

UEF | OAHOT @



Learning Analytics in Supporting Teaching and Learning – Pedagogical Perspectives

Professor Laura Hirsto

University of Eastern Finland, laura.hirsto@uef.fi

Keynote at CELDA 2022-conference

UEF// University of Eastern Finland

**BUSINESS
FINLAND**



Leverage from
the EU
2014–2020



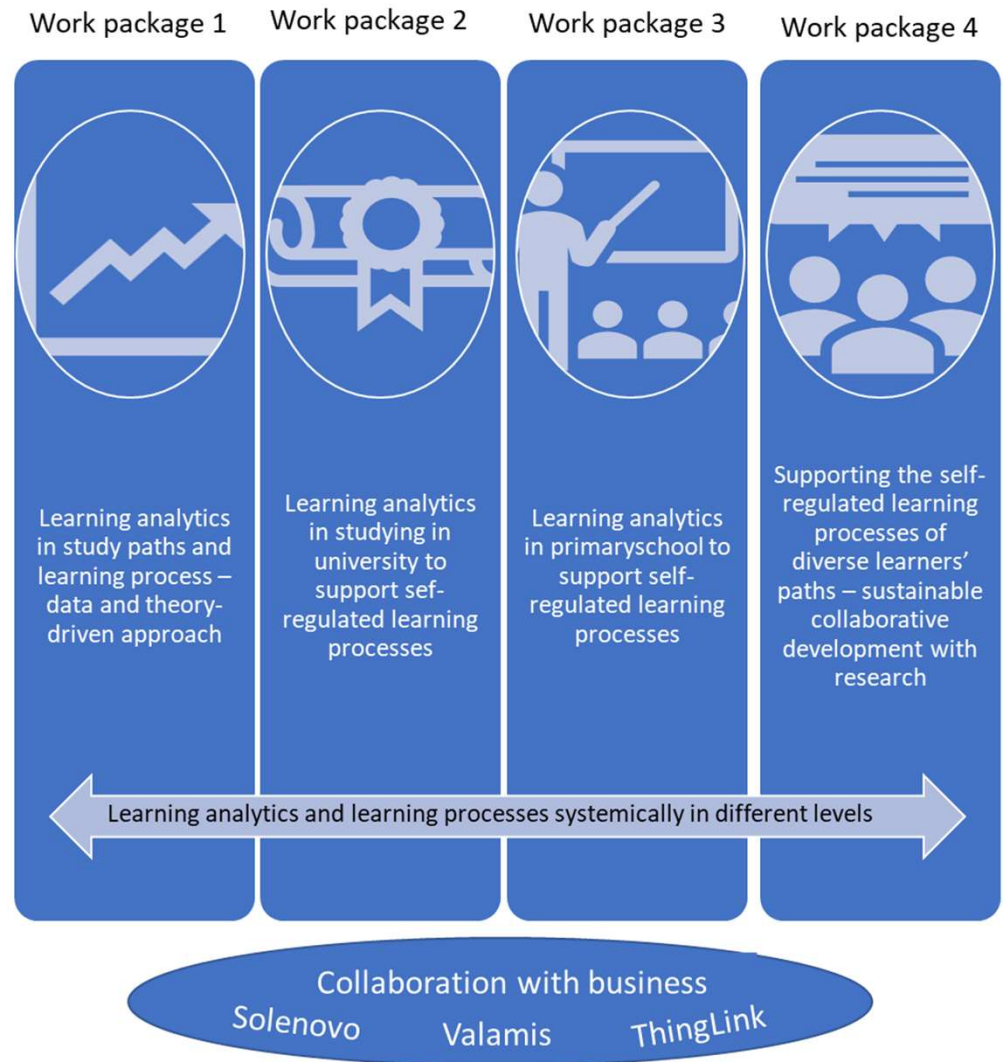
Utilizing Learning Analytics to support Self-regulated learning in various educational contexts – OAHOT 2020-22

- Laura Hirsto, PhD (Ed.psy), PI, Professor, University of Eastern Finland
- Sanna Väisänen, PhD (Ed.), Project manager, Postdoctoral researcher, University of Eastern Finland
- Matti Turtiainen, Dr. Professor, University of Eastern Finland
- Teemu Valtonen, PhD (Ed.), Professor, University of Eastern Finland
- Erkkö Sointu, PhD (Ed.), Professor, University of Eastern Finland
- Sonsoles López-Pernas, Assistant Professor, Universidad Politécnica de Madrid/ UEF
- Mohammed Saqr, PhD, Senior researcher, University of Eastern Finland
- Susanne Hallberg, MA (Ed.), Doctoral researcher, University of Eastern Finland
- Jenni Kankaanpää, MA (Ed.), Doctoral researcher, University of Eastern Finland
- Riina Kleimola, Phil.Lic (Ed.), Doctoral researcher, University of Lapland
- Jenni Bäckman, MA (Ed.), Project researcher, University of Eastern Finland
- Teija Paavilainen, Doctoral Researcher, Lecturer at the Rantakylä Teacher Training School, University of Eastern Finland
- Ville Tuominen, Doctoral researcher, Tampere University
- Lasse Heikkinen, PhD (Appl.phys), University lecturer, University of Eastern Finland
- Matias Huhtilainen, MA (Econ.), Doctoral researcher, University of Eastern Finland
- A number of Masters' thesis students

Contents

- OAHOT-project
- General perspectives on teachers' professional development and vocational education
- Perspectives on Learning analytics in higher education learning and pedagogy
- Learning analytics in elementary level teaching and learning
- Possibilities and challenges of pedagogy for/of LA

Utilizing Learning Analytics to support Self-regulated learning in various educational contexts - OAHOT 2020-22



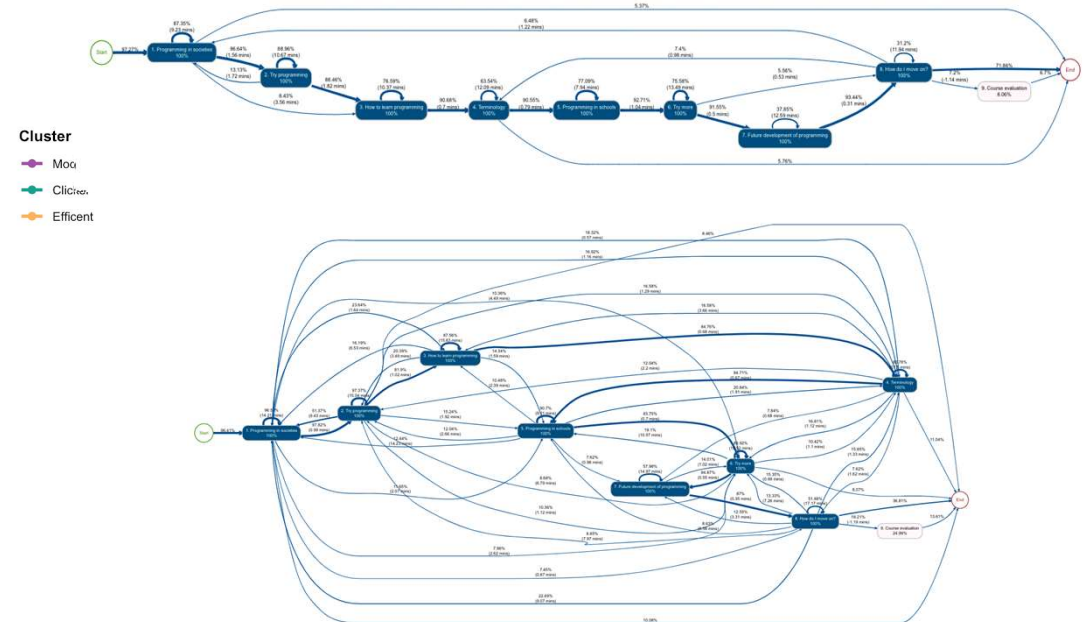
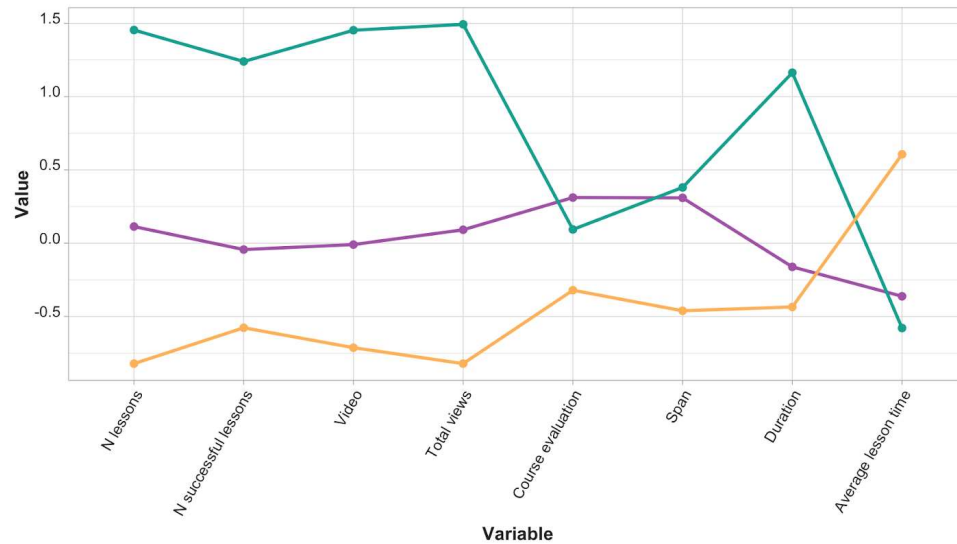
Utilizing Learning Analytics to support Self-regulated learning in various educational contexts - OAHOT 2020-22

- WP 1: Learning, motivational and SRL processes of teachers' professional development and vocational education (Prof. Matti Turtiainen)
- WP 2: LA and SRL, motivational and emotional processes in higher education context (Prof. Erkkö Sointu)
- WP 3: LA and SRL, reflective, motivational and emotional processes in elementary teaching and learning of phenomenon-based contexts (Prof. Teemu Valtonen)
- WP 4: Compiles an overall view of the critical factors of learning analytics for/of LA, study processes that are relevant in terms of the development and support of the learning process and regulation learning (Prof. Laura Hirsto)

General perspectives on LA of teachers' professional development and vocational education

Saqr, M., Tuominen, V., Valtonen, T., Sointu, E., Väisänen, S. & Hirsto, L. (2022). Teachers' learning profiles in learning programming: The big picture! *Frontiers in Education*, 7, 840178. doi: 10.3389/educ.2022.840178

Teachers' professional development - learning programming (Saqr, Tuominen, Valtonen, Sointu, Väisänen & Hirsto, 2022)

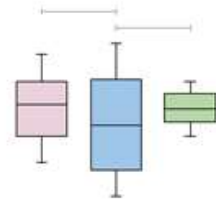


LA in vocational education – self-regulated learning and drop-outs? (Kleimola et al, Lopéz-Pernas et al.)

- Large cross-institutional LA data from various vocational education contexts
- Perspectives LA data provide on practical nurse students' motives to study?
- Challenge in institutional level data → processes of input of data vs. log-data
- Perspectives on motives to enter the training → e.g. obtaining a vocational qualification, improving career opportunities and having personal factors suitable for the field
- Helping others and personal calling less emphasized motive, although generally acknowledged as important in research → clusters of students: self-aware goal-achievers, qualification attainers and widely oriented humanitarians
- Relation between motives and achievement?
- Risk factors of dropping out of studies?

LA in vocational education – self-regulated learning and drop-outs? (Kleimola et al, Lopéz-Pernas et al.)

| | | |
|-------------------------------|-----|-----|
| I would like to get a degree | QIA | QUS |
| I want to work with people | HUM | |
| I want to make a lot of money | CAL | |
| I want to help others | INT | |
| I want to be just like my dad | FAM | |

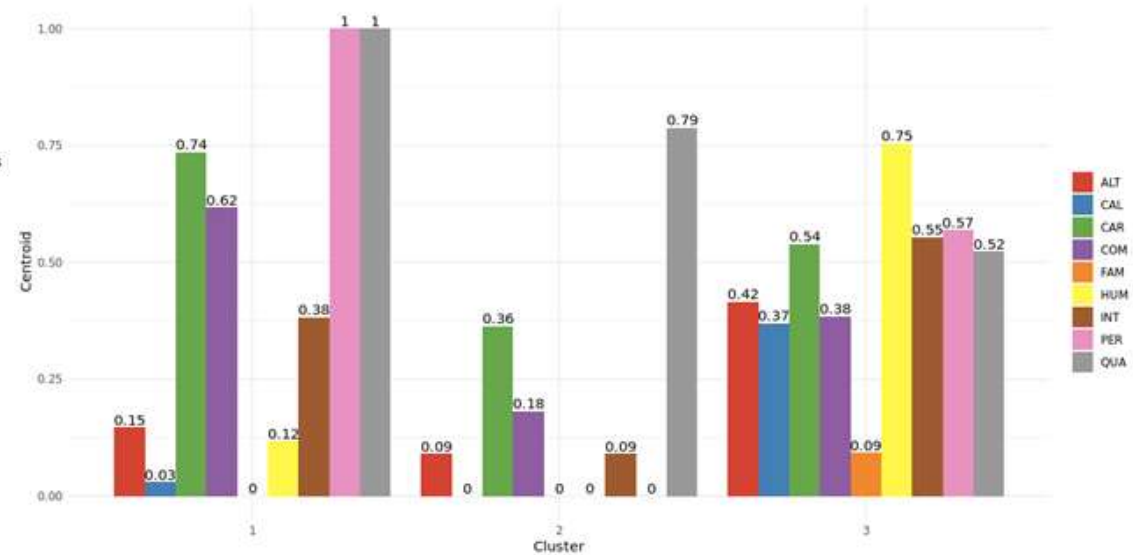


RQ1
Discovering motives through qualitative content analysis

RQ2
Clustering motives with LCA

RQ3
Exploring interplay between motives using ENA

RQ4
Investigating the relationship between motives and educational outcomes with ANOVA and Chi-squared tests



LA in higher education

- Sointu, E., Hirsto, L., Väisänen, S., Cutucache, C., & Valtonen, T. (2022) Insight of supporting the learning of a challenging content for special education preservice teachers with learning analytics. In T. Bastiaens (Ed.), Proceedings of EdMedia: World Conference on Educational Media and Technology (pp. 861-869). New York, NY, USA: Association for the Advancement of Computing in Education (AACE).
- Sointu, E., Saqr, M., Valtonen, T., Hallberg, S., Väisänen, S., Kankaanpää, J., Tuominen, V., & Hirsto, L. (2022). Emotional behavior in quantitative research methods course for preservice teachers. Learning analytics approach. In E. Langran (Ed.), Proceedings of Society for Information Technology & Teacher Education International Conference (pp. 2089-2098). San Diego, CA, United States: AACE.
- Sointu, E., Valtonen, T., Hallberg, S., Kankaanpää, J., Väisänen, S., Heikkinen, L., Saqr, M., Tuominen, V. & Hirsto, L. (2022). Learning analytics and flipped learning in online teaching for supporting preservice teachers' learning of quantitative research methods. Seminar.net – International Journal of Media, Technology & Life-long Learning, 18 (1): Special Issue MEC21. doi: 10.7577/seminar.4686

Design of the case-studies (WP2, WP3)

- Pre- ja post questionnaires
- Repeated reflective questionnaires (SRL, emotional processes, experiences) during the modules → Support for SRL process build into the modules (goals, monitoring, evaluation)
- Log-data from LMS
- Teachers', students' and pupils' interviews on SRL, Learning environment, LMS, LA and pedagogy of each module/case
- Observations of the teaching sessions x2

Emotional behavior

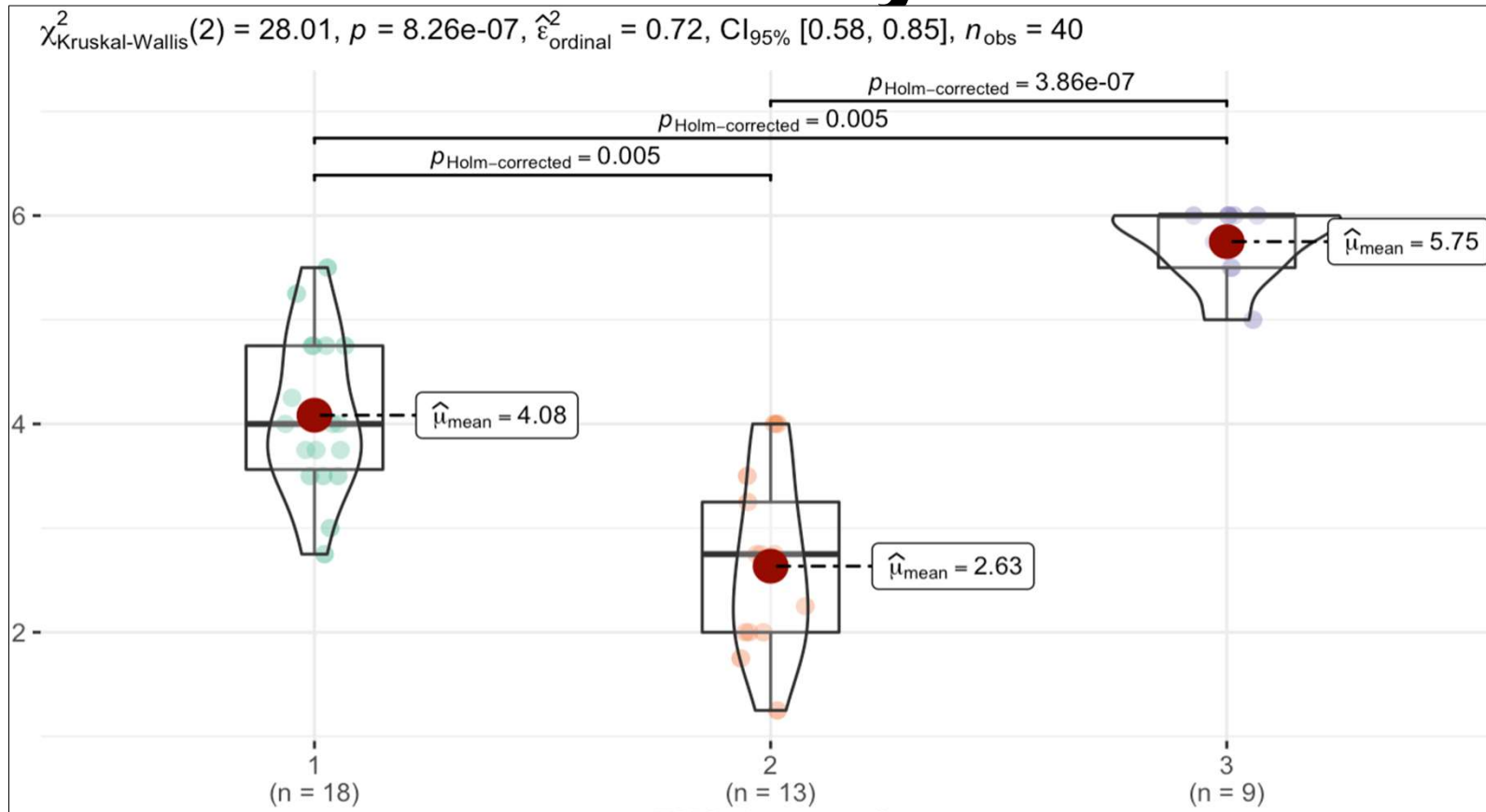
Sointu , E., Saqr, M., Valtonen, T., Hallberg, S., Väisänen, S., Kankaanpää, J., Tuominen, V. & Hirsto, L. (2022). Emotional behavior in quantitative research methods course for preservice teachers. Learning analytics approach. In E. Langran (Ed.) *Proceedings of Society for Information Technology & Teacher Education International Conference* (pp. 1880-1889). San Diego, CA, United States: Association for the Advancement of Computing in Education (AACE). Retrieved from <https://www.learntechlib.org/primary/p/220997/>.

Methods

Analysis

- DLA from **first measurement point** (T1)
 - Cluster analysis (K-means) of emotions
 - Goodness-of-fit
 - Silhouette for goodness of fit (Kodinariya & Makwana, 2013)
 - Separation based on Kruskal-Wallis (Ostertagová ym., 2014) with Holmen p (Aickin & Gensler, 1996)
 - Epsilon sqr ES, 95 % confidence interval (Rea & Parker, 2014)
- LA data **during the course** (learning materials use; time data)
 - Investigated within clusters
 - Uninterrupted students' activities (López-Pernas et al., 2021)

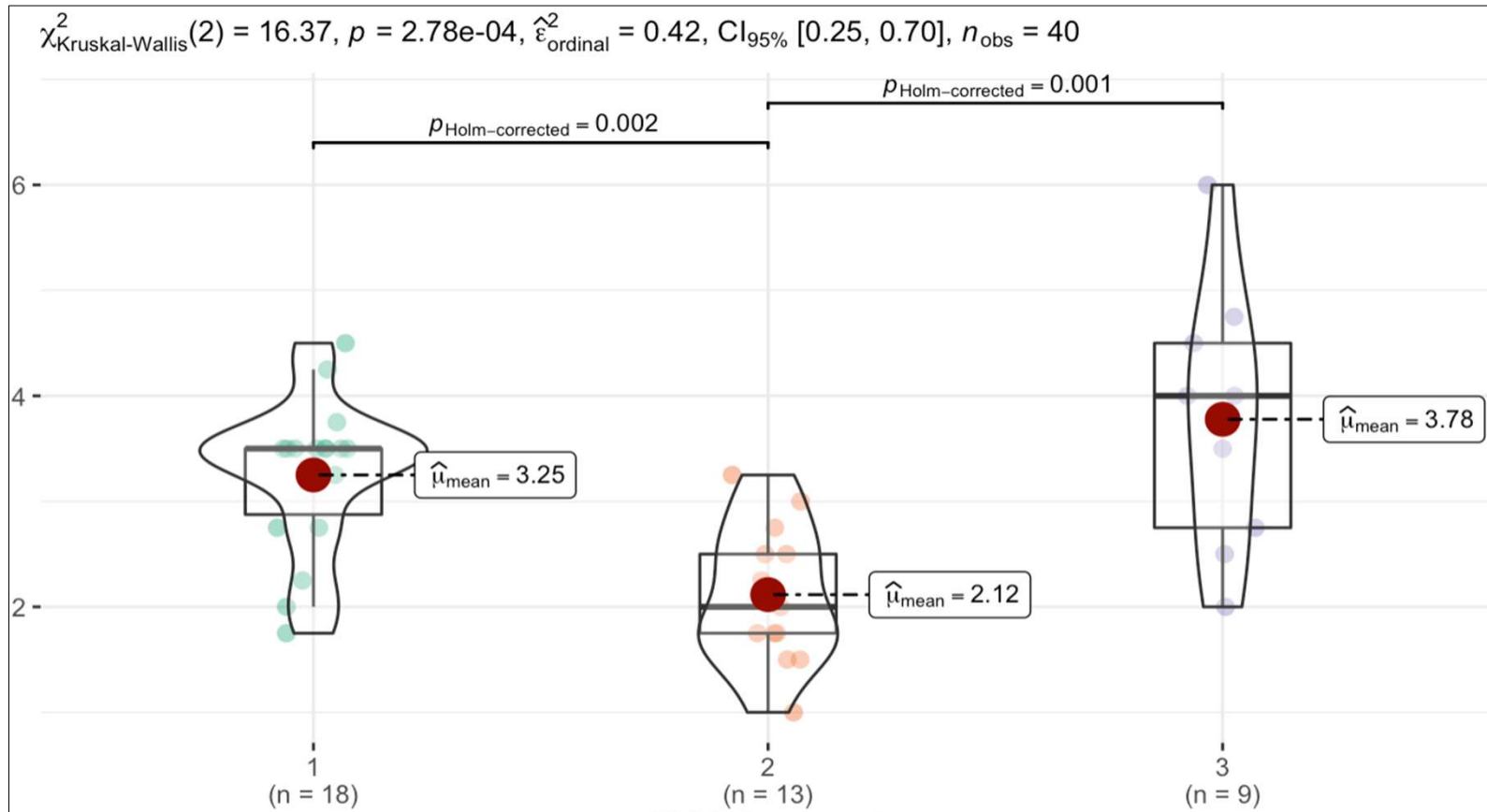
Anxiety



1 = Medium 2 = Pro quantitative 3 = Scared

Epsilon ES: negligible ($\epsilon^2 < 0.01$), weak ($\epsilon^2 = 0.01-0.04$), moderate ($\epsilon^2 = 0.04-0.16$), relatively strong ($\epsilon^2 = 0.16-0.36$), strong ($\epsilon^2 = 0.36-0.64$), very strong ($\epsilon^2 = 0.64-0.99$)

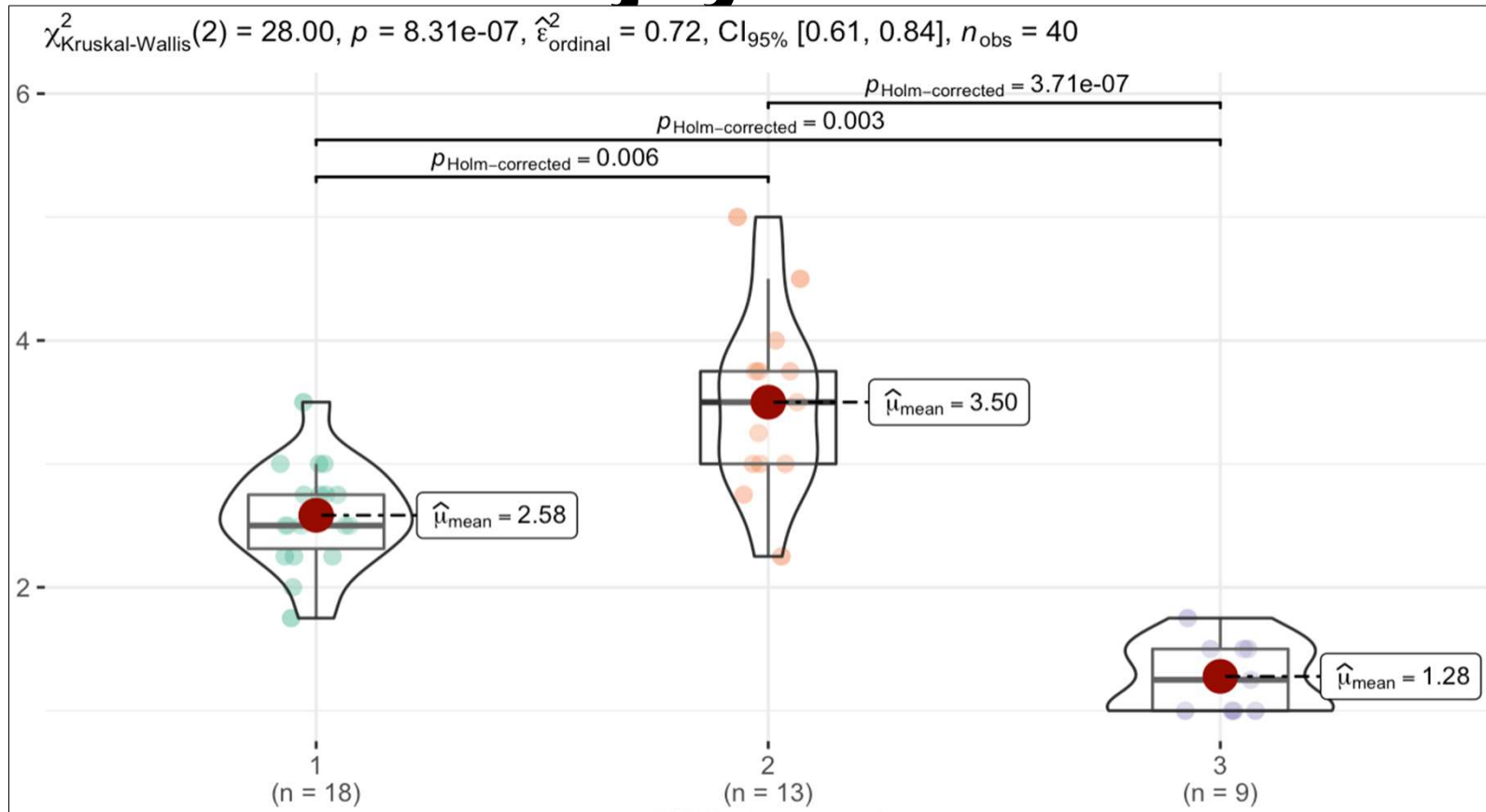
Boredom



1 = Medium 2 = Pro quantitative 3 = Scared

Epsilon ES : negligible ($\epsilon^2 < 0.01$), weak ($\epsilon^2 = 0.01 - 0.04$), moderate ($\epsilon^2 = 0.04 - 0.16$), relatively strong ($\epsilon^2 = 0.16 - 0.36$), strong ($\epsilon^2 = 0.36 - 0.64$), very strong ($\epsilon^2 = 0.64 - 0.99$)

Enjoyment



1 = Medium 2 = Pro quantitative 3 = Scared

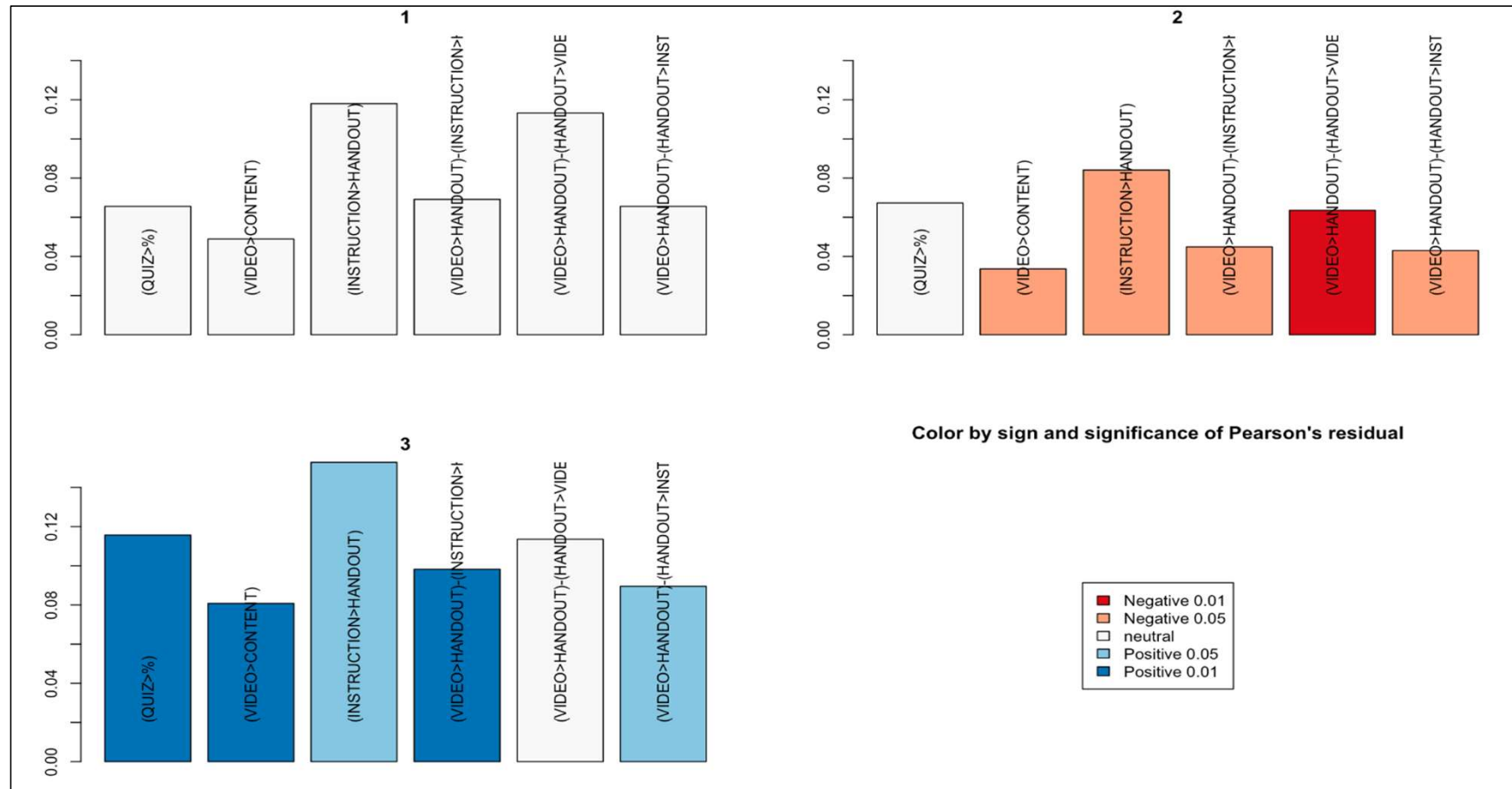
Epsilon ϵ^2 : negligible ($\epsilon^2 < 0.01$), weak ($\epsilon^2 = 0.01 - 0.04$), moderate ($\epsilon^2 = 0.04 - 0.16$), relatively strong ($\epsilon^2 = 0.16 - 0.36$), strong ($\epsilon^2 = 0.36 - 0.64$), very strong ($\epsilon^2 = 0.64 - 0.99$)

Use of learning materials

1 =
Medium

2 = Pro
quantitative

3 =
Scared



Students in Scared cluster were most active → emotions can be activating or deactivating
 → FL, LA and well-established digital learning environment support activation of learning

Students' approaches to learning (E.g Biggs, Entwistle)

- Deep approach, aiming at understanding
- Surface approach, aiming at remembering
- Strategic approach, strategically varying approach

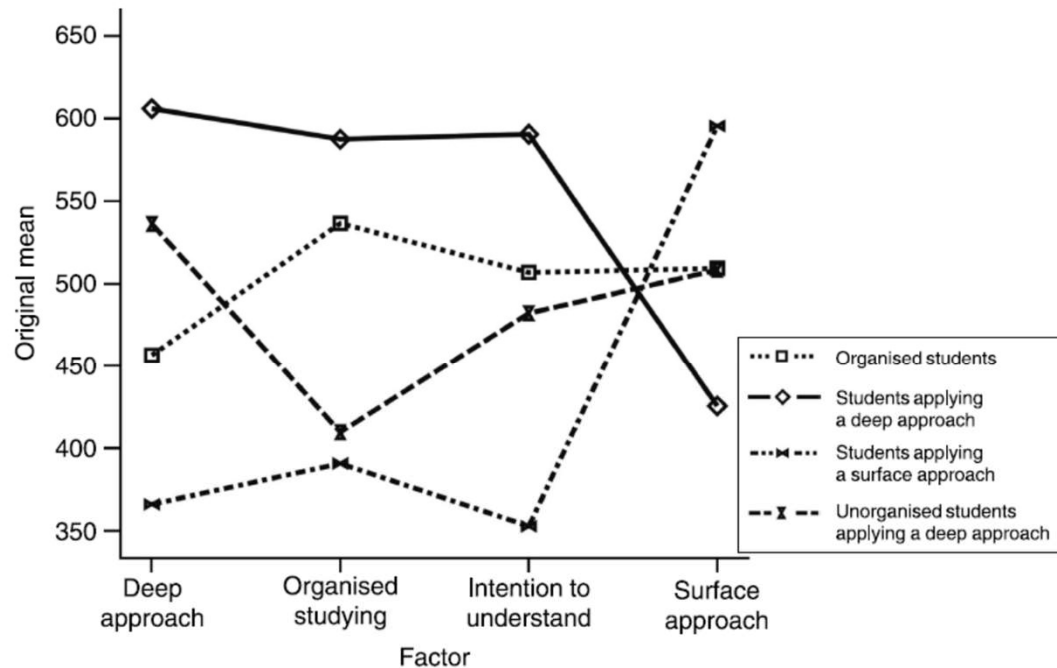


Figure 2. Cluster profiles.

Parpala, Lindblom-Ylänne, Komulainen, Litmanen & Hirsto, 2010)

LA in elementary education

- Hirsto, L., Valtonen, T., Saqr, M., Hallberg, S., Sointu, E., Kankaanpää, J. & Väisänen, S. (2022). Pupils' experiences of utilizing learning analytics to support self-regulated learning in two phenomenon-based study modules. In E. Langran (Ed.), Proceedings of Society for Information Technology & Teacher Education International Conference (pp. 1879-1885). San Diego, CA, United States: AACE.
- Väisänen, S., Hallberg, S., Valtonen, T., Tervo I.-A., Kankaanpää, J., Sointu, E. & Hirsto, L. (2022). Pupils' experiences of learning analytics visualizations in supporting self-regulated learning in an elementary school classroom. Seminar.net - International Journal of Media, Technology & Life-long Learning, 18 (1): Special Issue MEC21. doi: 10.7577/seminar.4690

Elementary school – Case Contexts

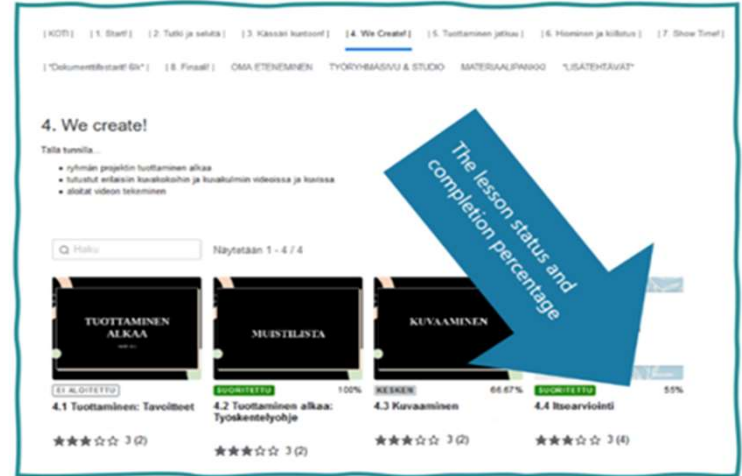
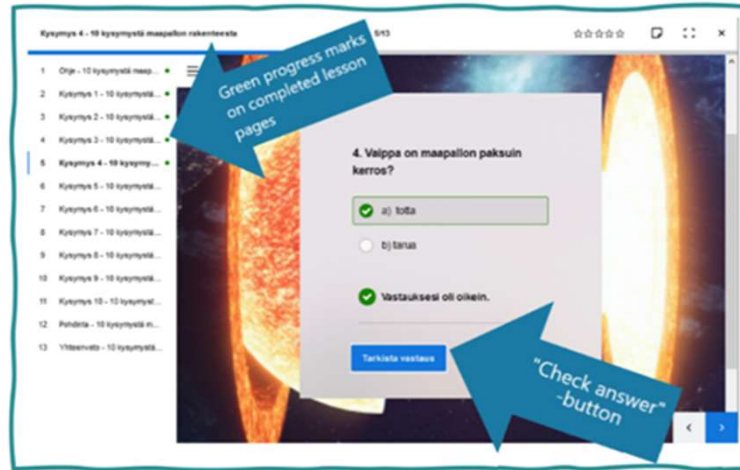
- Inquiry and phenomenon-based learning, emphasizing pupils' active roles, focusing on broader and typically interdisciplinary themes based on real-world phenomena (see e.g., Symeonidis & Schwartz, 2016), has received much attention lately.
- Especially within the Finnish elementary education the importance of phenomenon-based learning has been emphasized (e.g., Core Curriculum of Basic Education; FNBE, 2016).
- SRL with more personal technologies can transform the elementary level learning environment towards the environments where the role of the LA is more meaningful
 - - providing ways to better collect the user data and provide well targeted feedback and data for supporting pupils' SRL, especially their metacognitive thinking (Marzouk et al., 2016).

Elementary classroom environments

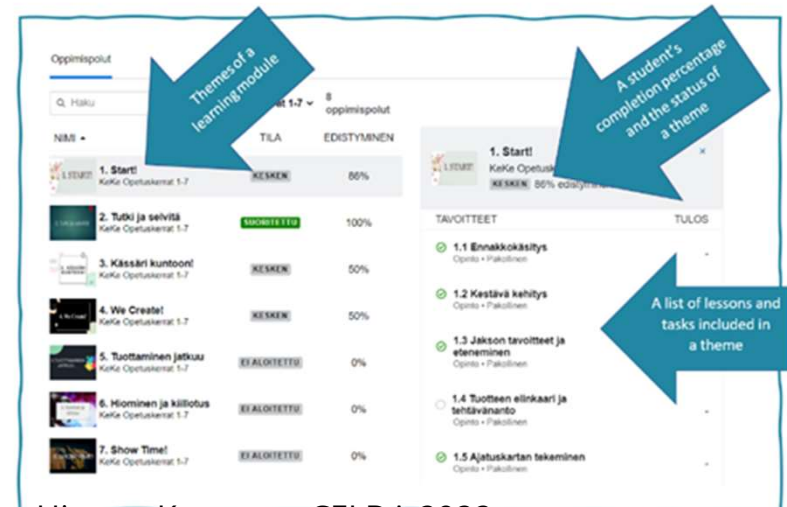
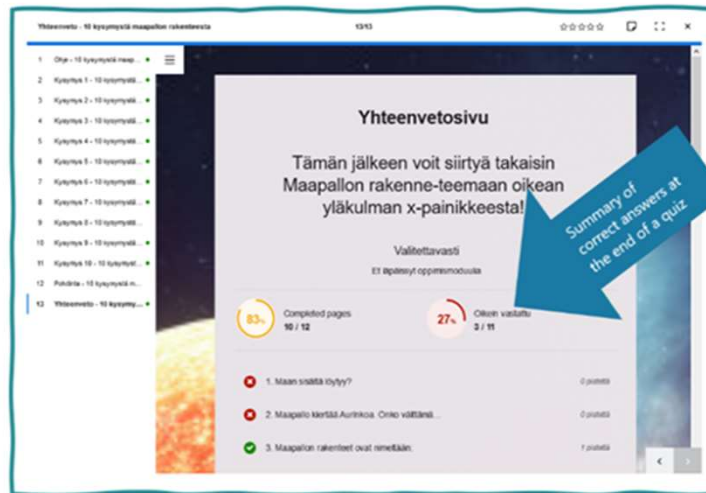


Elementary school - Case Contexts

Tools of Checking of Quizzes and an example of a theme page →



Examples of tools of a summary page and "My own Progress" -page →



Elementary school participants

- Elementary school pupils, 5th - 6th grade' (age 11-13)
- 89 pupils participated in the study modules
- UEF ethics approval (statement 11/2020), and informed consents from pupils and parents
- Data collected through LMS (logs and Dispositional Learning Analytics (DLA)) and separate end-questionnaire of the experiences
- LMS data for 89 pupils during two different kinds of modules
- 48/52 responded to the end-questionnaire (92%)
 - 58,3 % were 5th graders and 41,7 % 6th graders
 - 26% were 11 years, 52 % were 12 years, and 18 % were 13 years of age

Elementary school pupils' experiences

- Pupils' experience of self-regulated learning and learning analytics was positive and learning analytics was perceived as functional and motivating and to have helped their learning.
- Pupils also became increasingly self-directed during the study module.
 - However, setting goals, and managing to pursue them, appeared to be quite difficult for many pupils.
- The role of learning analytics as an important additional level of support for pupils' self-regulated learning.
- Need for further developing pedagogical approaches to using learning analytics within the context of the elementary level classroom.

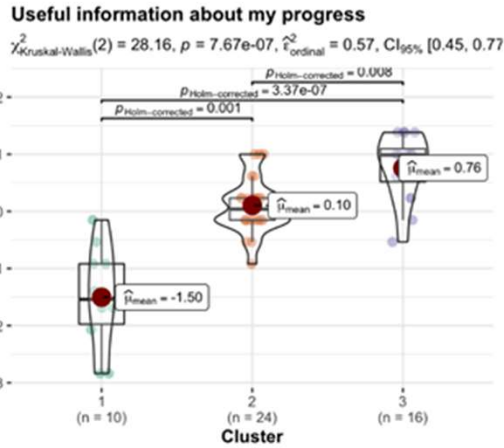
Pupils' experiences

Table 1. Descriptive statistics and correlation (Kendall's tau) of learning analytics subscales

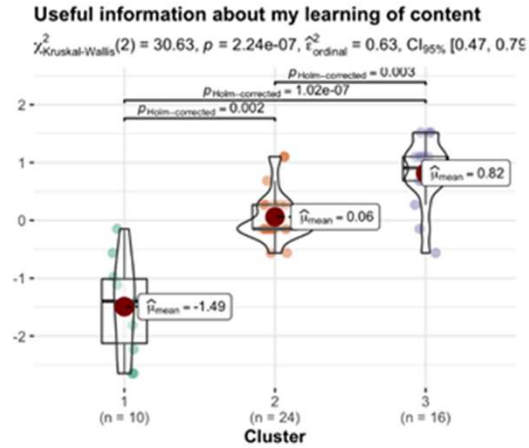
| Learning analytics subscale: | Descriptive statistics | Correlation | | | |
|---|------------------------|-------------|------|------|-----|
| | <i>M</i> (<i>SD</i>) | 1 | 2 | 3 | 4 |
| 1 Learning analytics has given useful information about my progress | 3.10 (0.65) | | | | |
| 2 LA has given me useful information about my learning of content | 3.09 (0.60) | .75 | | | |
| 3 Using LA has been frustrating | 1.53 (0.61) | -.35 | -.51 | | |
| 4 Using LA has strengthened my study skills | 2.68 (0.85) | .53 | .54 | -.44 | |
| 5 Using LA has strengthened my self-efficacy for learning | 2.60 (0.85) | .54 | .55 | -.38 | .78 |

Note., *M* mean, *SD* standard deviation, results presented in *M* and *SD* to keep the original metric of the response categories (i.e., 1 = Strongly disagree - 4 = Strongly agree) for interpretation. Number in the correlation column represents learning analytics subscale, all correlations statistically significant $p < 0.01$.

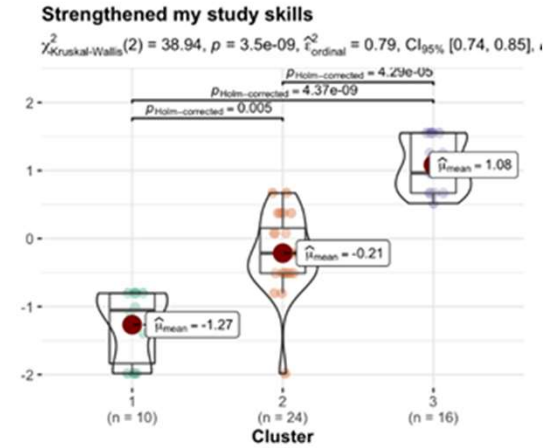
Clusters of experiences



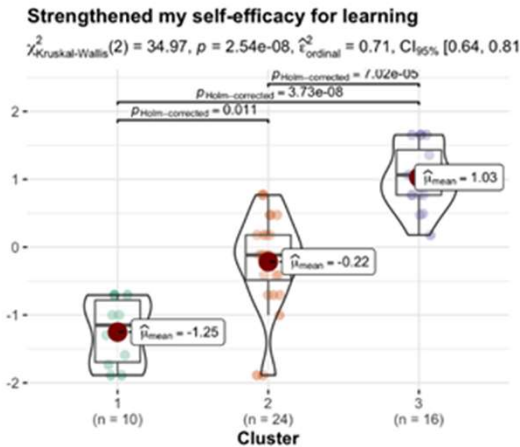
Pairwise test: **Dunn test**; Comparisons shown: **only significant**



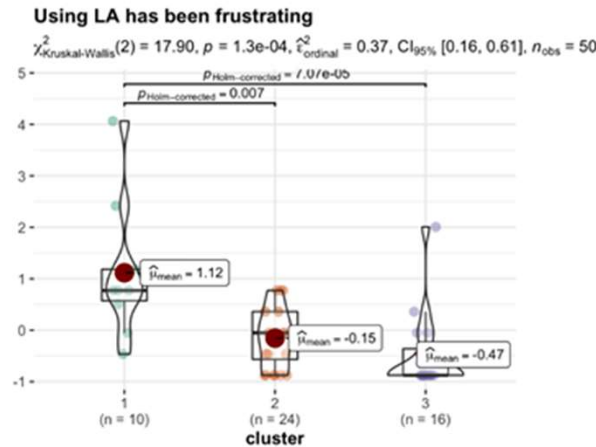
Pairwise test: **Dunn test**; Comparisons shown: **only significant**



Pairwise test: **Dunn test**; Comparisons shown: **only significant**



Pairwise test: **Dunn test**; Comparisons shown: **only significant**



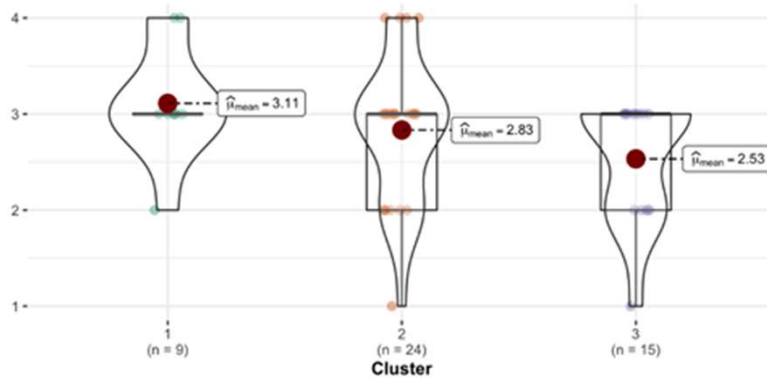
Pairwise test: **Dunn test**; Comparisons shown: **only significant**

Epsilon ES : negligible ($\epsilon^2 < 0.01$), weak ($\epsilon^2 = 0.01 - 0.04$), moderate ($\epsilon^2 = 0.04 - 0.16$), relatively strong ($\epsilon^2 = 0.16 - 0.36$), strong ($\epsilon^2 = 0.36 - 0.64$), very strong ($\epsilon^2 = 0.64 - 0.99$)

Experiences in relation to usage of La

Followed my own progress page

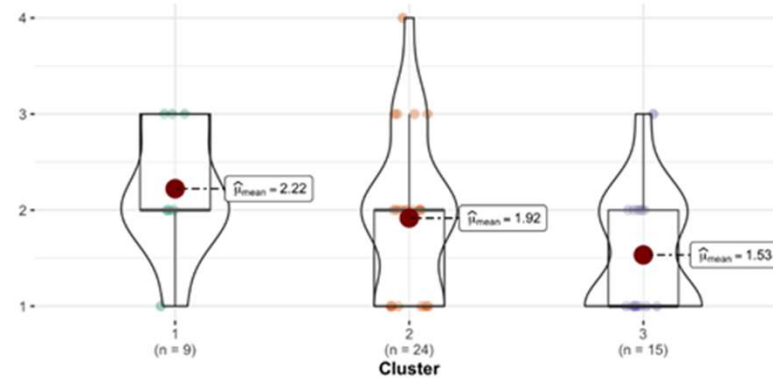
$\chi^2_{Kruskal-Wallis}(2) = 3.83, p = 0.147, \hat{\epsilon}^2_{ordinal} = 0.08, CI_{95\%} [0.01, 0.27], n_{obs} = 48$



Pairwise test: Dunn test; Comparisons shown: only significant

Followed the theme page

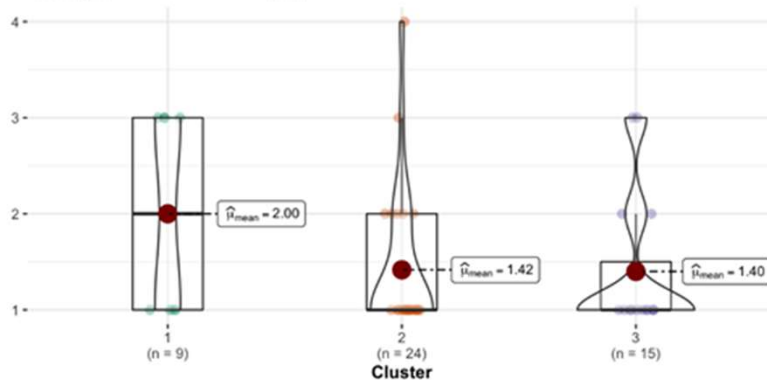
$\chi^2_{Kruskal-Wallis}(2) = 5.21, p = 0.074, \hat{\epsilon}^2_{ordinal} = 0.11, CI_{95\%} [0.01, 0.36], n_{obs} = 48$



Pairwise test: Dunn test; Comparisons shown: only significant

Followed checking of quizzes

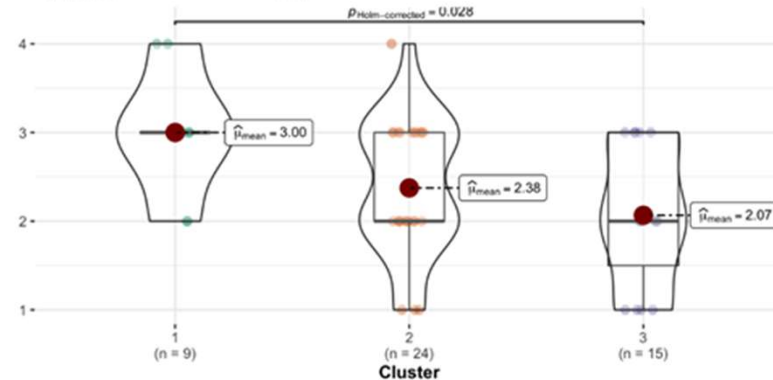
$\chi^2_{Kruskal-Wallis}(2) = 3.38, p = 0.185, \hat{\epsilon}^2_{ordinal} = 0.07, CI_{95\%} [6.48e-03, 0.46], n_{obs} = 48$



Pairwise test: Dunn test; Comparisons shown: only significant

Followed summary pages

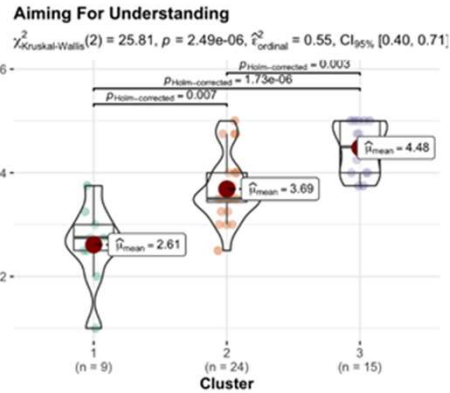
$\chi^2_{Kruskal-Wallis}(2) = 6.80, p = 0.033, \hat{\epsilon}^2_{ordinal} = 0.14, CI_{95\%} [0.03, 0.38], n_{obs} = 48$



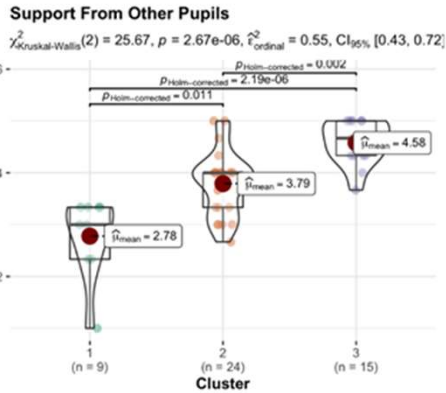
Pairwise test: Dunn test; Comparisons shown: only significant

Epsilon ϵ^2 : negligible ($\epsilon^2 < 0.01$), weak ($\epsilon^2 = 0.01 - 0.04$), moderate ($\epsilon^2 = 0.04 - 0.16$), relatively strong ($\epsilon^2 = 0.16 - 0.36$), strong ($\epsilon^2 = 0.36 - 0.64$), very strong ($\epsilon^2 = 0.64 - 0.99$)

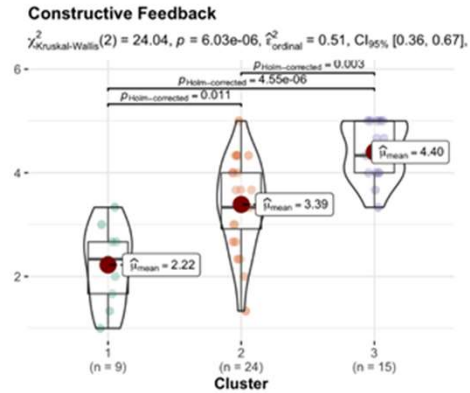
General experiences of T-L-environment



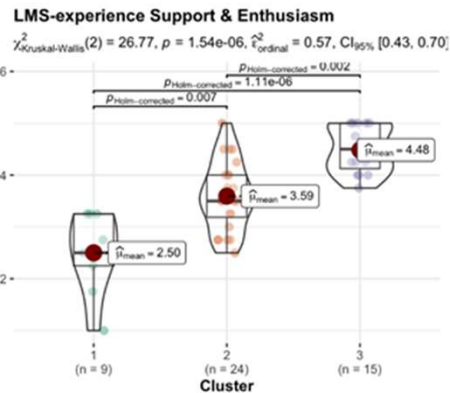
Pairwise test: **Dunn test**; Comparisons shown: **only significant**



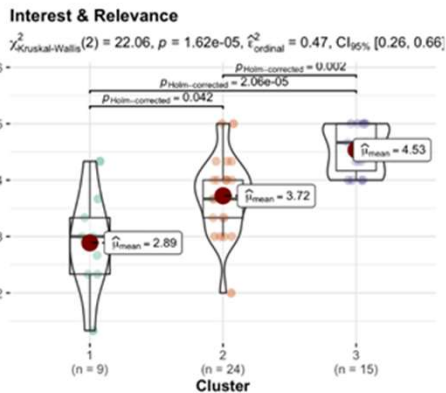
Pairwise test: **Dunn test**; Comparisons shown: **only significant**



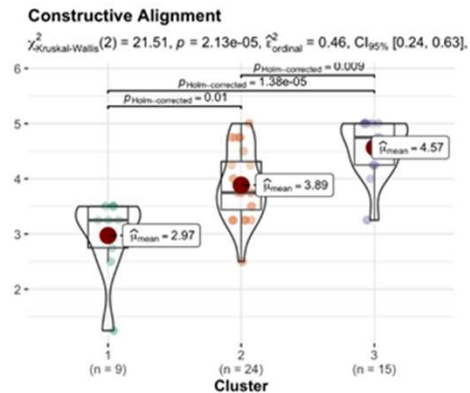
Pairwise test: **Dunn test**; Comparisons shown: **only significant**



Pairwise test: **Dunn test**; Comparisons shown: **only significant**



Pairwise test: **Dunn test**; Comparisons shown: **only significant**

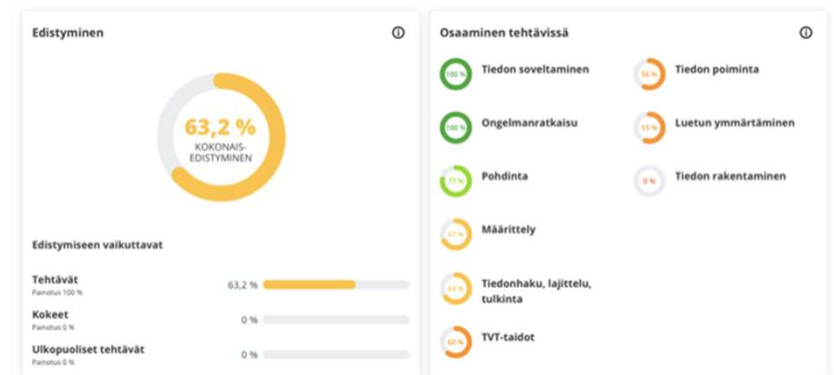
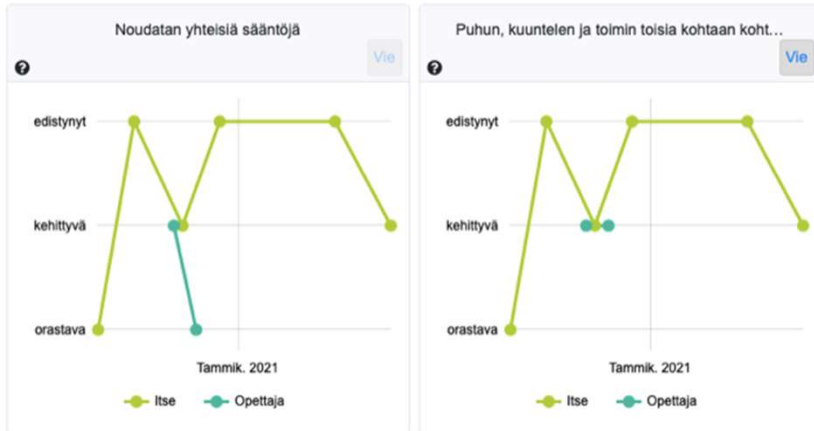
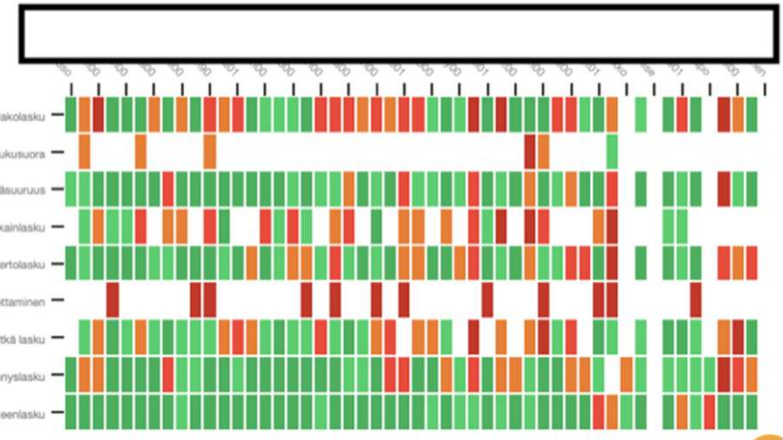
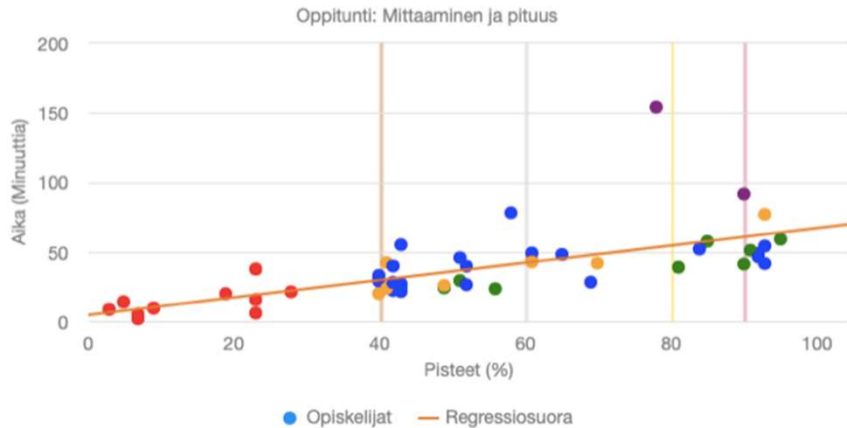


Pairwise test: **Dunn test**; Comparisons shown: **only significant**

Theoretical perspectives to education and curriculum

- Hirsto, L., Sointu, E., Valtonen, T., Turtiainen, M. & Väisänen, S. (2022). Learning analytics in teaching and learning processes in multiple contexts. In T. Bastiaens (Ed.), Proceedings of EdMedia: World Conference on Educational Media and Technology (pp. 359-861). New York, NY, USA: Association for the Advancement of Computing in Education (AACE).
- Valtonen, T., Hirsto, L., Sointu, E. & Väisänen, S. (2022). Learning Analytics Pedagogy - Possibilities and Challenges. In T. Bastiaens (Ed.), Proceedings of EdMedia: World Conference on Educational Media and Technology (pp. 362-366). New York, NY, USA: Association for the Advancement of Computing in Education (AACE).
- Saqr, M., Elmoazen, R., Tedre, M., López-Pernas, S. & Hirsto, L. (2022). How well centrality measures capture student achievement in computer-supported collaborative learning? – A systematic review and meta-analysis. Educational Research Review, 35, 100437. <https://doi.org/10.1016/j.edurev.2022.100437>.

Visualizations from various learning applications



Measuring and collecting data for:

Visualizations Personalization Assessment Research

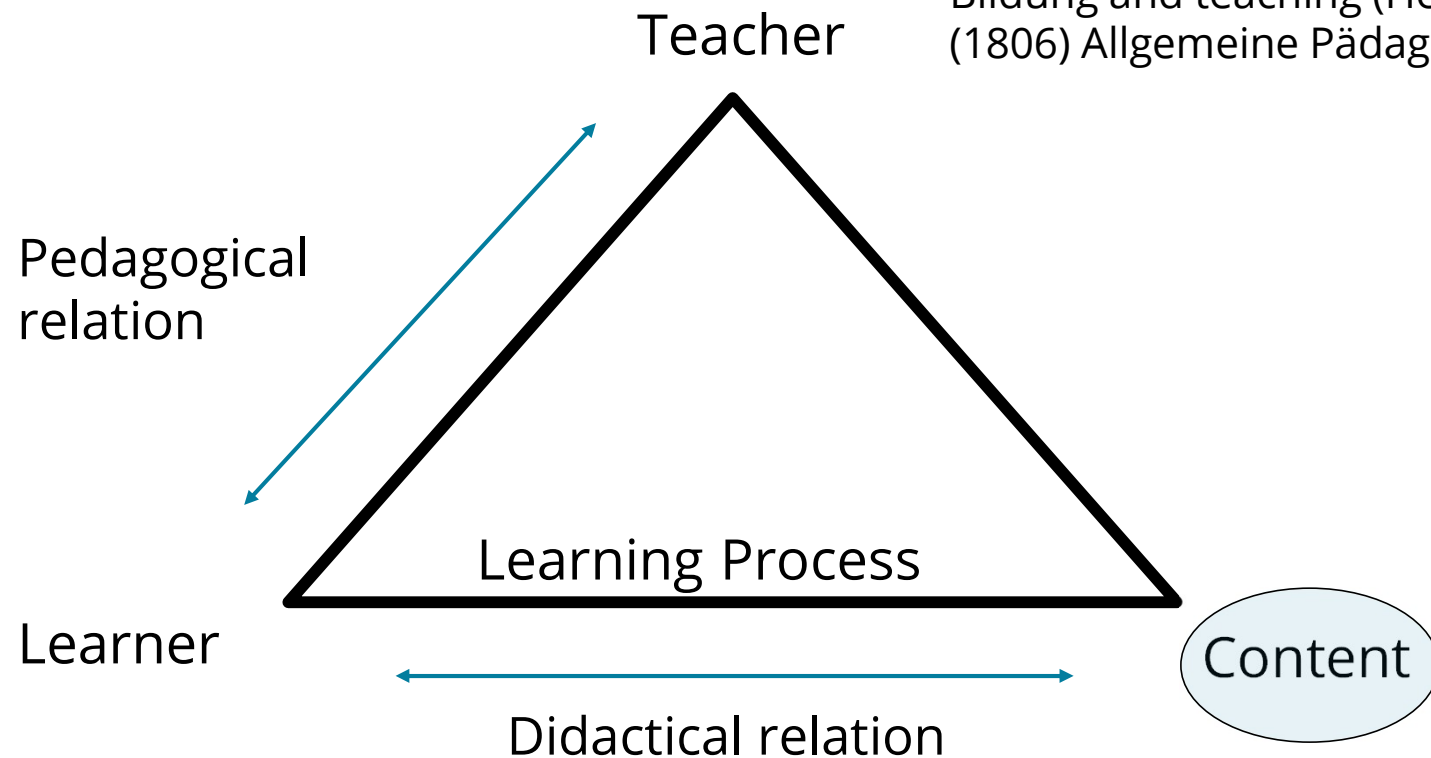
Centrality measures and achievement?

(Saqr, Elmoazen, Tedre, Lopéz-Pernas & Hirsto, 2022)

- A systematic review and meta-analysis of 19 studies that included 33 cohorts and 16 centrality measures
- Achievement was operationalized in most of the reviewed studies as final course grade
- This finding corroborates the individual studies' claims for robustness and reliability of degree- and eigenvector-based centrality measures in translating students' interactions into achievement indicators.
 - Degree centrality: usually computed as the number of posts, comments, or contacts a learner makes or receives
 - Eigenvector centrality is a measure of an individual's importance based on the total centralities of the individual's neighbors, where connection to other important (influential) nodes results in higher eigenvector scores.
- In contrast, betweenness and closeness centralities have shown mixed or weak correlations with achievement.
 - Betweenness: Betweenness centrality reflects the number of times a person has connected with others
 - Closeness: measures the distance to all other collaborators and, by emphasizing all, it penalizes selectivity
- These findings support the use of centrality measures for monitoring interactions in collaborative learning settings

Didactical triangle (e.g. Siljander; 2002, 51)

The difference between
Bildung and teaching (Herbart
(1806) Allgemeine Pädagogik)



Pedagogical implications of behaviorism

- 1) Set behavioral goals
- 2) Divide the study material into sub-components
- 3) Identify appropriate behavioral enhancers (rewards, punishments)
- 4) Teaching is carried out step by step
- 5) Evaluate the results at the end

Pedagogical implications of constructivism

- 1) The learner's previous knowledge as a basis for new learning
- 2) Learning is the result of the learner's own activities
-> Development of metacognitive skills
- 3) Understanding is more important than memorization
-> From fact-based to problem-oriented
- 4) Taking into account the situational nature of learning
-> Development of versatile representations
- 5) Highlighting the proportionality of information and production methods
- 6) Emphasis on social interaction
- 7) Goals oriented learning is a skill that can be learned

Theoretizing teacher thinking and actions

Pedagogical reasoning, Shulman, 1987

The Reflective Practitioner, Schön, 1983

Craft knowledge, Grimmett & MacKinnon, 1992

Conceptions of Teaching, Kember, 1997

Technological Pedagogical Content Knowledge, Mishra & Koehler, 2006

Discussion

Perspectives on the role of LA in education

- Bildung –approach vs. Curriculum –approach
 - Teachers' role/ teachers' pedagogical thinking?
 - Motivational, emotional, epistemic processes/ learning orientations, learning approaches, conceptions of learning?
- Assessment?
 - Diagnostic, Formative, Summative, and/or Assessment for learning?
- Function of LA in teaching and pedagogy?

Discussion and ideas for the future

- Blended facilities provide opportunities for using LA within elementary context
- LA vs. DLA
- Combining visualizations
- Learning to read and interpret data – quantitative methods for teachers
- Added value vs. special requirements
- Possibilities for co-constructive development of LA for teachers

References

- Hirsto, L., Valtonen, T., Saqr, M., Hallberg, S., Sointu, E., Kankaanpää, J. & Väisänen, S. (2022). Pupils' experiences of utilizing learning analytics to support self-regulated learning in two phenomenon-based study modules. In E. Langran (Ed.), *Proceedings of Society for Information Technology & Teacher Education International Conference* (pp. 1879-1885). San Diego, CA, United States: AACE.
- Hirsto, L., Sointu, E., Valtonen, T., Turtiainen, M. & Väisänen, S. (2022). Learning analytics in teaching and learning processes in multiple contexts. In T. Bastiaens (Ed.), *Proceedings of EdMedia: World Conference on Educational Media and Technology* (pp. 359-861). New York, NY, USA: Association for the Advancement of Computing in Education (AACE).
- Saqr, M., Elmoazen, R., Tedre, M., López-Pernas, S. & Hirsto, L. (2022). How well centrality measures capture student achievement in computer-supported collaborative learning? – A systematic review and meta-analysis. *Educational Research Review*, 35, 100437. <https://doi.org/10.1016/j.edurev.2022.100437>.
- Saqr, M., Tuominen, V., Valtonen, T., Sointu, E., Väisänen, S. & Hirsto, L. (2022). Teachers' learning profiles in learning programming: The big picture! *Frontiers in Education*, 7, 840178. doi: 10.3389/educ.2022.840178
- Sointu, E., Hirsto, L., Väisänen, S., Cutucache, C., & Valtonen, T. (2022) Insight of supporting the learning of a challenging content for special education preservice teachers with learning analytics. In T. Bastiaens (Ed.), *Proceedings of EdMedia: World Conference on Educational Media and Technology* (pp. 861-869). New York, NY, USA: Association for the Advancement of Computing in Education (AACE).
- Sointu, E., Saqr, M., Valtonen, T., Hallberg, S., Väisänen, S., Kankaanpää, J., Tuominen, V., & Hirsto, L. (2022). Emotional behavior in quantitative research methods course for preservice teachers. Learning analytics approach. In E. Langran (Ed.), *Proceedings of Society for Information Technology & Teacher Education International Conference* (pp. 2089-2098). San Diego, CA, United States: AACE.
- Sointu, E., Valtonen, T., Hallberg, S., Kankaanpää, J., Väisänen, S., Heikkinen, L., Saqr, M., Tuominen, V. & Hirsto, L. (2022). Learning analytics and flipped learning in online teaching for supporting preservice teachers' learning of quantitative research methods. *Seminar.net – International Journal of Media, Technology & Life-long Learning*, 18 (1): Special Issue MEC21. doi: 10.7577/seminar.4686
- Valtonen, T., Hirsto, L., Sointu, E. & Väisänen, S. (2022). Learning Analytics Pedagogy - Possibilities and Challenges. In T. Bastiaens (Ed.), *Proceedings of EdMedia: World Conference on Educational Media and Technology* (pp. 362-366). New York, NY, USA: Association for the Advancement of Computing in Education (AACE).
- Valtonen, T., López-Pernas, S., Saqr, M., Vartiainen, H., Sointu, E. T., & Tedre, M. (2022). The nature and building blocks of educational technology research. *Computers in Human Behavior*, 128, 107123.
- Väisänen, S., Hallberg, S., Valtonen, T., Tervo I.-A., Kankaanpää, J., Sointu, E. & Hirsto, L. (2022). Pupils' experiences of learning analytics visualizations in supporting self-regulated learning in an elementary school classroom. *Seminar.net - International Journal of Media, Technology & Life-long Learning*, 18 (1): Special Issue MEC21. doi: 10.7577/seminar.4690

UEF | OAHOT

www.uef.fi/oahot

<https://uefconnect.uef.fi> + OAHOT

laura.hirsto@uef.fi

Follow at



@LauraHirsto

@UEF_OAHOT



KIITOS!

UEF// University of Eastern Finland

**BUSINESS
FINLAND**



Leverage from
the EU
2014–2020

