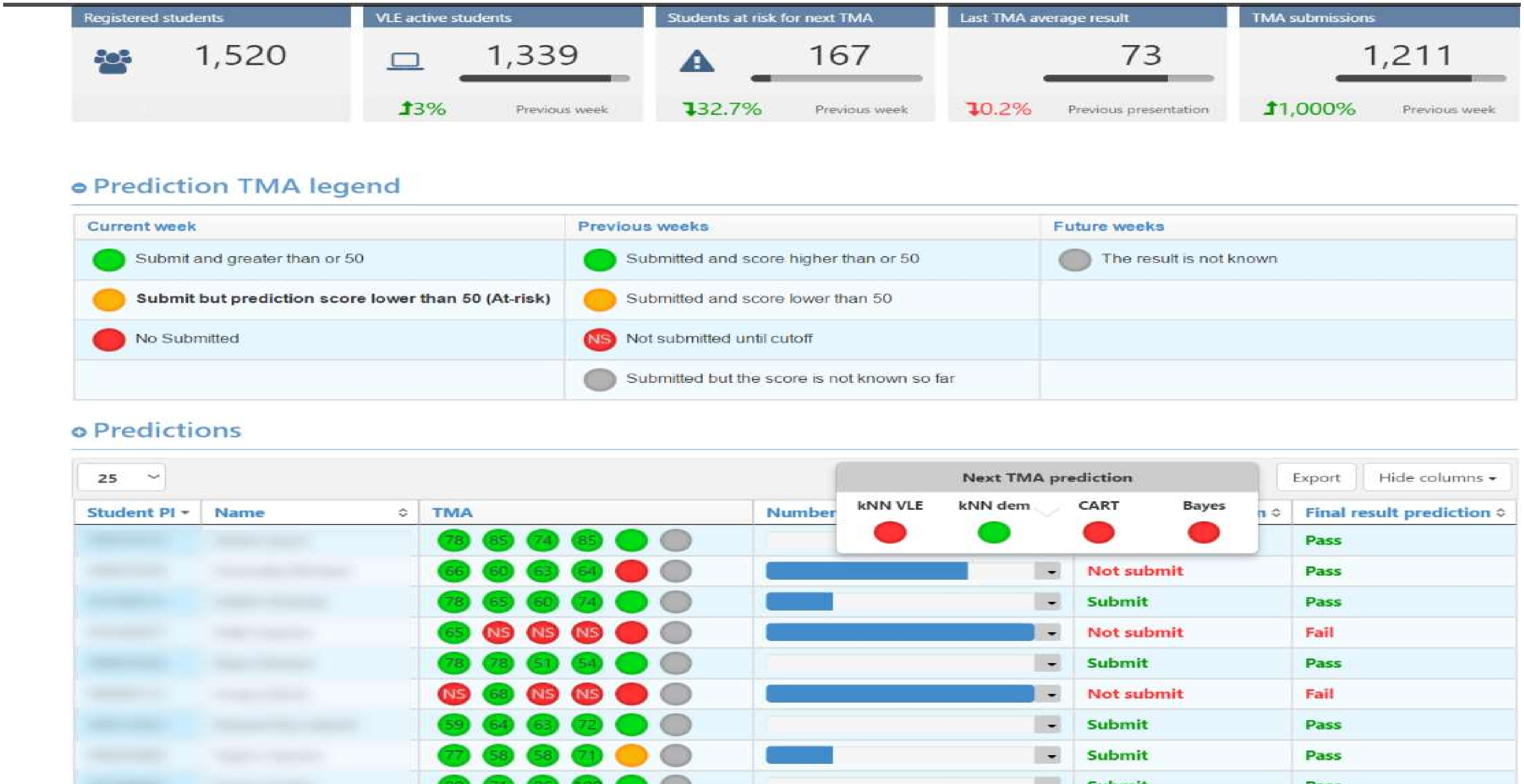


Hlosta, M., Herrmannova, D., Zdrahal, Z., & Wolff, A. (2015). OU Analyse: analysing at-risk students at The Open University. Learning Analytics Review, 1-16.

Nearest students

Scores

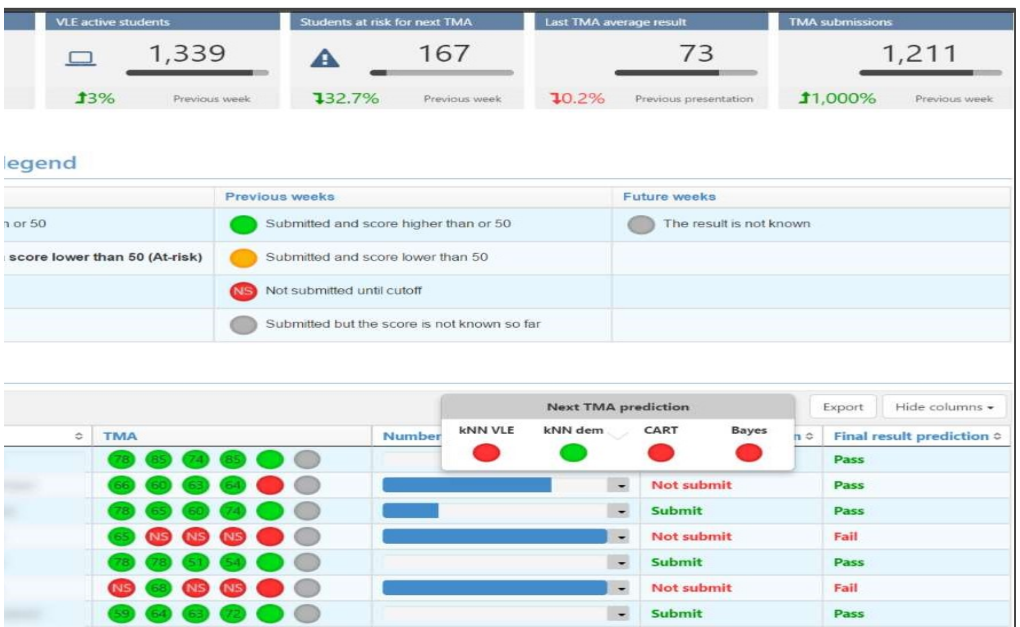
Assignment	Prediction	REAL	Justification
TMA 01	**Submit**	**88**	Resource VLE activity in week 4 >=0 Resource VLE activity in week 3 >=0 quiz VLE activity in week 3 >=0
TMA 02	**Submit**	**74**	quiz VLE activity in week 7 >=0 oucollaborate VLE activity in week 7 >=0 quiz VLE activity in week 8 >=0
TMA 03	**Submit**	**Not submit**	Forum VLE activity in week 10 >=0 Homepage VLE activity in week 12 >=0 summary VLE activity in week 12 >=0
TMA 04	NA	NA	NA
TMA 05	NA	NA	NA

Activity recommender

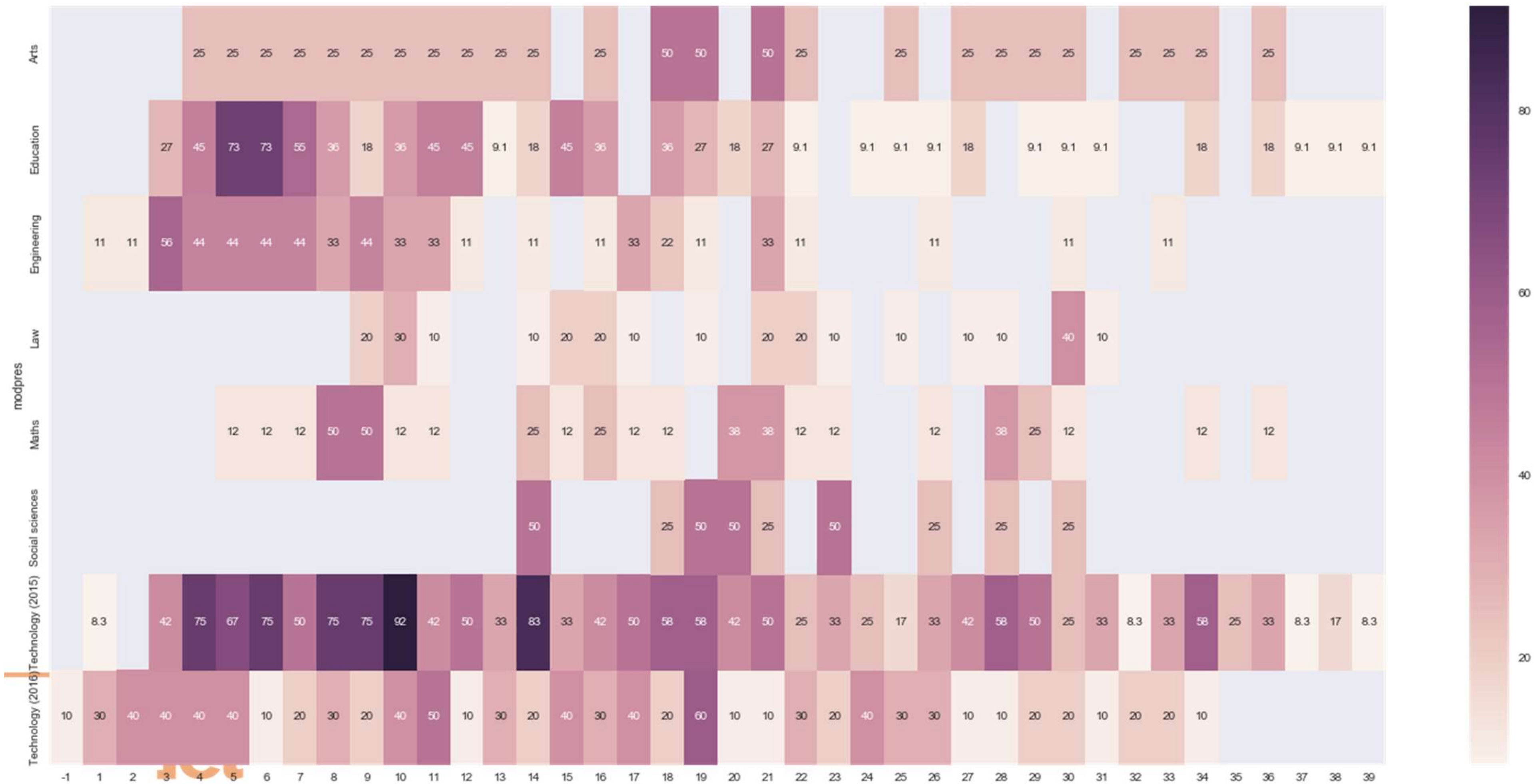
- Visit Block 2 Part 2 (online version).
- Visit Activity 28.
- Visit Introduction to spreadsheets.
- Visit Activity 18.
- Visit The Penalty Kick (story for Activity 37).
- Visit TMA questions and guidance.

Hlosta, M., Herrmannova, D., Zdrahal, Z., & Wolff, A. (2015). OU Analyse: analysing at-risk students at The Open University. Learning Analytics Review, 1-16.

So what happens when you give learning analytics data about students to teachers?



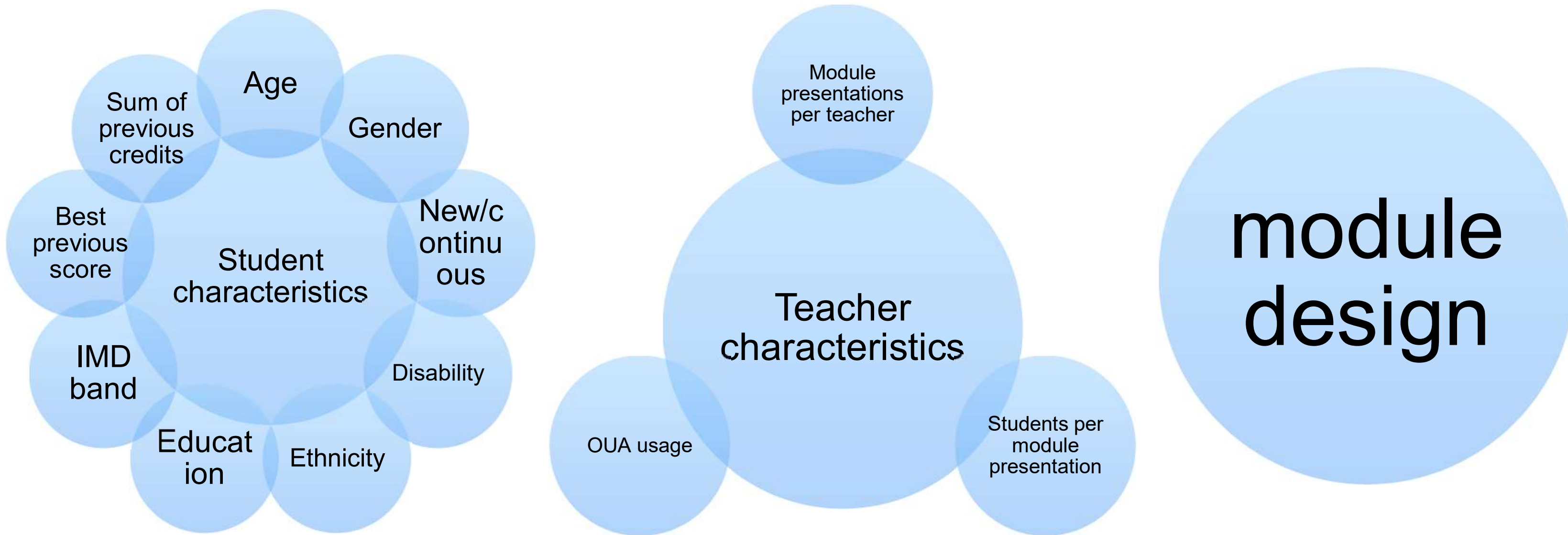
1. How did 240 teachers within the 10 modules made use of PLA data (OUA predictions) and visualisations to help students at risk?
2. To what extent was there a positive impact on students' performance and retention when using OUA predictions?
3. Which factors explain teachers' uses of OUA?



Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M., & Naydenova, G. (2017). Implementing predictive learning analytics on a large scale: the teacher's perspective. Paper presented at the *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, Vancouver, British Columbia, Canada, pp. 267-271

Regression analysis

Which factors better predict pass and completion rates?



Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M. (Submitted: 01-08-2017). Using Predictive Learning Analytics to Support Just-in-time Interventions: The Teachers' Perspective Across a Large-scale Implementation.

Logistic regression results (pass rates)

Significant model (pass: χ^2= 76.391, p < .001, df = 24).

- Nagelkerke's R2 = .185 (model explains 18% of the variance in passing rates)
- Correctly classified over 70% of the cases (prediction success overall was 70.2%: 33.5 % for not passing a module and 88.7% for passing a module).
- Significant predictors of both pass and completion rates:
  - OUA usage (p=.006)
  - Best previous module score achieved (p=.005)
  - All other predictors were not significant.

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M. (Submitted: 01-08-2017). Using Predictive Learning Analytics to Support Just-in-time Interventions: The Teachers' Perspective Across a Large-scale Implementation.

How can learning analytics empower teachers?

- Learning analytics can enhance and facilitate teaching practice, especially within distance learning contexts
- Strong variation in teachers' degree and quality of engagement with learning analytics/design.
- Lack of consensus about intervention strategies

Conclusions and moving forwards

1. Learning design and teachers strongly influences student engagement, satisfaction and performance
2. Visualising learning design and learning analytics to teachers lead to more interactive/communicative designs and improved student retention

Conclusions and moving forwards

1. Learning analytics approaches can help researchers and practitioners to test and validate **big and small** theoretical questions
2. Giving students access to learning analytics data and insight next frontier

The Open University

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Professor of Learning Analytics

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A review of five years of implementation and research in aligning learning design with learning analytics at the Open University UK

ASCILITE SIG LA Webinar
20 September 2017

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SHAPING THE FUTURE OF TERTIARY EDUCATION