SNOLA

Reflexiones sobre el estado de las analíticas de aprendizaje en España desde la perspectiva de la red SNOLA

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SNOLA (Red Española de Analítica de Aprendizaje)

Analíticas académicas y de aprendizaje en educación superior
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Educación, Medios, Informática y Cultura

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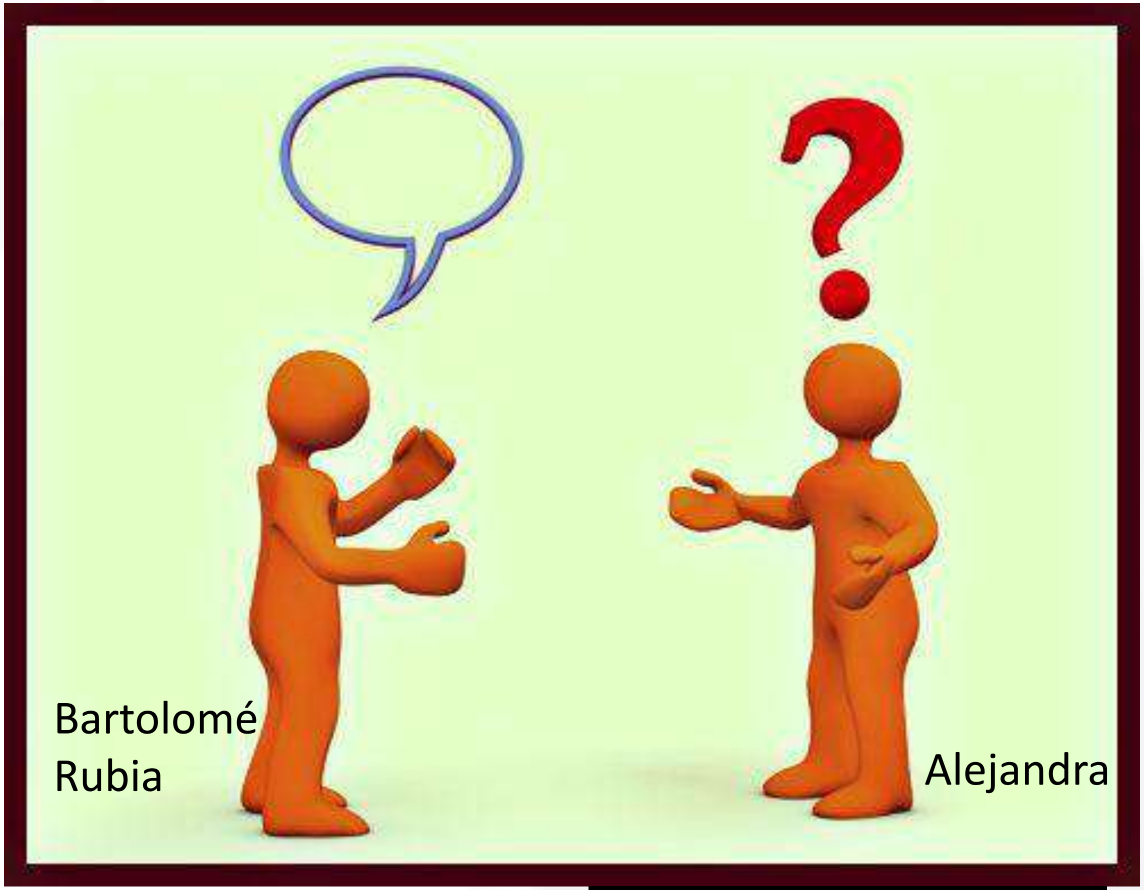
Una breve historia …



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Mi objetivo para esta charla

¡Tender Puentes

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Índice

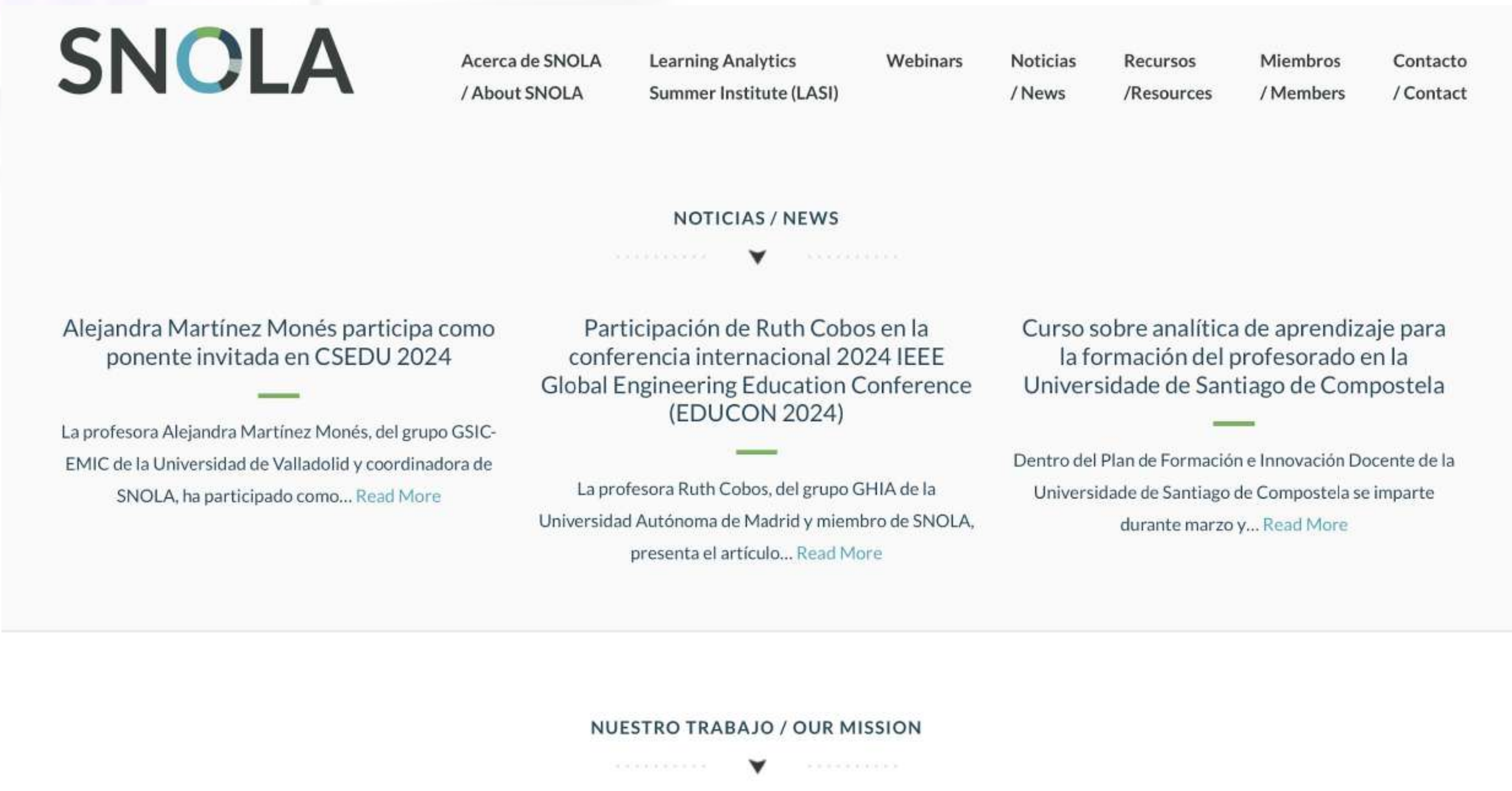
- Introducción
- SNOLA
  - Breve perspectiva histórica
  - Líneas de investigación en SNOLA
  - Acciones de SNOLA
- Cuestiones finales

Introducción

- Las redes están en el corazón de cualquier disciplina (Latour, 2005)
- Learning Analytics ha crecido como es gracias a las redes:
- En España:

SNOLA

snola.es



SNOLA - Componentes

GaLan

GIST

GRUPO DE ROBÓTICA

GSIC-EMIC

GRIAL

LAIKA

upf. TIDE

e-UCM e-learning group

Gradient

Tige

GHIA Grupo de Herramientas Interactivas Avanzadas

BigDataLab Control and Communications Systems Department UNED

UCA Universidad de Cádiz

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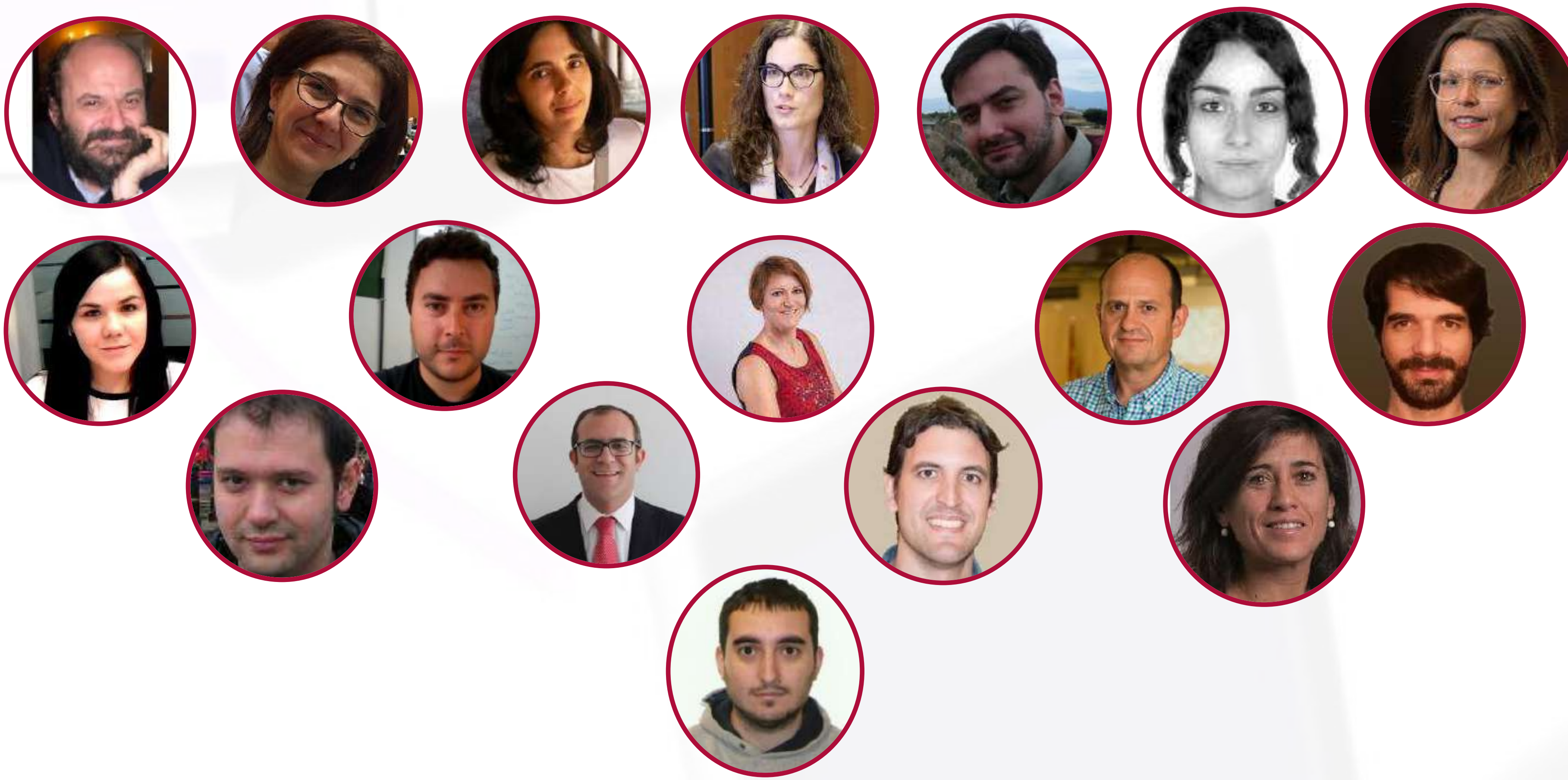

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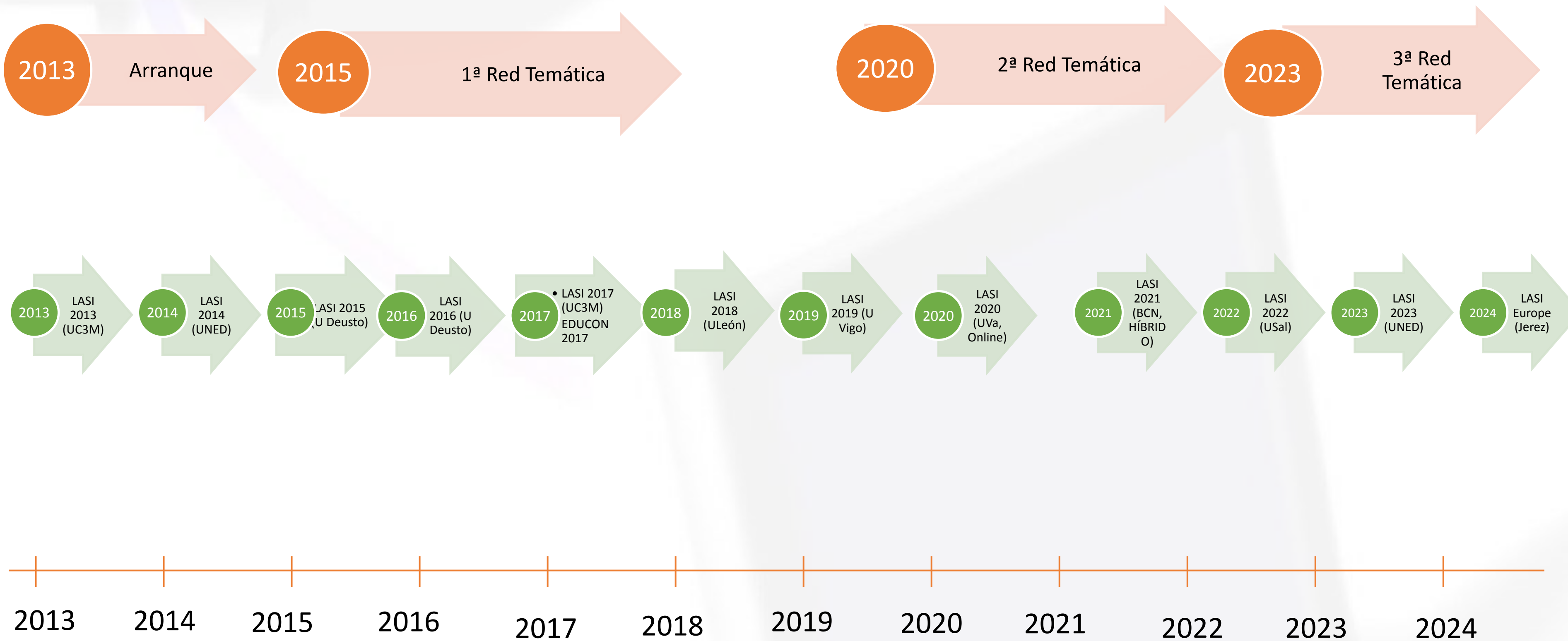
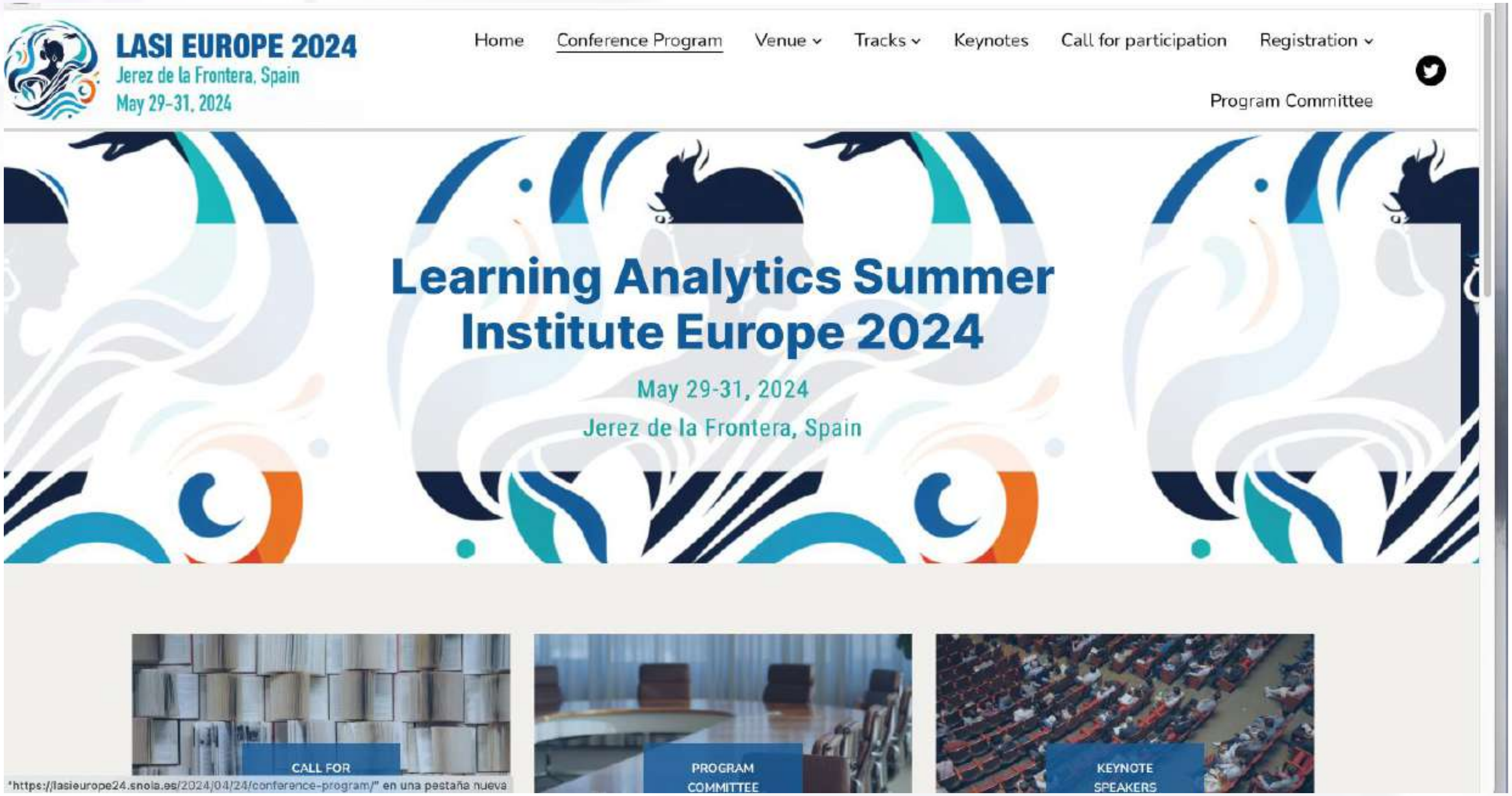
SNOLA - Historia



Conferencias LASI
LASI Europe 2024



Índice

- Introducción
- SNOLA
  - Breve perspectiva histórica
  - Líneas de investigación en SNOLA
  - Acciones de SNOLA
- Retos, … ¿colaboraciones?

Líneas de investigación en SNOLA

Basado en el estudio:

Martínez-Monés, A., Dimitriadis, Y., Acquila-Natale, E., Álvarez, A., Caerio-Rodríguez, M., Cobos, R., Conde-González, M. A., García-Peñalvo, F. J., Hernández-Leo, D., Menchaca, I., Muñoz-Merino, P. J., Ros, S., y Sancho-Vinuesa, T. (2020). **Achievements and challenges in learning analytics in Spain: The view of SNOLA**. *RIED. Revista Iberoamericana de Educación a Distancia, 23*(2).

Goals and method

- Goals:
  - What has been the trajectory of the network?
  - What are the main research goals of its members?
  - What are the challenges in the field according to its members?
- Method
  - Review of archival data
  - Open ended questionnaire to the members of the network
  - Further elaboration with the respondents
- Slight update for this talk

Current research trends

- Analysis of the open questionnaire
- Main results
  - Characterization of the network
  - Identification of 7 (non-orthogonal) research trends
  - Goals (most cited):
    - Increase learner retention and performance (26)
    - Improve the quality of the learning environment (16)
    - Identify indicators for learning / elements of the learner model (7+4)

S: Student
T: Teacher
R: Researcher
M: Manager
ID: Instructional designer

Research Trends

Predictive learning analytics

Research line	Publication	User(s)	Data sour	
Prediction of learning results and dropout	(Moreno-Marcos et al., 2020)	S / T / M	Students' actions (MOOC)	Random Forest, Regression, Neural Networks, Decision Trees
Identification of engineering students at risk	(Martínez et al. 2019)	S / T	Students actions (Moodle and Virtual Campus)	Predictive analysis
Prediction of learning results and dropout	(Cobos & Olmos, 2018)	T / M	Students actions (MOOCs)	Predictive analytics, Machine Learning, Statistical analysis
Actionable information based on prediction of academic engagement in MOOCs	(Bote-Lorenzo & Gómez-Sánchez, 2018)	S / T	Students' actions (MOOC)	Feature selection, Machine Learning
Analysis and classification of student data with prediction purposes (Interactions)	(Agudo-Peregrina et al., 2014)	T / M / R	Student's actions (Moodle)	Log data classification, Regression
Educational data mining	(Guerrero-Higueras et al., 2019)	S / T	Students actions (Version system)	Machine Learning
Definition of high-level actionable indicators based on low level data.	(Alexandron et al., 2017)	S / T	Students' actions (MOOC)	Machine Learning, Artificial Intelligence Techniques, Semantic modelling, Heuristics

Research Trends

Predictive learning analytics

DROPOUT PREDICTION

- Self-paced MOOCs
- Event-based SRL variables are useful to predict dropout
- Good predictions from 25-33% of the theoretical MOOC duration

DATA USE to PREDICT

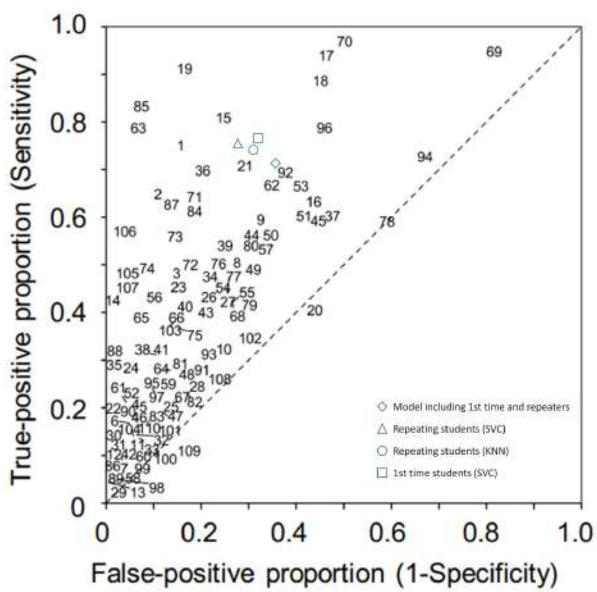
- Videos ✓
- Exercises ✓
- Activity ✓
- Self-regulated learning (SRL)
  - Self-reported SRL ✗
  - Event-based SRL ✓
- Demographics and intentions ✗

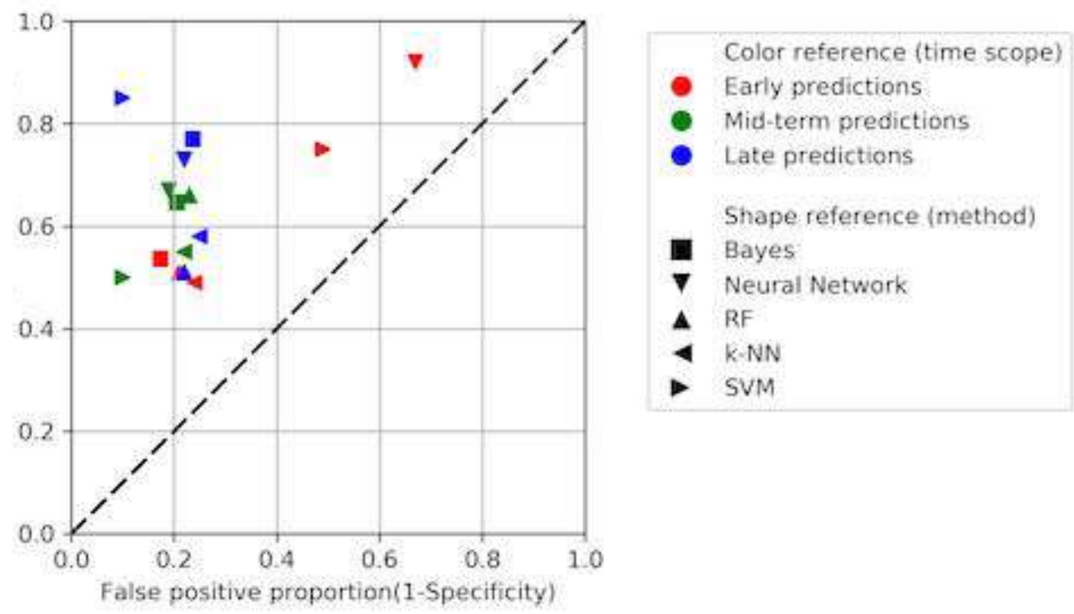
Moreno-Marcos, P. M., **Muñoz-Merino, P. J.,** Maldonado-Mahauad, J., Pérez-Sanagustín, M., Alario-Hoyos, C., & **Delgado-Kloos, C.** (2020). Temporal analysis for dropout prediction using self-regulated learning strategies in self-paced MOOCs. *Computers & Education*, *145*, 103728.

Research Trends

Predictive learning analytics

- Identification of engineering students at risk





Martínez, J. A., Campuzano, J., **Sancho-Vinuesa, T.,** & Valderrama, E. (2019). Predicting student performance over time. A case study for a blended-learning engineering course. *CEUR Workshop Proceedings*, *2415*, 43–55.

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Research Trends
Visual analytics

Research line	Publication	User(s)	Data sources	Analysis techniques
Visual analytics of eLearning systems (VeLA)	(Gómez-Aguilar et al., 2014)	T	Students' actions on the VLE, Grades	Visual analytics
LA Dashboards for virtual labs	(Tobarra et al., 2014)	S	Platforms logs	Heuristics
Visual Analytics of students' actions	(Ruipérez-Valiente, et al., 2015)	S / T	Students' actions on the system (MOOC)	Visual analytics
LA Dashboard for MOOCs	(Cobos et al., 2016)	T / M	Students' actions on the system (MOOC), grades, demographics, self-reported data	Descriptive Statistics
Visualization of peer and self-assessment data in Moodle (MWDEX)	(Chaparro-Peláez, et al., 2019)	T	Peer-assessment grades (Moodle Workshops)	Visual Analytics
Automatic generation of adapted dashboards	(Vázquez-Ingelmo et al., 2019)	S / T / M / R	-	Multi-Dimensional Analysis (MDA), ML
Graph generation of educational data in online learning for social network analytics (GraphFES)	(Hernández-García & Suárez-Navas, 2017)	T / M	Student activity (Moodle log data-Forums)	Social Network Analysis, Data visualization

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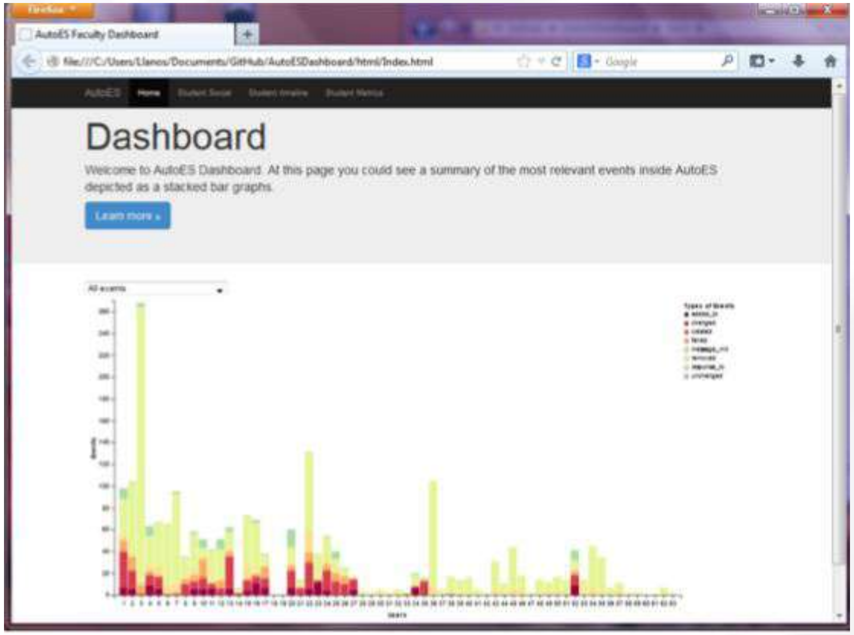
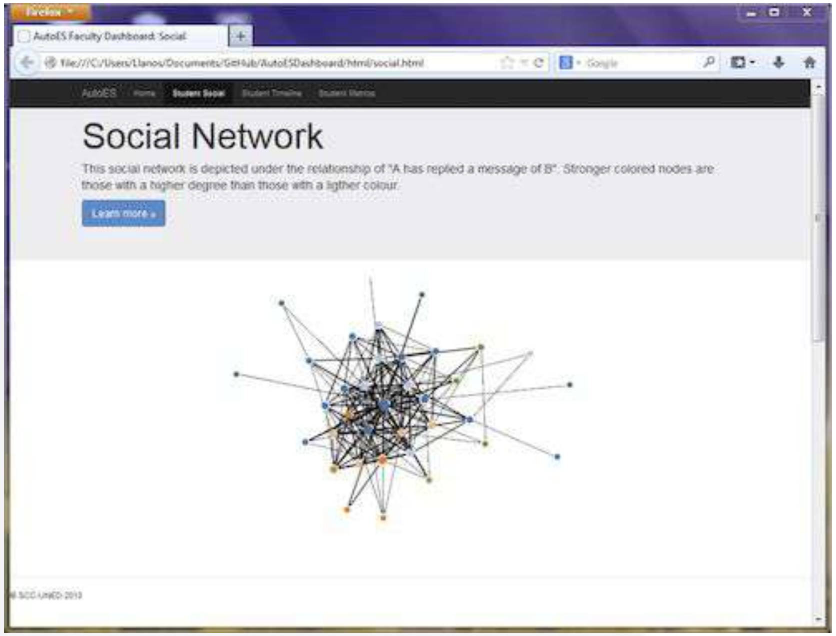
Research Trends
Visual analytics

- Dashboard for virtual evaluation laboratories



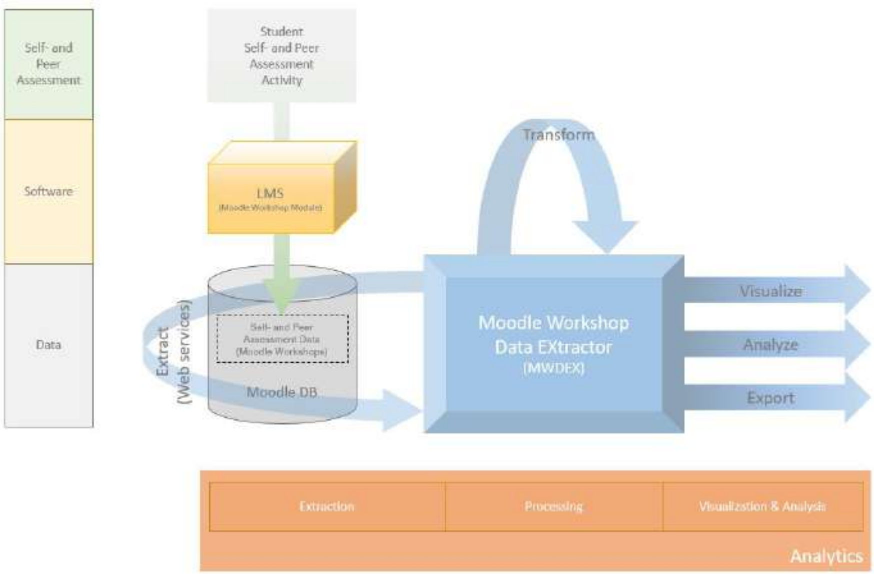


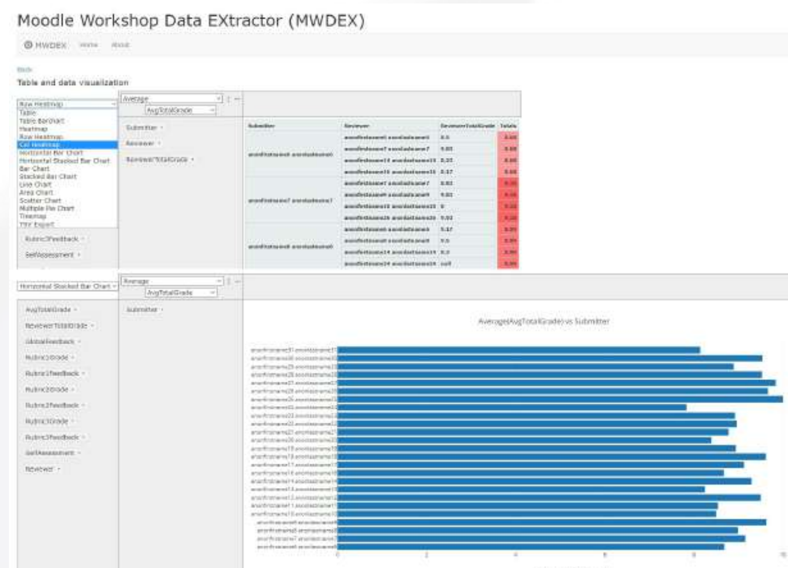
Tobarra, L., **Ros, S.,** Hernández, R., Robles-Gómez, A., **Caminero, A. C.,** & Pastor, R. (2014). Integrated Analytic dashboard for virtual evaluation laboratories and collaborative forums. In *2014 XI Tecnologías Aplicadas a la Enseñanza de la Electrónica (TAEE)*

Research Trends

Visual analytics

- Visualization of peer and self-assessment data in Moodle – Moodle Workshop Data EXtractor (MWDEX)

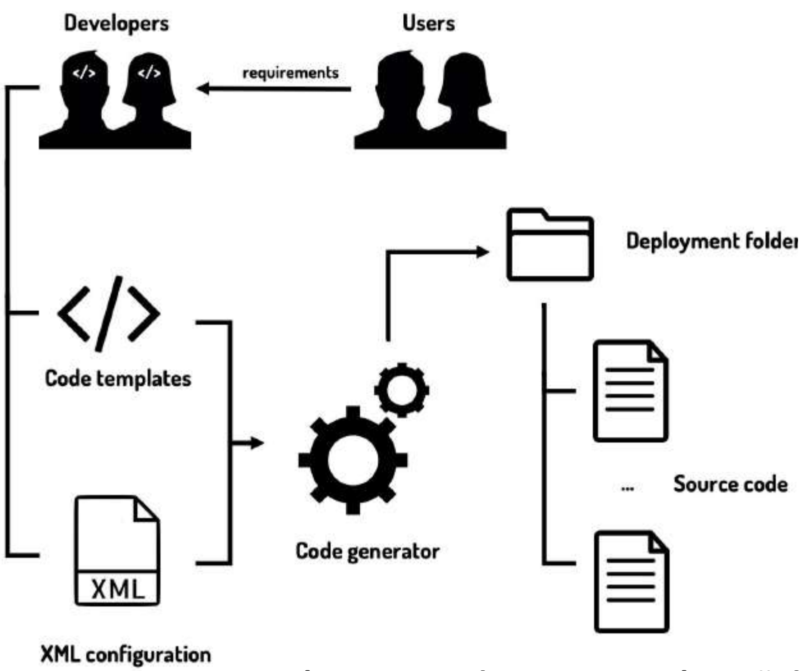


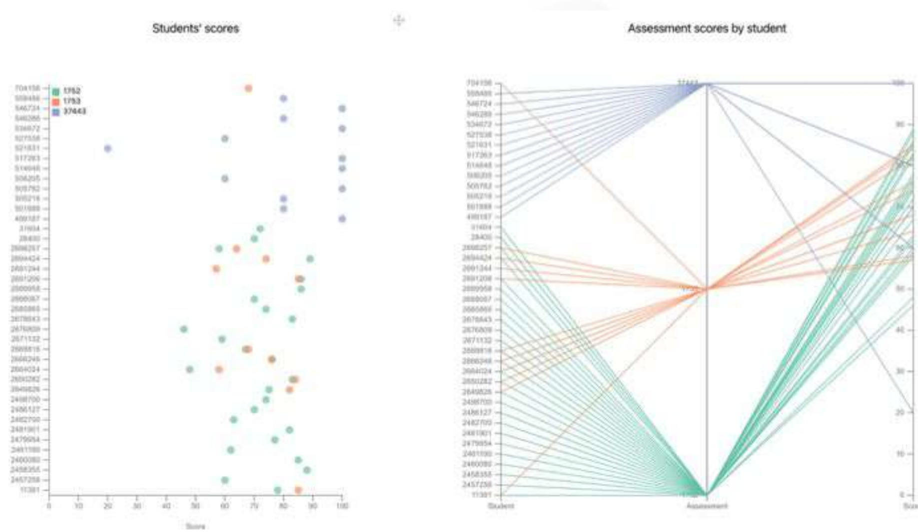


Chaparro-Peláez, J., Iglesias-Pradas, S., Rodríguez-Sedano, F. J., & **Acquila-Natale, E.** (2019). Extraction, Processing and Visualization of Peer Assessment Data in Moodle. *Applied Sciences*, *10*(1). https://doi.org/10.3390/app10010163

Visual analytics

- Automatic generation of adapted dashboards





Vázquez-Ingelmo, A., García-Peñalvo, F. J., & Therón, R. (2019). Taking advantage of the software product line paradigm to generate customized user interfaces for decision-making processes: A case study on university employability. *PeerJ Computer Science*, *5*. https://doi.org/10.7717/peerj-cs.203

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Research Trends

Support to active learning strategies

Research line	Publication	User(s)	Data sources	Analysis techniques
Orchestration of collaborative learning activities (PyramidApp)	(Amarasinghe, et al., 2019)	S / T	Actions on PyramidApp: progress in the activity, answers to the tasks, students' discussions	ML, descriptive statistics, data visualization
Adaptive learning based on user models	(Muñoz-Merino et al., 2018)	S / T	Students' actions on the system (Intelligent Tutoring Systems)	Bayesian networks, rules, Item Response Theory.
Support to dialogic peer feedback (Synergy)	(Er et al., 2019)	S / T	Students actions on the system, content of the feedback,	Descriptive statistics
Social learning supported by learning analytics	(Claros et al., 2015)	S / T	Students actions on the system (content and social)	SNA, CSCL
Learning analytics to improve Flipped Classrooms	(Rubio-Fernández et al., 2019)	S / T	Students' actions on the system (SPOC)	Visual analytics, clustering, adaptation
Definition of design criteria for self-regulated learning support tools	(Manso-Vázquez, et al., 2018)	M	xAPI profile	-

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Research Trends

Support to active learning strategies

- Supporting the scalability of collaborative peer feedback
  - Based on a model of dialogic peer feedback
  - Instructor dashboards for class-wide interventions
  - Student dashboards for supporting:
    - Self-regulation, co-regulation, and socially shared regulation of learning.
  - LA-empowered online platform:
    - Synergy, synergylearn.net

Er, E., **Dimitriadis, Y.,** & Gaseviç, D. (2019). An analytics-driven model of dialogic peer feedback. In *13th International Conference on Computer Supported Collaborative Learning (CSCL 2019).*

Research Trends

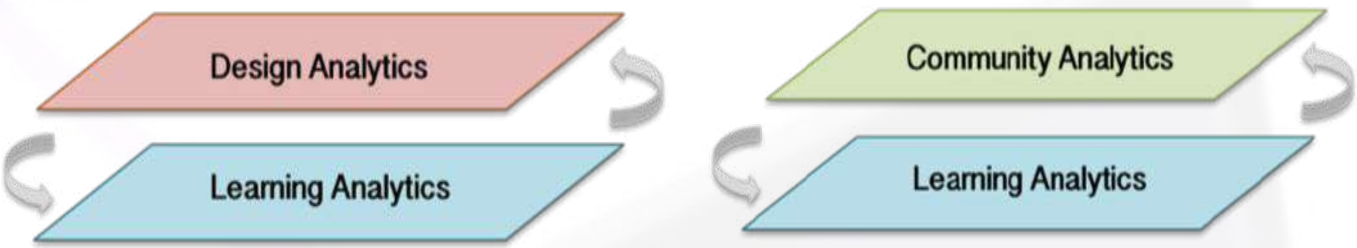
Learning analytics for Learnig Design

Research line	Publication	User(s)	Data sources	Analysis techniques
Support to learning design processes (ILDE2)	(Michos, Hernández-Leo, & Albó, 2018)	T	Actions on ILDE2, (a kind of social network for teachers), feedback on teachers' and students	Social Network Analysis (SNA), data visualization, descriptive statistics
Learning analytics for learning design (OrLA, T-Glade, TAP)	(Wiley, Dimitriadis, Bradford, & Linn, 2020)	T / R	Students actions on the system (WISE science inquiry system); submission of results; grades	TAP (an NLP method)

Research Trends

LA for Learning Design

- How can teachers investigate the impact of learning activities in their context (e.g. schools)?
- An approach that connects LA with analytics of learning designs across multiple educators in a community



- Technology supporting teachers:
  - Design of learning activities
  - Formulation of inquiries
  - Collecting, aggregating visualizing data
  - Community sharing, community inquiry

Michos, K., **Hernández-Leo, D.**, Albó, L. (2018). Teacher-led inquiry in technology-supported school communities. BJET 49(6), 1077-1095.

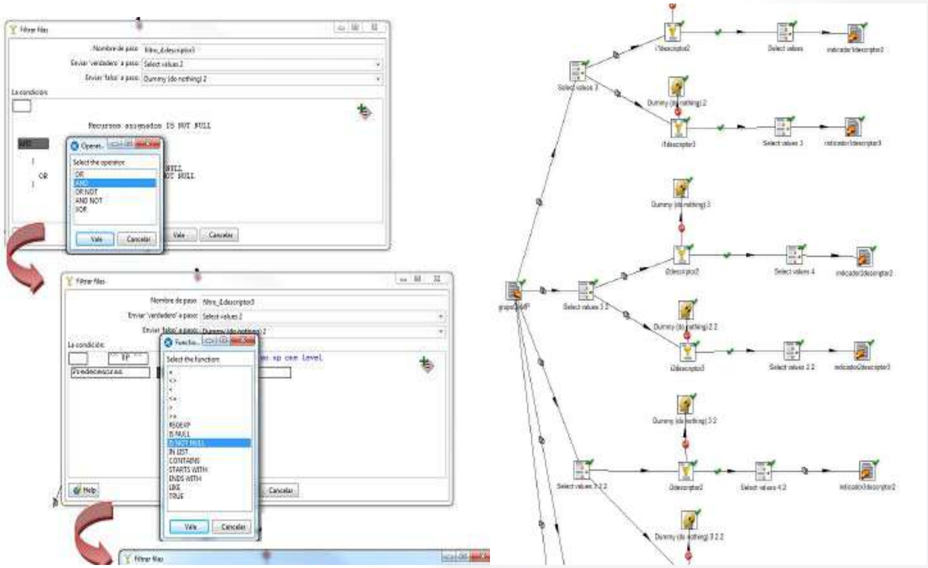
Research Trends

Assessment support

Research line	Publication	User(s)	Data sources	Analysis techniques
Definition and adjustment of assessment processes (Ramon / TEA)	(Villamañe et al., 2017)	S / T / ID	Students' answers, grades	Statistics, Regression, NNLS, Data visualization
Learning analytics for the assessment of 21st-century skills	(Menchaca et al., 2018)	S / T	Grades	Heuristics
Analysis of Moodle logs for decision making and workgroup assessment	(Tobarra et al., 2017)	S / T	MOOC platform logs	Heuristic
Workgroup assessment	(Conde et al., 2018)	S / T	Students' actions on the system (VLE)	Quantitative analysis and heuristics
Measurement and analysis of teamwork indicators in online education (TeamworkRM)	(Hernández-García et al., 2018)	T	Students' actions (Moodle log data-Forums & wikis)	Data classification (ETL), Regression

Assessment support

- Assessment of 21st century skills
  - Integrate formative student assessment data from different tools
  - Criteria for data analysis based on assessment rubrics.

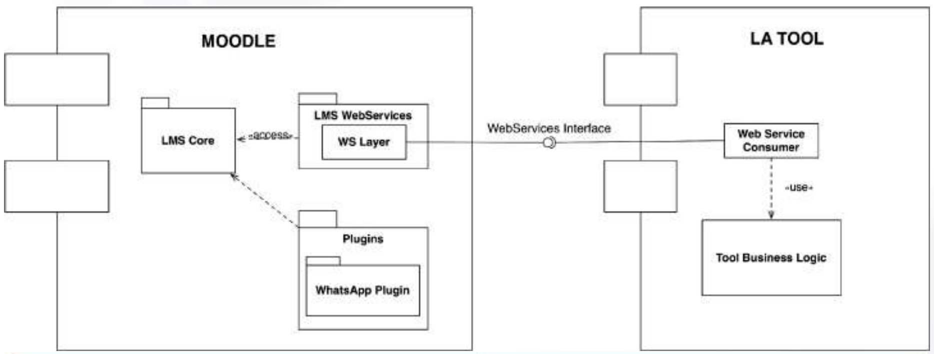


Menchaca Sierra, I., Guenaga, M., & Solabarrieta, J. (2018). Learning analytics for formative assessment in engineering education. *The International Journal of Engineering Education*, *34*(3), 953–967.

Research Trends

Assessment support

- Assessment of teamwork to populate a competence ontology




Porcentaje de mensajes largos de la disusión: 45%

Número de mensajes cortos por usuario: 43.75

Número de mensajes largos por usuario: 35.25

Show 10 entries Search:

Nombre de la discusión	Fecha de creación	Mensajes	Mensajes cortos	Mensajes largos	Vistas
BUSQUEDA MIEMBRO RESTANTE	2018/12/05 19:27:05	5 (1.58%)	5 (1.58%)	0 (0%)	34
CREACCION Y REPARTO DE TAREAS	2018/12/17 11:20:35	24 (7.59%)	17 (5.38%)	7 (2.22%)	108
ELECCIÓN COORDINADOR DEL GRUPO	2018/12/05 19:16:11	8 (2.53%)	8 (2.53%)	0 (0%)	61
EVOLUCIÓN PRÁCTICA	2018/12/18 13:26:50	83 (26.27%)	34 (10.76%)	49 (15.51%)	317
MISIÓN Y OBJETIVOS	2018/12/11 14:27:42	18 (5.7%)	11 (3.48%)	7 (2.22%)	105
NOMBRE DEL GRUPO	2018/12/11 14:14:56	8 (2.53%)	7 (2.22%)	1 (0.32%)	44
REPARTO DE TRABAJO Y CREACIÓN WIKI	2018/12/11 13:59:14	20 (6.33%)	15 (4.75%)	5 (1.58%)	92
TAREA 1: MAIN	2018/12/19 23:27:29	19 (6.01%)	14 (4.43%)	5 (1.58%)	66
TAREA 3:ACCIONES USUARIO	2018/12/19 23:30:15	47 (14.87%)	24 (7.59%)	23 (7.28%)	185
TAREA 4: ACCIONES FACTURADOR	2018/12/19 23:30:54	45 (14.24%)	20 (6.33%)	25 (7.91%)	164

Showing 1 to 10 of 12 entries Previous Next

Resultados evaluación sumativa

Show 10 entries Search:

Nombre	Apellidos	Mensajes	Mensajes cortos	Mensajes largos
[illegible]	[illegible]	64 (20.25%)	44 (13.92%)	20 (6.33%)
[illegible]	[illegible]	77 (24.37%)	41 (12.97%)	36 (11.39%)
[illegible]	[illegible]	68 (21.52%)	31 (9.81%)	37 (11.71%)
[illegible]	[illegible]	107 (33.86%)	59 (18.67%)	48 (15.19%)

Showing 1 to 4 of 4 entries Previous Next

Conde, M. A., Colomo-Palacios, R., García-Peñalvo, F. J., & Larrucea, X. (2018). Teamwork assessment in the educational web of data: A learning analytics approach towards ISO 10018. *Telematics and Informatics*, *35*(3), 551–563. https://doi.org/https://doi.org/10.1016/j.tele.2017.02.001

Research Trends

Multimodal and contextual data

Research line	Publication	User(s)	Data sources	Analysis techniques
Students monitoring in blended learning environments (CASA, AdESMuS)	(Villamañe et al., 2020)	S / T	Grades	Statistics, Linear Regression, Data visualization
Multimodal learning analytics of f2f collaborative learning	(Vujovic & Hernández-Leo, 2019)	T / R	Multimodal data, motion capture, EDA, sound, students' self-reported data	ML, statistic analysis
Use of wearables to estimate levels of stress and sleep quality.	(de Arriba-Pérez et al. 2018)	S	Biometric signals	ML
Design-aware learning analytics (GLUE!-CASS, Glimpse)	(Rodríguez-Triana et al. 2015)	T	Students actions on the system (DLE), data from the learning design, self-reported data	Heuristics

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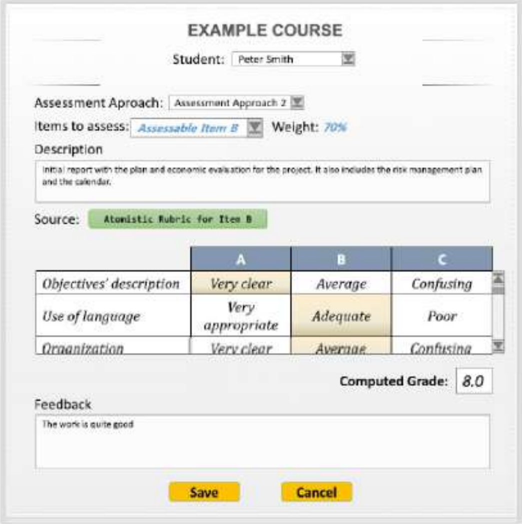
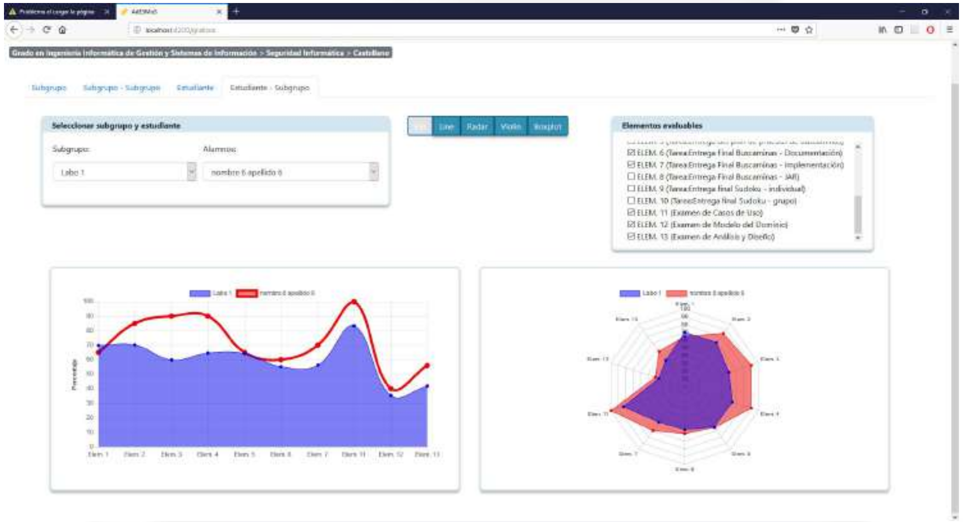
Research Trends

Multimodal and contextual data

- Helping teachers to
  - Define the multiple assessment approaches in a course
  - Integrate and analyze the collected data





Villamañe, M., **Alvarez, A.,** & Larrañaga, M. (2020). CASA, An Architecture to Support Complex Assessment Scenarios. *IEEE Access*. https://doi.org/10.1109/ACCESS.2020.2966595

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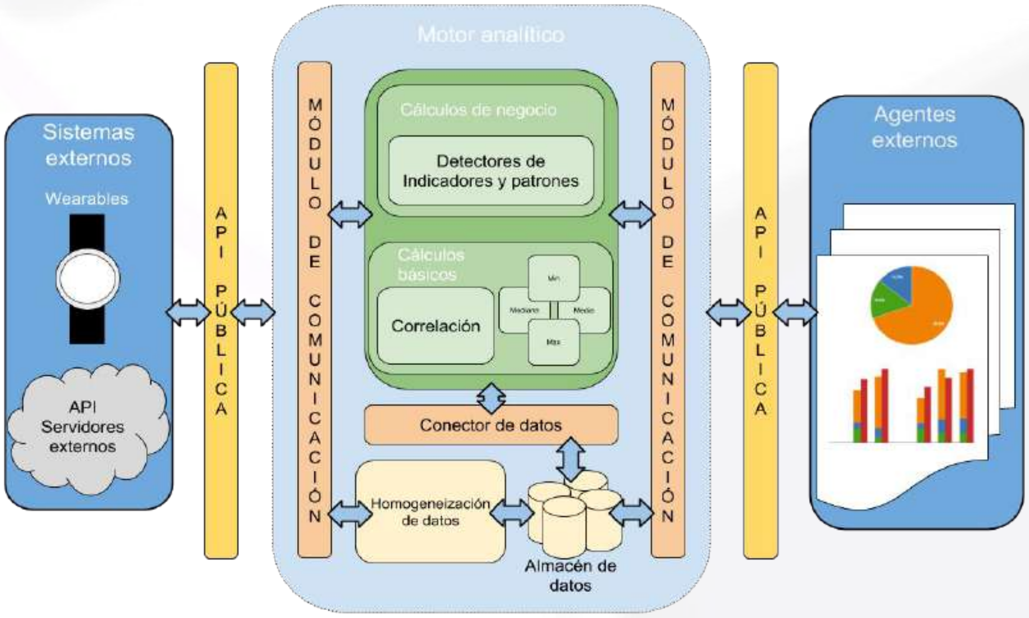
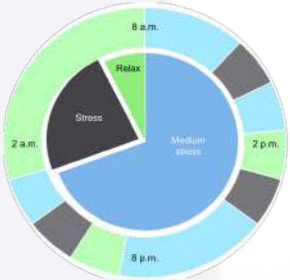
Research Trends

Multimodal and contextual data

- Do sensors in wearables provide adequate data to estimate stress and sleep quality?



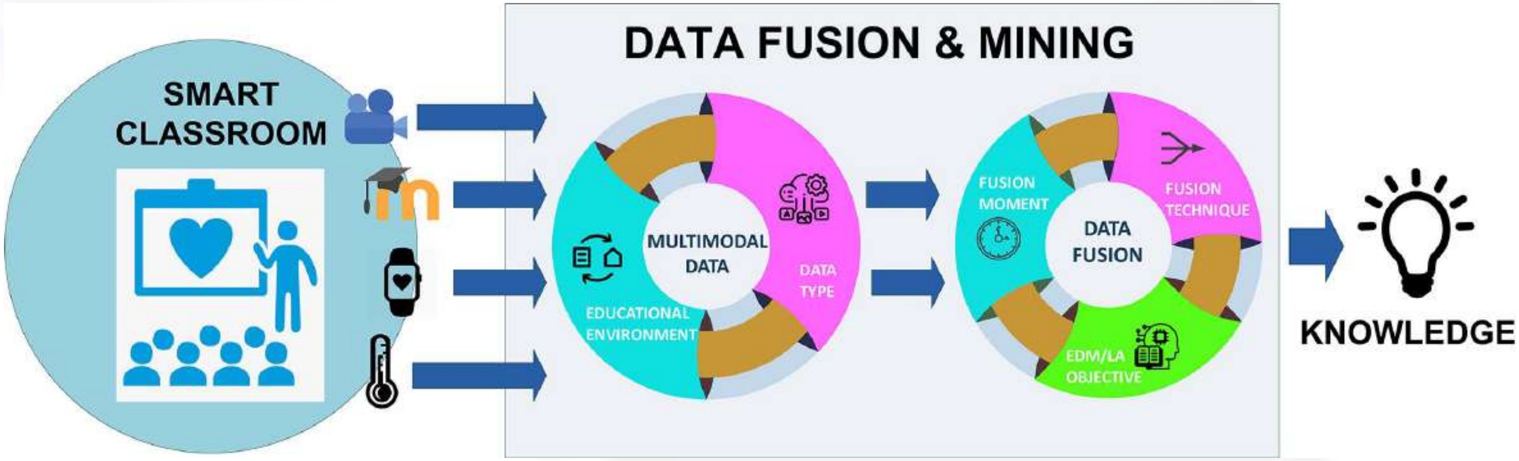


de Arriba-Pérez, F., **Caeiro-Rodríguez, M.**, & Santos-Gago, J. M. (2018). How do you sleep? Using off the shelf wrist wearables to estimate sleep quality, sleepiness level, chronotype and sleep regularity indicators. *Journal of Ambient Intelligence and Humanized Computing*, 9(4), 897–917. https://doi.org/10.1007/s12652-017-0477-5

Research Trends

Multimodal and contextual data

- Proposal of models (e.g.: Data Fussion)



Chango, W., Lara, J. A., Cerezo, R., & Romero, C. (2022). A review on data fusion in multimodal learning analytics and educational data mining. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *12*(4), e1458.

Sentiment analysis

Research line	Publication	User(s)	Data sources	Analysis techniques
Social and sentiment analysis	(Ros et al., 2017)	S / T	Forum messages	Heuristics
Academic success prediction based on emotion modelling (PresenceClick)	(Ruiz et al., 2018)	S / T	Sensors, self-reported emotions	Transition matrix, Decision trees, Data visualization
Sentiment Analysis	(Cobos et al., 2019)	T / M	Student. actions on the system (MOOCs), MOOC contents	Descriptive analytics, Natural Language Processing (NLP), Sentiment Analysis

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Research Trends

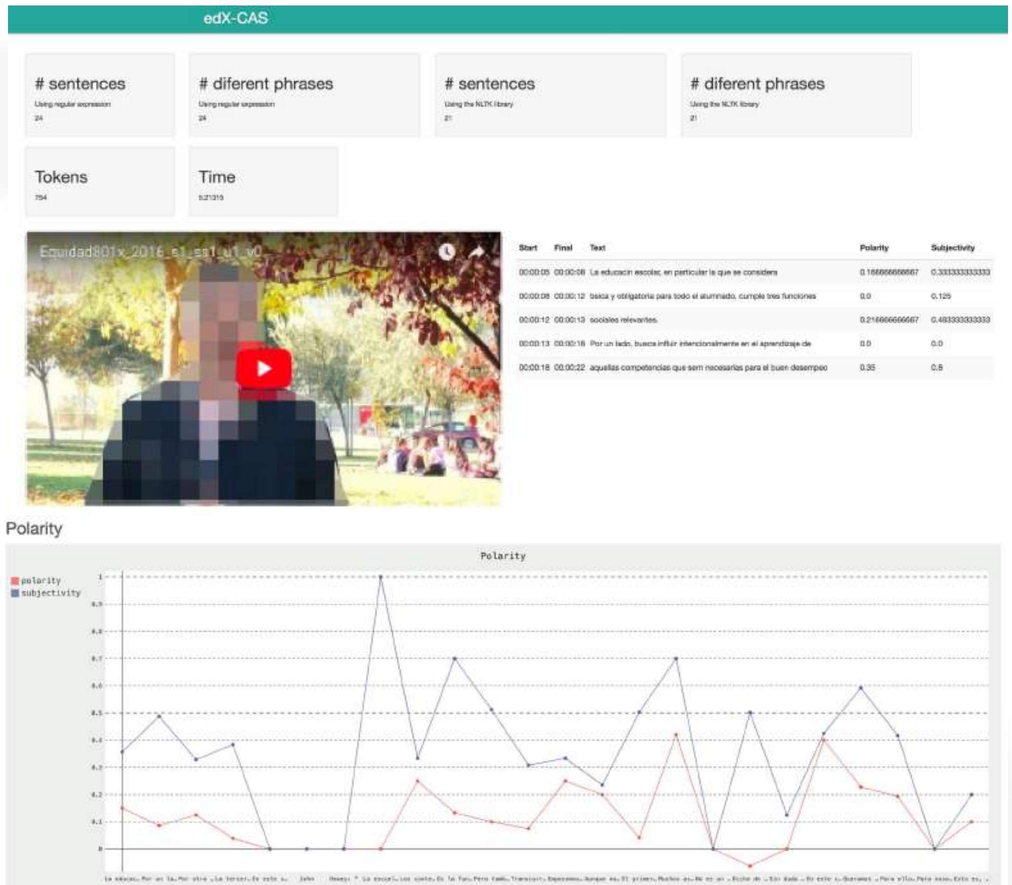
Sentiment analysis

GHIA

Grupo de Herramientas Interactivas Avanzadas

edX-CAS

A Content Analysis System that supports Sentiment Analysis for Subjectivity and Polarity detection in Online Courses at edX



Cobos, R, Jurado, F., & Blázquez-Herranz, A. (2019). A Content Analysis System that supports Sentiment Analysis for Subjectivity and Polarity detection in Online Courses. *IEEE Revista Iberoamericana de Tecnologías Del Aprendizaje*, *14*(4), 177–187. https://doi.org/10.1109/rita.2019.2952298

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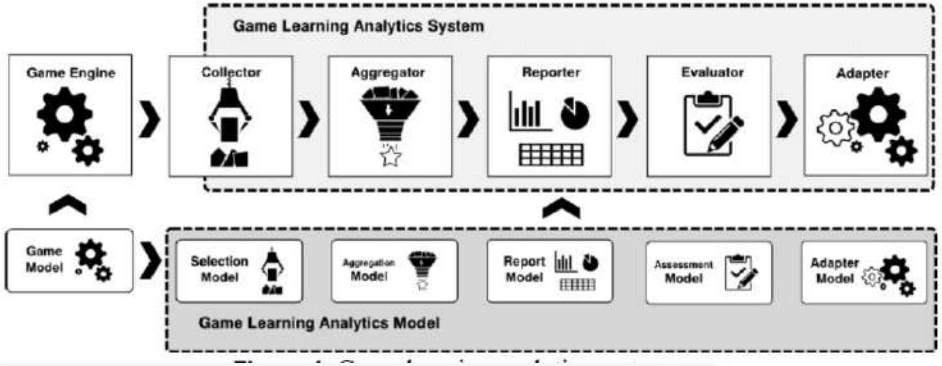
Research Trends
Game Learning Analytics

- Game learning analytics collect, analyze,and visualize interactions in serious games to provide information about player actions for different stakeholders.
- Experience API for Serious Games (xAPI-SG) Profile
- The combination of both an exploratory and visual tool (T-MON) with data mining models has allowed us to obtain an in-depth analysis of the relationship between player interactions in the game and their learning results.



Freire, M., Serrano-Laguna, Á., Manero Iglesias, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2023). Game learning analytics: Learning analytics for serious games. In *Learning, design, and technology: An international compendium of theory, research, practice, and policy* (pp. 3475-3502). Cham: Springer International Publishing.

Research Trends
Other

- Data Mashups Privacy Preservation for Learning Analytics
- LA for the detection of fraudulent behaviour
- Human-Centered Learning Analytics

… and others available in:

https://snola.es/observatorio-de-publicaciones/

Balderas, A., Palomo-Duarte, M., Caballero-Hernández, J. A., Rodriguez-Garcia, M., & Dodero, J. M. (2021). Learning analytics to detect evidence of fraudulent behaviour in online examinations.

Challenges

- Increase adoption by end users (8)
- Ethical, privacy, and security issues (7)
- Quality of process and the results (6)
- Increase personalization / adaptation / interoperability of data and tools (5)
- Improve real learning (5)
- Apply LA at an institutional level (5)

+ How to integrate Gen(AI) tools

Índice

- Introducción
- SNOLA
  - Breve perspectiva histórica
  - Líneas de investigación en SNOLA
  - Proyectos actuales
- Retos, … ¿colaboraciones?

Proyectos actuales

- Divulgación:
  - Creación de tres nanoMOOCs (en marcha)
  - Orientados a público en general y a docentes que quieran usar LA para investigar sobre su práctica docente
- Profundizar en el conocimiento sobre las expectativas de docents y estudiantes en universidades españolas
  - Estudio SELAQ+

Estudio SELAQ+
Introducción

- Existe preocupación en LA por la (falta de) adopción de las herramientas
- Interés en estudiar expectativas de los usuarios
- Escala SELAQ (*Student Expectations of Learning Analytics Questionnaire)*
  - Whitelock-Wainwright A, Gašević D, Tejeiro R, Tsai Y-S, Bennett K. The Student Expectations of Learning Analytics Questionnaire. *J Comput Assist Learn*. 2019; 35: 633–666. https://doi.org/10.1111/jcal.12366
- Adaptada a docentes en *Kollom, et al., (2021)*
  - *Kollom, K.,. . . Ley, T. (2021). A four-country cross-case analysis of academic staff expectations about learning analytics in higher education. The Internet and Higher Education, 49 , 100788,*

Estudio SELAQ+ Introducción (cont.)

- Existen diferentes factores (incluidos culturales) que pueden afectar a la percepción de los actores involucrados
  - Varios estudios han explorado expectativas en diferentes regiones del planeta:
    - LALA - Chile y Ecuador:
      - *Hilliger, I., Pérez-Sanagustín, M. (2020). Identifying needs for learning analytics adoption in latin american universities: A mixed-methods approach The Internet and Higher Education, 45 , 100726,*
    - 4 países europeos:
      - *Kollom, K.,. . . Ley, T. (2021). A four-country cross-case analysis of academic staff expectations about learning analytics in higher education. The Internet and Higher Education, 49 , 100788,*
    - Brasil:
      - *Pontual Falcao, T.,. . . Ferreira Mello, R. (2022). A penny for your thoughts: students and instructors' expectations about learning analytics in brazil. unknown (Ed.), Proceedings of the seventh international learning analytics & knowledge conference (p. 186–196). New York, NY, USA: Association for Computing Machinery*
- SNOLA se planteó contribuir a esta línea

Escala SELAQ - Presentación

- 2 escalas Likert (1 = Strongly Disagree, 7 = Strongly Agree)
  1. Qué **desean** los docentes (**ideal expectations**) y
  2. Que **esperan** de forma realista (**predicted expectations**) …

  de un servicio de LA
- 16 ítems
- 4 temas:
  1. Metas de analítica de aprendizaje (2 ítems)
  2. Necesidades de LA de los docentes (4 ítems),
  3. Percepciones de los docents sobre las necesidades de estudiantes sobre los servicios LA (5 ítems),
  4. Retos relativos a la implementación de los servicios LA en la Universidad (5 ítems).

Escala SELAQ

- Q01 The university will provide me with guidance on how to access learning analytics about my students.
- Q02 The University will provide staff with opportunities for professional development in using learning analytics for teaching.
- Q03 The university will facilitate open discussions to share experience of learning analytics services.
- Q04 I will be able to access data about my students' progress in a course that I am teaching/tutoring
- Q05 I will be able to access data about any students within a programme
- Q06 The learning analytics service will allow students to make their own decisions based on the data they receive.
- Q07 The university will provide support (e.g., advice from personal tutors) as soon as possible if the analysis of a student's educational data suggests they may be having some difficulty or problem (e.g., underperforming or at-risk of failing)
- Q08 The university will regularly update students about their learning progress based on the analysis of their educational data.
- Q09 The learning analytics service will collect and present data that is accurate (i.e., free from inaccuracies such as incorrect grades).
- Q10 The learning analytics service will show how a student's learning progress compares to their learning goals/the course objectives.
- Q11 The feedback from the learning analytics service will be presented in a format that is both understandable and easy to read.
- Q12 The learning analytics service will present students with a complete profile of their learning across every course (e.g., number of accesses to online material, learning outcomes, and attendance).
- Q13 The teaching staff will be competent in incorporating analytics into the feedback and support they provide to students.
- Q14 The teaching staff will have an obligation to act (i.e., support students) if the analytics show that a student is at-risk of failing, under-performing, or that they could improve their learning.
- Q15 The feedback from the learning analytics service will be used to promote students' academic and professional skill development (e.g., essay writing and referencing) for their future employability.
- Q16 The use of learning analytics will allow me to better understand my students' learning performance.

Escala SELAQ – Metas

- Q01 The university will provide me with guidance on how to access learning analytics about my students.
- Q02 The University will provide staff with opportunities for professional development in using learning analytics for teaching.
- Q03 The university will facilitate open discussions to share experience of learning analytics services.
- Q04 I will be able to access data about my students' progress in a course that I am teaching/tutoring
- Q05 I will be able to access data about any students within a programme
- Q06 The learning analytics service will allow students to make their own decisions based on the data they receive.
- Q07 The university will provide support (e.g., advice from personal tutors) as soon as possible if the analysis of a student's educational data
- suggests they may be having some difficulty or problem (e.g., underperforming or at-risk of failing)
- Q08 The university will regularly update students about their learning progress based on the analysis of their educational data.
- ….

- Q15 The feedback from the learning analytics service will be used to promote students' academic and professional skill development (e.g., essay writing and referencing) for their future employability.
- Q16 The use of learning analytics will allow me to better understand my students' learning performance.

Escala SELAQ – Necesidades de los docents relativas a LA

- Q01 The university will provide me with guidance on how to access learning analytics about my students.
- Q02 The University will provide staff with opportunities for professional development in using learning analytics for teaching.
- Q03 The university will facilitate open discussions to share experience of learning analytics services.
- Q04 I will be able to access data about my students' progress in a course that I am teaching/tutoring
- Q05 I will be able to access data about any students within a programme
- ….
- Q12 The learning analytics service will present students with a complete profile of their learning across every course (e.g., number of accesses to
- online material, learning outcomes, and attendance).
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- Q14 The teaching staff will have an obligation to act (i.e., support students) if the analytics show that a student is at-risk of failing, underperforming, or that they could improve their learning.
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- Q16 The use of learning analytics will allow me to better understand my students' learning performance.

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Preguntas del estudio SELAQ+

- RQ1. ¿Cuáles son las diferencias entre las expectativas deseadas y esperadas?
- RQ2 ¿Cómo se diferencian los resultados en este estudio en España con los realizados en otros estudios previos equivalentes?
- RQ3 ¿Qué grupos de docentes se pueden identificar con base en las diferencias en sus expectativas sobre servicios de LA?
- RQ4 ¿Se pueden observar diferencias en las expectativas según variables como edad, género, área de conocimiento, etc.?

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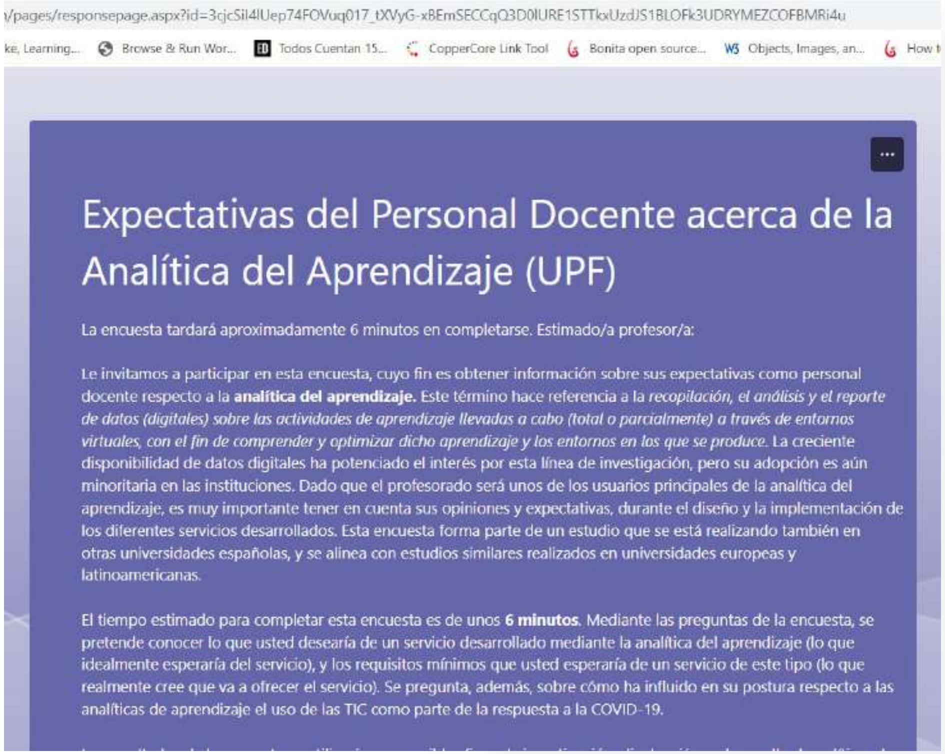
SELAQ+. Participantes

- Se recogieron 490 respuestas de 7 universidades
  - UAM (70), UNED (108), UOC (61), UPF (92), UPV (49), UVa (74) and UVigo (36).



Expectativas del Personal Docente acerca de la Analítica del Aprendizaje (UPF)

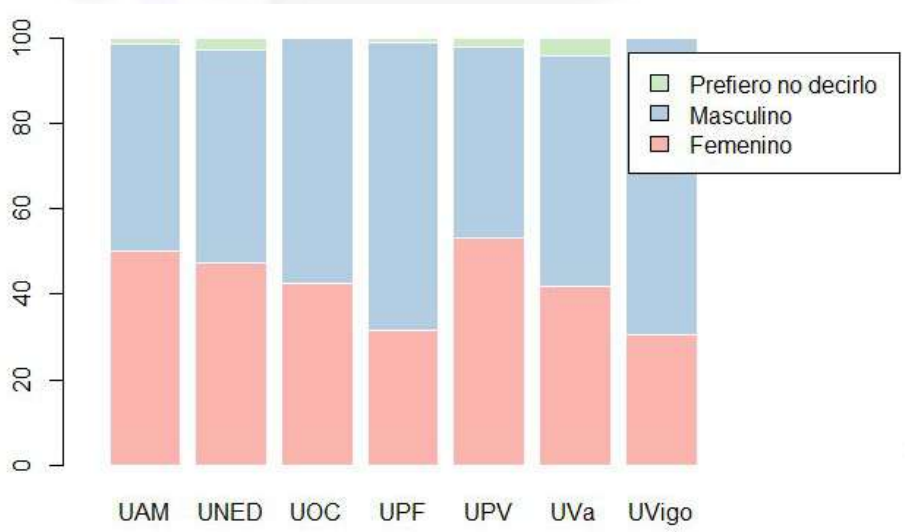
La encuesta tardará aproximadamente 6 minutos en completarse. Estimado/a profesor/a:

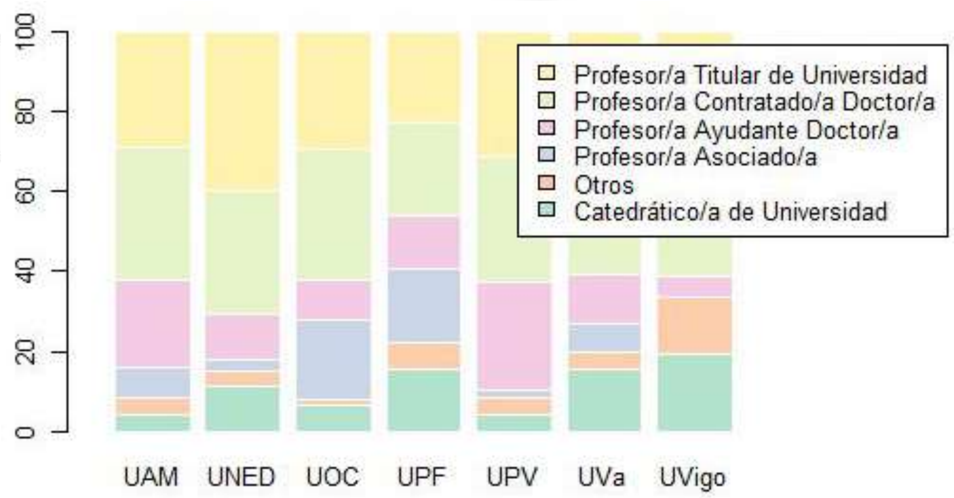
Le invitamos a participar en esta encuesta, cuyo fin es obtener información sobre sus expectativas como personal docente respecto a la **analítica del aprendizaje.** Este término hace referencia a la *recopilación, el análisis y el reporte de datos (digitales) sobre las actividades de aprendizaje llevadas a cabo (total o parcialmente) a través de entornos virtuales, con el fin de comprender y optimizar dicho aprendizaje y los entornos en los que se produce.* La creciente disponibilidad de datos digitales ha potenciado el interés por esta línea de investigación, pero su adopción es aún minoritaria en las instituciones. Dado que el profesorado será unos de los usuarios principales de la analítica del aprendizaje, es muy importante tener en cuenta sus opiniones y expectativas, durante el diseño y la implementación de los diferentes servicios desarrollados. Esta encuesta forma parte de un estudio que se está realizando también en otras universidades españolas, y se alinea con estudios similares realizados en universidades europeas y latinoamericanas.

El tiempo estimado para completar esta encuesta es de unos **6 minutos**. Mediante las preguntas de la encuesta, se pretende conocer lo que usted desearía de un servicio desarrollado mediante la analítica del aprendizaje (lo que idealmente esperaría del servicio), y los requisitos mínimos que usted esperaría de un servicio de este tipo (lo que realmente cree que va a ofrecer el servicio). Se pregunta, además, sobre cómo ha influido en su postura respecto a las analíticas de aprendizaje el uso de las TIC como parte de la respuesta a la COVID-19.

SELAQ+. Datos sociodemográficos

Género y puesto académico por universidad participante





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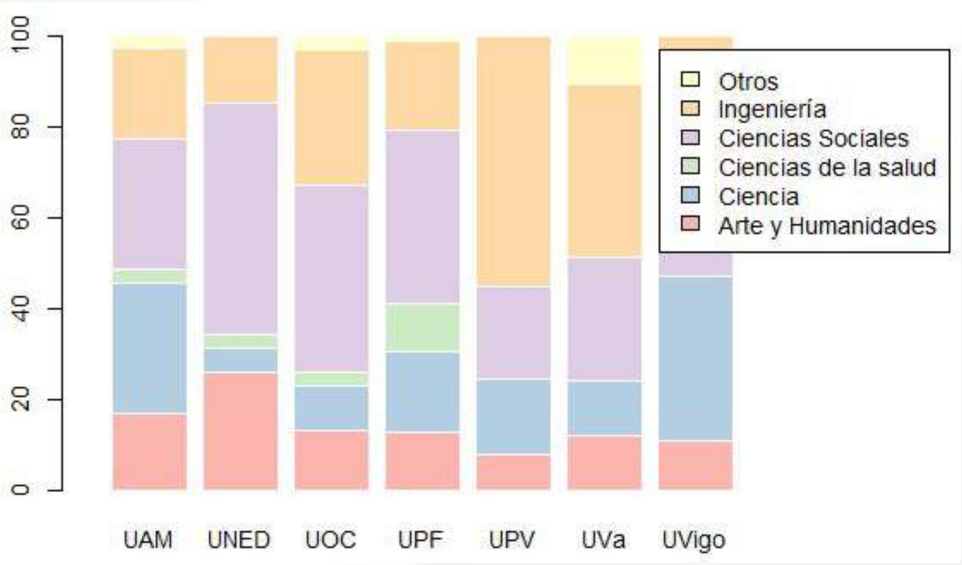
SELAQ+. Datos sociodemográficos.

Áreas de conocimiento



RQ1.Qué diferencias hay entre las expectativas ideales y esperadas? (Wilcoxon Signed-Rank Test)

Teaching staff' ideal and predicted expectations. Format based on [5].

Item	Ideal expectations 25th	Ideal expectations Mean	Ideal expectations 75th	Predicted expectations 25th	Predicted expectations Mean	Predicted expectations 75th	p-value	r
Q11 (Feedback format)	6.00	6.39(1.12)	7.00	3.00	3.95(1.74)	5.00	<0.001	0.54
Q07 (Early intervention)	5.00	5.92(1.39)	7.00	2.00	3.65(1.62)	5.00	<0.001	0.53
Q09 (Data accuracy)	6.00	6.06(1.36)	7.00	3.00	4.07(1.71)	5.00	<0.001	0.51
Q15 (Skill development)	5.00	5.53(1.65)	7.00	2.00	3.48(1.59)	4.00	<0.001	0.51
Q16 (Understanding learning)	5.00	5.93(1.47)	7.00	3.00	4.17(1.71)	5.00	<0.001	0.51
Q06 (Student agency)	5.00	5.57(1.58)	7.00	2.00	3.62(1.63)	5.00	<0.001	0.49
Q10 (Learning goals)	5.00	5.91(1.47)	7.00	3.00	3.97(1.70)	5.00	<0.001	0.49
Q13 (LA in feedback)	5.00	5.67(1.60)	7.00	3.00	3.71(1.62)	5.00	<0.001	0.49
Q02 (Professional development)	5.00	5.93(1.42)	7.00	3.00	4.11(1.69)	5.00	<0.001	0.47
Q03 (Shared experience)	5.00	5.72(1.46)	7.00	3.00	4.00(1.70)	5.00	<0.001	0.47
Q04 (Class progress)	6.00	6.25(1.22)	7.00	3.00	4.47(1.80)	6.00	<0.001	0.47
Q08 (Regular updates)	5.00	5.77(1.54)	7.00	3.00	3.85(1.65)	5.00	<0.001	0.47
Q01 (Guidance)	6.00	6.02(1.47)	7.00	3.00	4.26(1.68)	5.00	<0.001	0.44
Q05 (Data access)	4.00	5.24(1.93)	7.00	2.00	3.61(1.89)	5.00	<0.001	0.44
Q12 (Complete profile)	5.00	5.83(1.46)	7.00	3.00	4.34(1.68)	6.00	<0.001	0.42
Q14 (Obligation to act)	3.00	4.71(2.09)	7.00	2.00	3.48(1.70)	5.00	<0.001	0.33

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RQ1. Qué diferencias hay entre las expectativas ideales y esperadas? (Wilcoxon Signed-Rank Test)

Teaching staff' ideal and predicted expectations. Format based on [5].

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RQ1.What are the differences between teaching staff ideal and predicted expectations?

Ideal expectations

1. Goals of learning analytics

2. Teachers’ needs for LA services

3. Teachers’ perceptions about students’ needs for LA services

4. Challenges regarding implementation of LA services at HEIs

- Q01. Guidance
- Q04. Class progress
- Q09. Data accuracy
- Q11. Feedback format

Predicted expectations

1. Goals of learning analytics

- Q16. Understanding learning

2. Teachers’ needs for LA services

3. Teachers’ perceptions about students’ needs for LA services

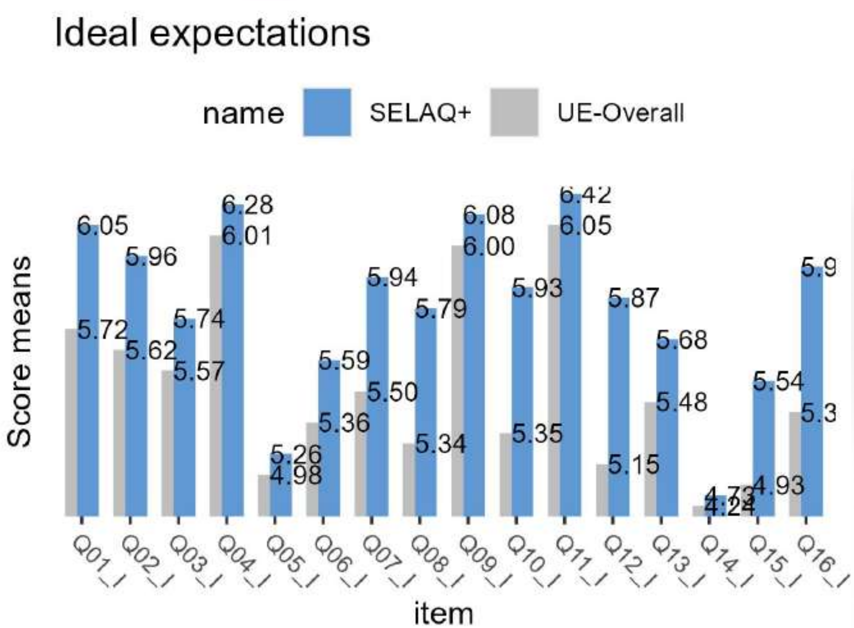
- Q12. Complete profile

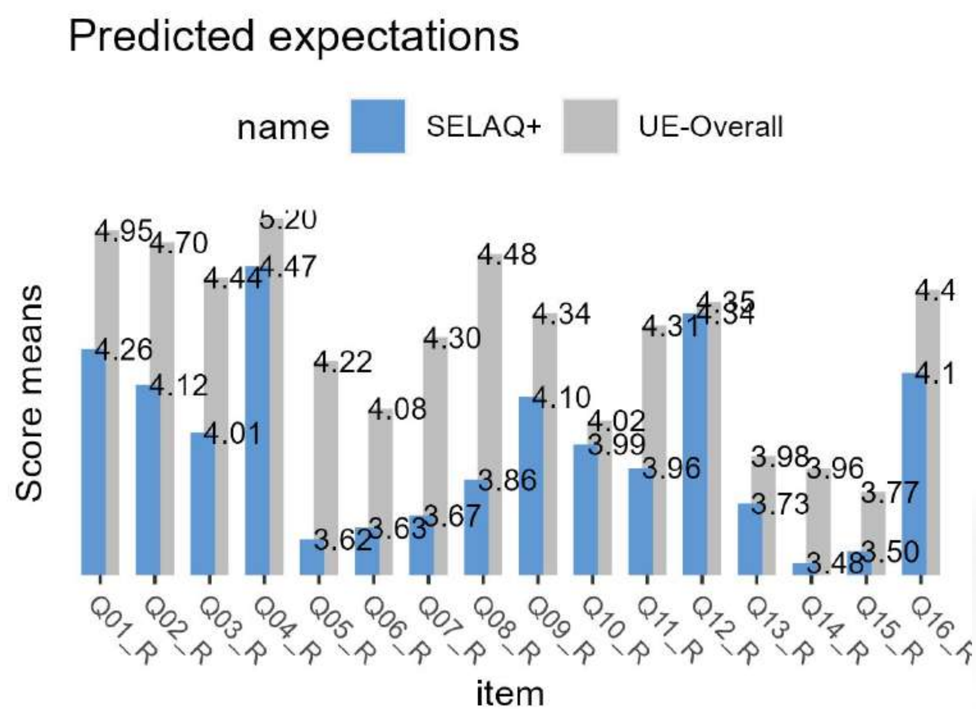
4. Challenges regarding implementation of LA services at HEIs

- Q01. Guidance
- Q04. Class progress

RQ2 ¿Que diferencias se pueden observar entre el estudio SELAQ+ y otros similares?

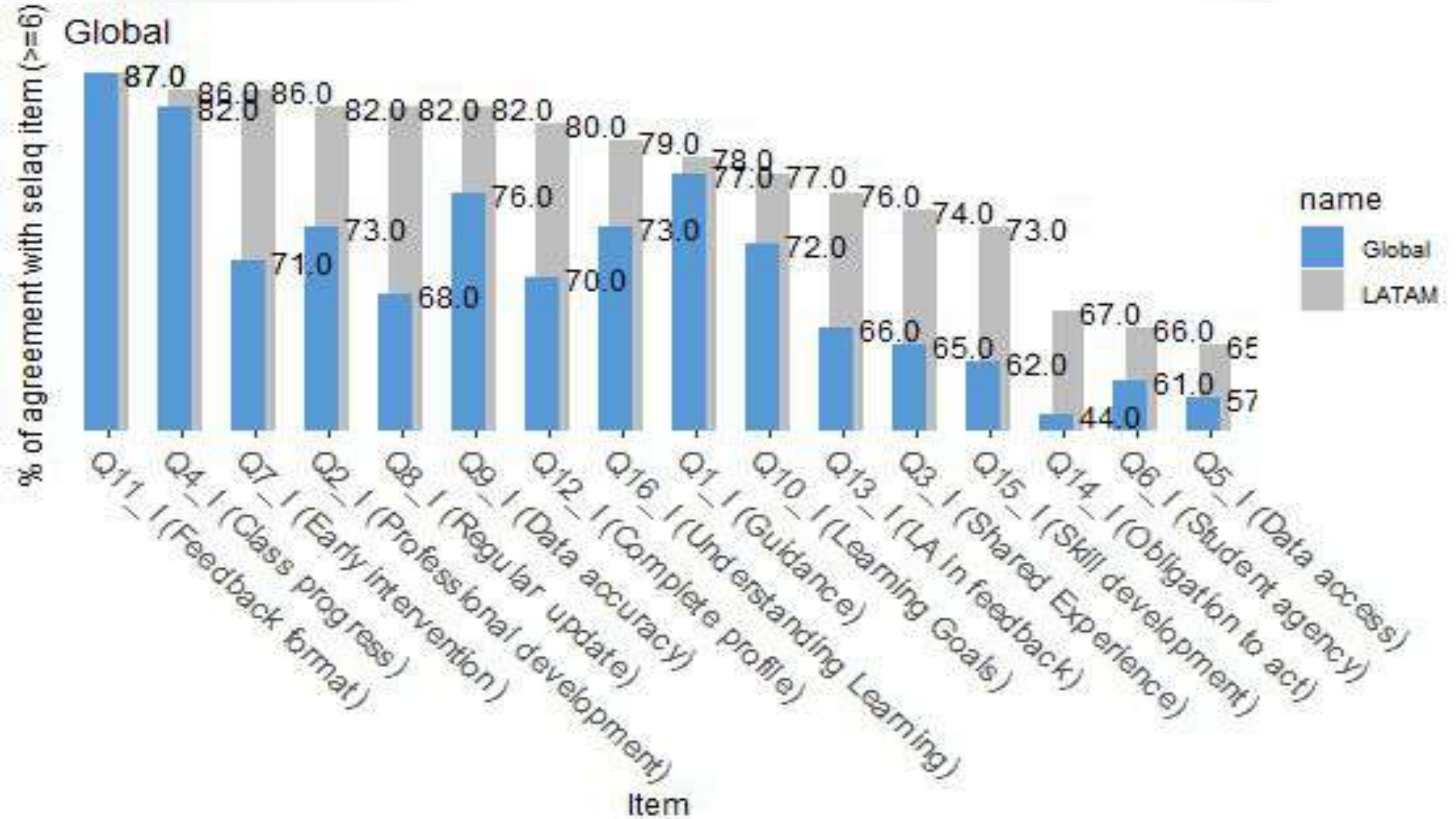
SNOLA vs (media de resultados en) 4 países europeos (Estonia, Netherlands, UK y España)





RQ2 ¿Que diferencias se pueden observar entre el estudio SELAQ+ y otros similares?

Estudio LALA (Hilliger et al. 2022)



RQ3 ¿Qué grupos se pueden distinguir?

- Tres grupos:
  - Escépticos (8,37%)
  - Positivos (36.73%)
  - Entusiastas (54,90%)

Table 3: Clusters vs row mean (all SELAQ items)

	SELAQ+ study							EU study[1]			
Cluster	N	%	mean	SD	Median	Min	Max	Np	%	Minp	Max$p$
1.Skeptics	38	8.37	3.09	0.96	3.44	1	4.19	29	13.68	2.45	4.59
2.Positive	180	36.73	5.26	0.47	5.44	4.19	5.94	89	41.98	3.30	6.03
3.Enthusiasts	269	54,90	6.53	0.39	6.56	5.81	7	94	44.34	5.67	6.67

[1] p-value$<$ 0.001, all items

RQ4 ¿Se pueden observar diferencias en las expectativas según variables como edad, género, área de conocimiento, etc.?

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Table 5: Proportions (%) of groups displaying significant differences concerning the LA adoption regarding the SELAQ items (Gender and Academic areas)

	Gender		Academic areas					
SELAQ clusters	F	M	Art. & Hum.	Sci.	Healt sci.	Soc. sci.	Eng.	Other
Enthusiasts	8.1	7.7	12.2	7.9	0.0	10.5	3.8	0.0
Positives	62.7	50	62.2	46.1	73.1	50.9	60.0	50.0
Skeptics	29.2	42.3	25.7	46.1	26.9	38.6	36.2	50.0

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SELAQ+ Conclusions

- Los docentes tienen expectativas positivas sobre el uso potencial de LA en sus instituciones
- Hay expectativas más altas en los aspectos relacionados con “retos de implementación”
  - Necesidad de recibir información en el formato apropiadoNeed to receive information in the right format,
  - accuracy and scope,
  - Necesidad de guíado para acceder a datos con eficacia
- En comparación con otras zonas geográficas:
  - Más optimistas en cuanto a expectativas ideales que el estudio de Europa
  - Más pesimistas que el estudio de LATAM
  - El aspecto que genera una expectativa más baja es Q14 (obligation to act in support of students whose analytical results show poor performance)
- Contribuye con conocimiento acerca de expectativas sobre LA en diferentes zonas del planeta

SELAQ+ Limitations

- No cubre todas las regiones
- El muestreo no es probabilístico.
- Se necesita más comprensión mediante aproximaciones cualitativas para entender mejor qué se necesita

Índice

- Introducción
- SNOLA
  - Breve perspectiva histórica
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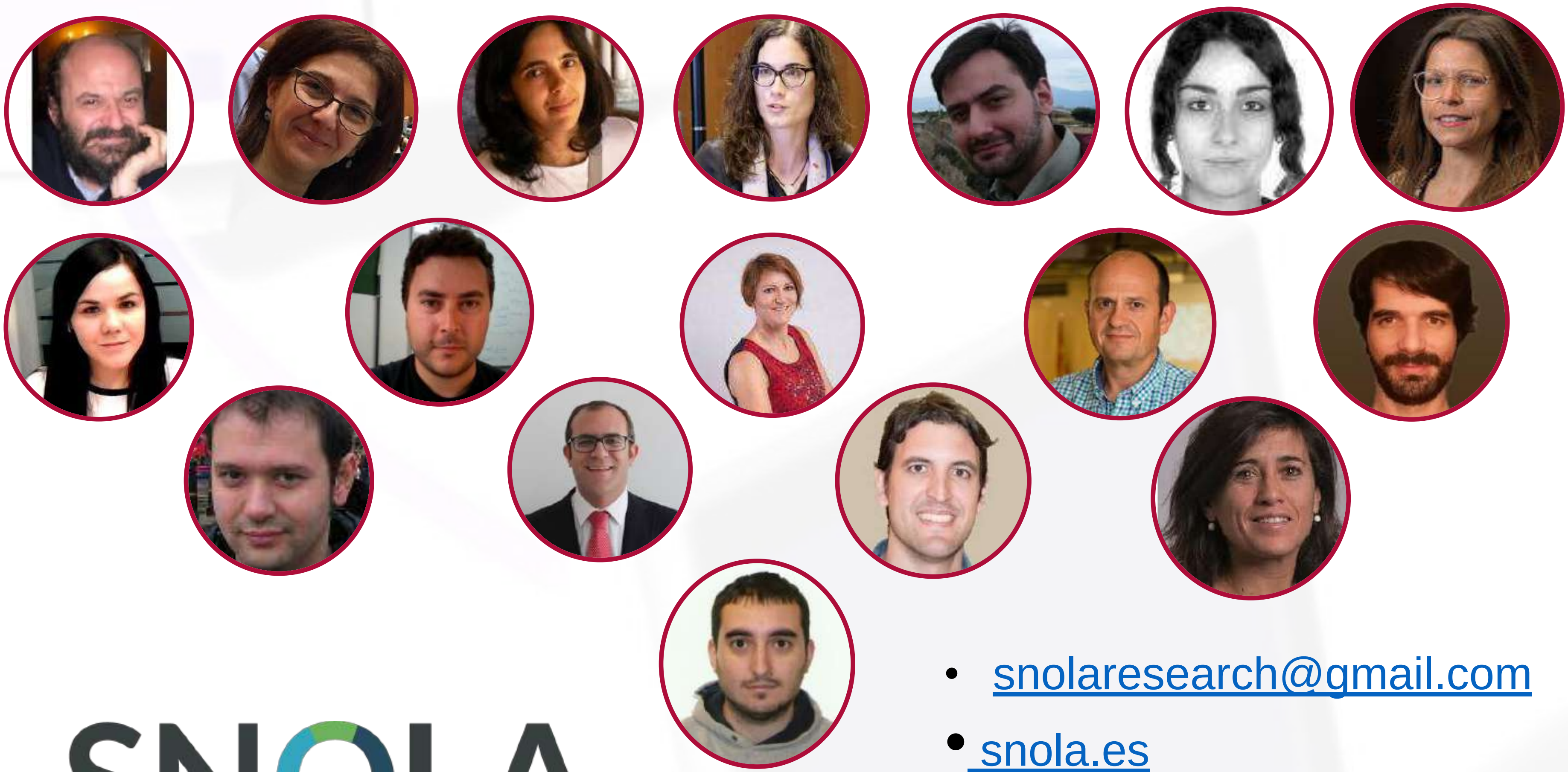
  - Acciones de SNOLA
- Reflexiones finales

Reflexiones finales

- La red SNOLA ha mantenido una actividad sostenida en el tiempo y ha servido de conexión con la comunidad de LA a nivel internacional
- La investigación se realiza desde áreas relacionadas con las TIC (incluso en grupos interdisciplinares), y hasta ahora ha conectado con pocas personas que trabajan en el tema en otras áreas (en España)
- El apoyo institucional existe, pero es limitado. Sin embargo, seguimos con ganas de realizar nuevos proyectos:
  - nanoMOOCs
  - Estudio sobre expectativas sobre LA en España

  ¿Otros que se puedan plantear?

Gracias de parte de todo el equipo de SNOLA!



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