Classroom Collaboration Analytics: Designing and Building Automated Systems for Collaboration Monitoring in Classroom Settings

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TALLINN UNIVERSITY

AGENDA

Introduction

Research Gaps

Research Questions

Research Methodology

Contributions

Discussion

Ethical concerns NEW

Limitations and Future work

Conclusion

3

2

1

INTRODUCTION

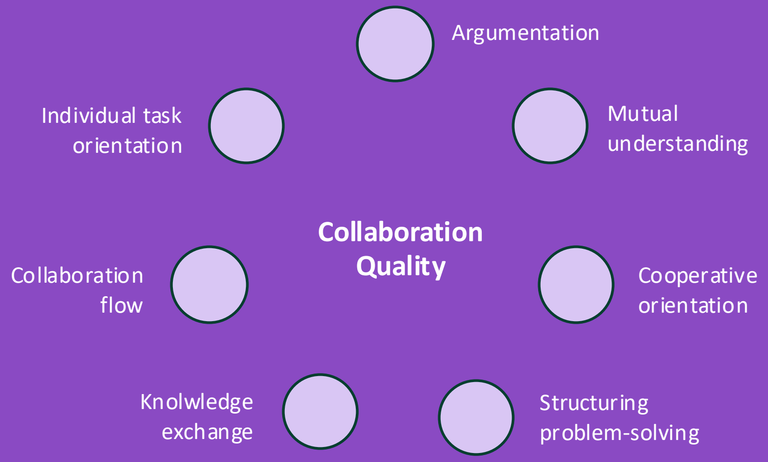
3

2

COLLABORATION

Difficult for teachers to monitor and detect problems **(Chounta & Avouris, 2016)**

Collaboration is a complex construct **(Rummel et al., 2011).**



1 **INTRODUCTION**

3

MULTIMODAL LEARNING ANALYTICS

Captures multimodality of students' interactions.

Uses sensors along with log data **(Ochoa et al., 2017).**

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INTRODUCTION

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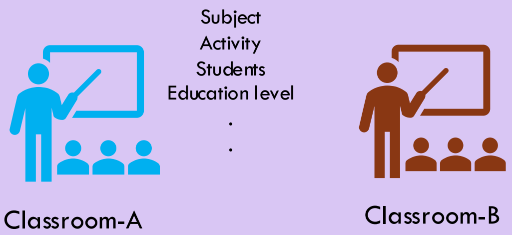
GENERALIZABILITY

Ability of machine learning models to perform well on unseen data (**Raschka, 2018**).

Example: a engagement model developed on class A's data applied in class B (across-context).



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1

INTRODUCTION

RESEARCH GAPS

1

Lack of systematization in generalizability evaluation of MMLA based solutions

Reilly & Schneider, 2019

2

Lack of knowledge over building generalizable collaboration quality estimation models

Grover et al., 2016

Bassiou et al., 2016

3

Lack of knowledge over extent of generalizability of collaboration estimation models in classroom settings

Viswanathan & Vanlehn, 2018

RESEARCH QUESTIONS

NEW

How to build and assess across-context generalizable machine learning models for the estimation of collaboration quality and its dimensions in small groups in authentic classroom face-to-face settings?

1

How can we systematically assess and report the generalizability of collaboration quality models?

2

NEW

How to build across-context generalizable collaboration quality estimation models?

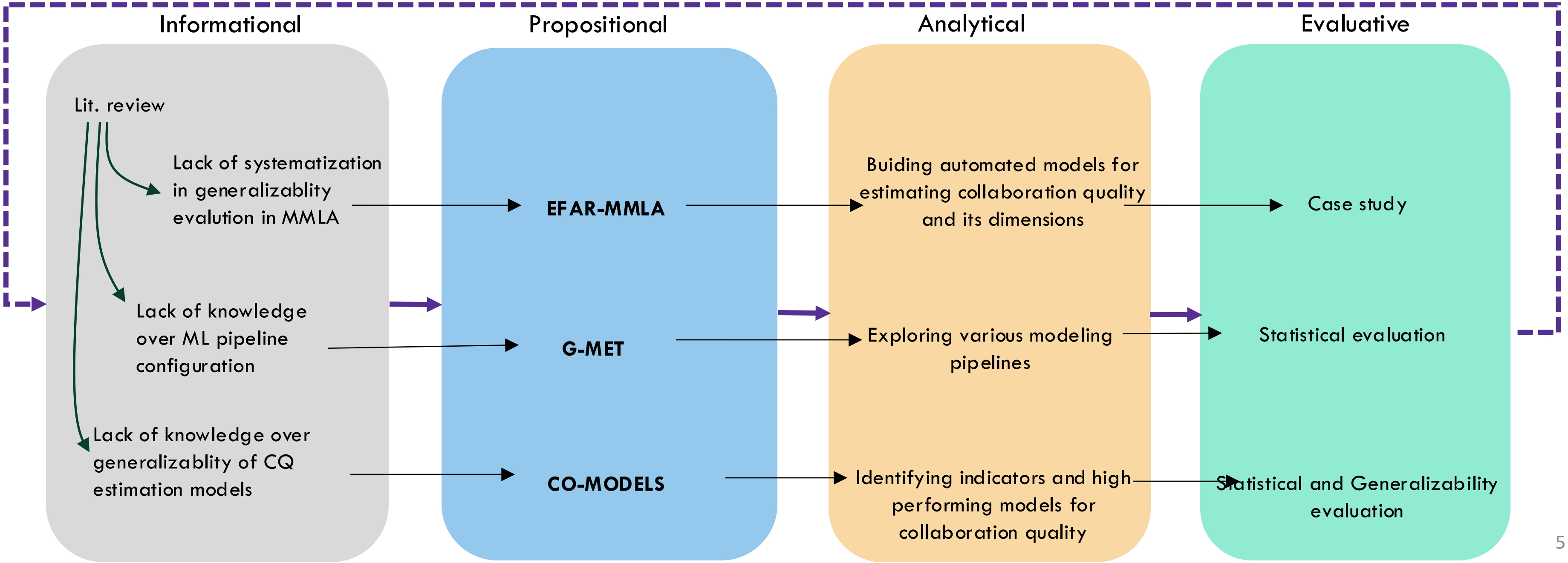
3

How well do estimation models for collaboration quality perform across contexts?

RESEARCH METHODOLOGY

Engineering Method

(Basili et al., 1993)



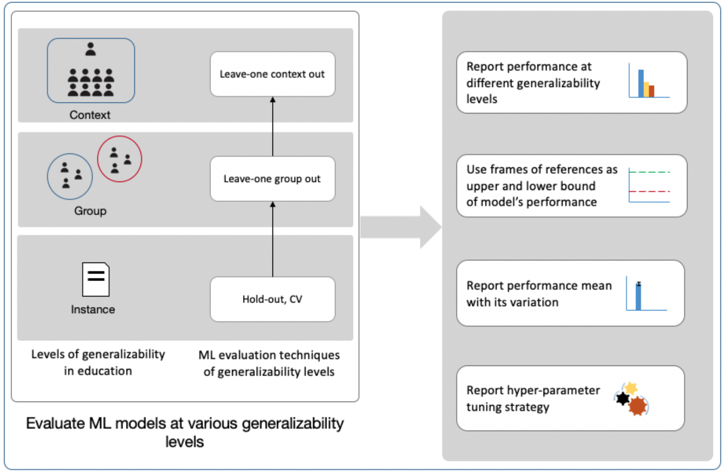
CONTRIBUTIONS

1. EFAR-MMLA
2. G-MET
3. CO-MODELS
4. COTRACK

CONTRIBUTIONS

1

EFAR-MMLA: Evaluation framework for assessing and reporting generalizability



Chejara, P., Prieto, L. P., Ruiz-Calleja, A., Rodríguez-Triana, M. J., Shankar, S. K., & Kasepalu, R. (2021). EFAR-MMLA: An evaluation framework to assess and report generalizability of machine learning models in MMLA. *Sensors* (21), 2863.

2 G-MET

3 CO-MODELS

4 COTRACK

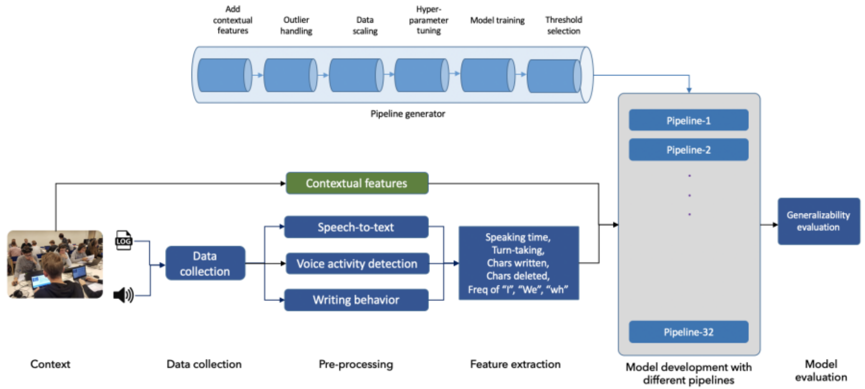
CONTRIBUTIONS

1

EFAR-MMLA

2

G-MET: Methodology for building more generalizable collaboration estimation models



Chejara, P., Prieto, L. P., Rodríguez-Triana, M. J., Ruiz-Calleja, A., & Khalil, M. (2023). Impact of window size on the generalizability of collaboration quality estimation models developed using multimodal learning analytics. *In the 13th International Learning Analytics and Knowledge Conference (LAK23)* (pp. 559-565). ACM

Chejara, P., Prieto, L. P., Ruiz-Calleja, A., Rodríguez-Triana, M. J., Kasepalu, R. & Shankar, S. K., (2023). How to build more generalizable models for collaboration quality? Lessons learned from exploring multi-contexts audio-log datasets using multimodal learning analytics. *In the 13th International Learning Analytics and Knowledge Conference (LAK23)* (pp. 111-121). ACM.

3

CO-MODELS

4

COTRACK

CONTRIBUTIONS

1

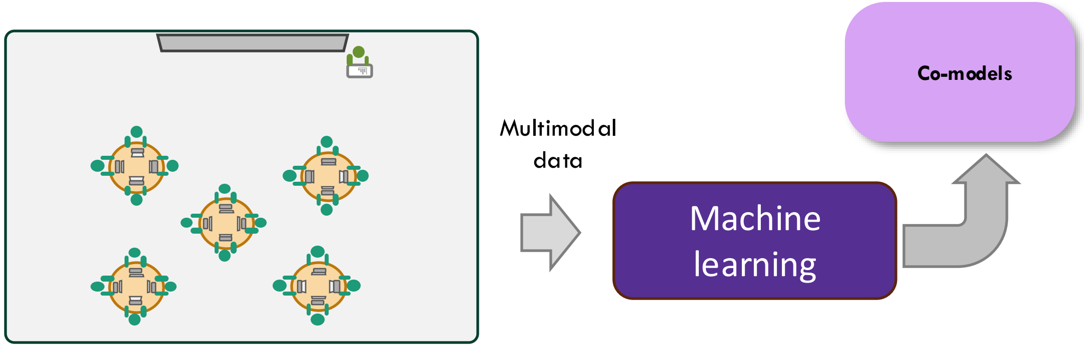
EFAR-MMLA

2

G-MET

3

CO-MODELS: Machine learning models for estimating collaboration quality using multimodal data



Chejara, P., Prieto, L., P., Dimitriadis, Y., Rodríguez-Triana, M. J., Ruiz-Calleja, A., Kasepalu, R., & Shankar, S. K., (2023). Impact of data noise on the performance of supervised machine learning models using multimodal data to estimate collaboration quality. *Journal of Learning Analytics*. https://doi.org/10.18608/jla.2024.8253

Chejara, P., Kasepalu, R., Prieto, L., P., Rodríguez-Triana, M. J., Ruiz-Calleja, A., & Schneider, B. (2023). How well do collaboration quality estimation models generalize across authentic school contexts. *British Journal of Educational Technology*, 00, 1–23. https://doi.org/10.1111/bjet.13402.

4

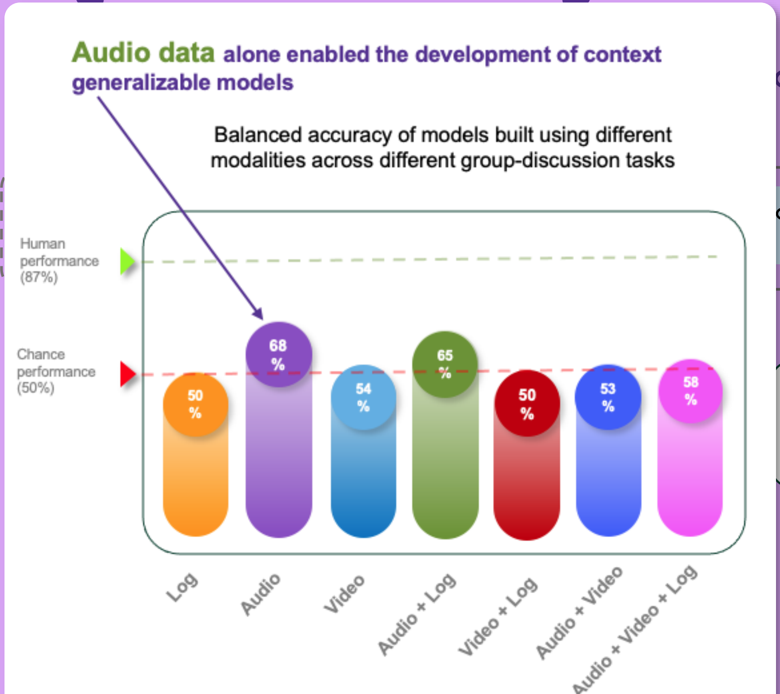
COTRACK

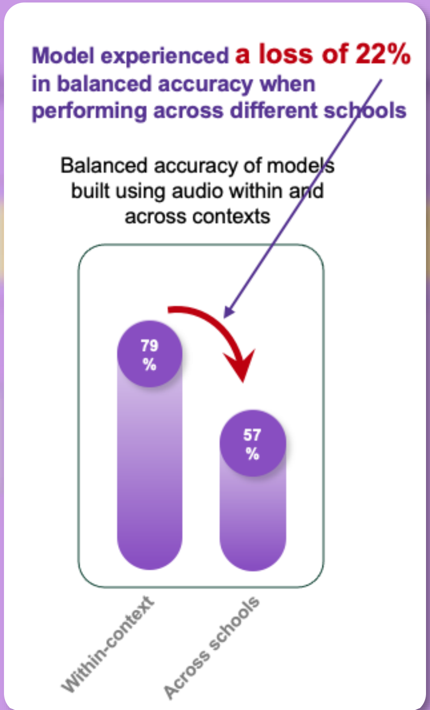
CO-MODELS [zoom-in]

RQ #3: How well do estimation models for collaboration quality perform across contexts?

	Informational	Proposal	Analytical	Evaluative
Iteration-1	Lit-review on noise impact on model's performance	Noise impact study design	Buidling automated models for CQ (audio and log)	Across contexts evaluation (single school)
Iteration-2	Lit-review on collaboration indicators in classroom	Proposal of an un-supervised learning-based method	Analyzing relationship between video and log data, and CQ	Statistical evalution
Iteration-3	Extended lit-review on generalizability evaluation	Across school evalution study design	Buidling automated models for CQ (audio, video and log)	Across schools generalizability evalution

CO-MODELS [zoom-in]





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EFAR-MMLA

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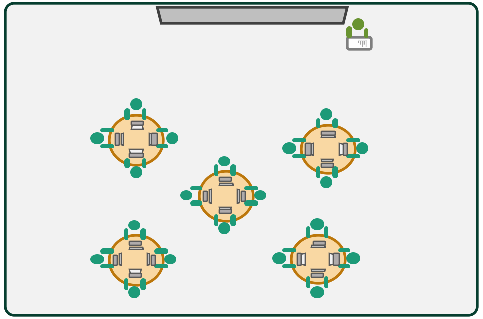
CO-MODELS: Machine models for estimating collaboration quality using multimodal data



Multimodal data

Machine learning

Automated models for collaboration quality and its dimensions

Co-models

Chejara, P., Prieto, L., P., Dimitriadis, Y., Rodríguez-Triana, M. J., Ruiz-Calleja, A., Kasepalu, R., & Shankar, S. K., (2023). Impact of data noise on the performance of supervised machine learning models using multimodal data to estimate collaboration quality. *Journal of Learning Analytics*. https://doi.org/10.18608/jla.2024.8253

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COTRACK

CONTRIBUTIONS

1 EFAR-MMLA

2 G-MET

3 CO-MODELS

4 COTRACK

BEST DEMO AWARD
LAK, USA (2023)

SPECIAL RESEARCH AWARD
Education and Youth Board, Estonia (2021)

CoTrack

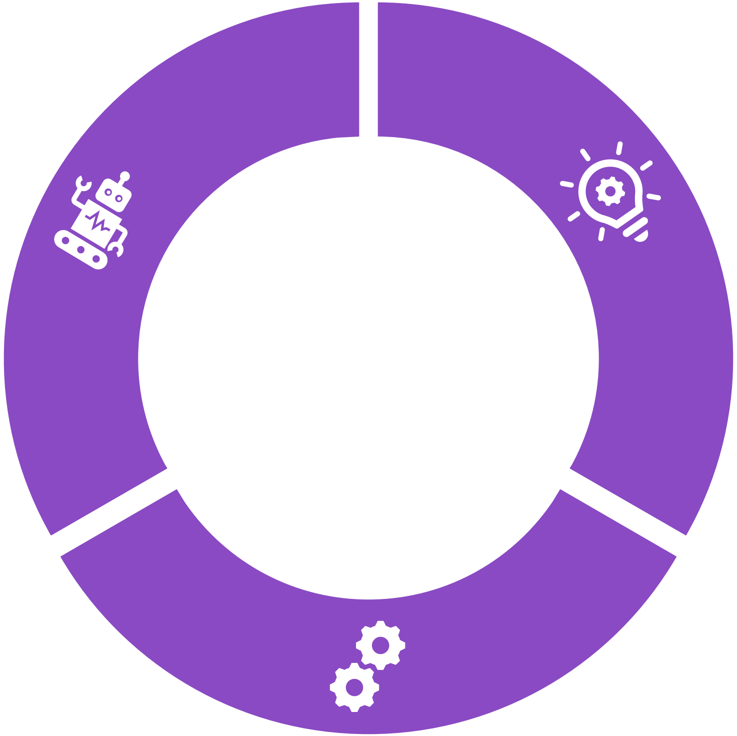
https://www.cotrack.website

6 Researchers | 58 Teachers | 600 Students

Chejara, P., Kasepalu, R. Prieto, L. P., Ruiz-Calleja, A., Rodríguez-Triana, M. J., & Shankar, S. K., (2023). Multimodal learning analytics research in the wild: challenges and their potential solution. In CrossMMLA workshop at 13th International Learning Analytics and Knowledge Conference (LAK23) (pp. 36-42). CEUR workshop proceedings.

Chejara, P., Kasepalu, R., Prieto, L., P., Rodríguez-Triana, M. J., & Ruiz-Calleja, A. (2024). Bringing collaboration analytics using multimodal data to the masses: Evaluation and design guidelines for developing a mmla system for research and teaching practices in CSCL. In the 14th International Learning Analytics and Knowledge Conference (LAK24)

DISCUSSION



GAP #1: Lack of systematization in generalizability evaluation of MMLA based solutions

EFAR-MMLA

- … brings another perspective of bias identification
- … complements MMLA conceptual tools (e.g., MLeaM, M-DVC)

Di Mitri et al., 2018   Shankar et al., 2020

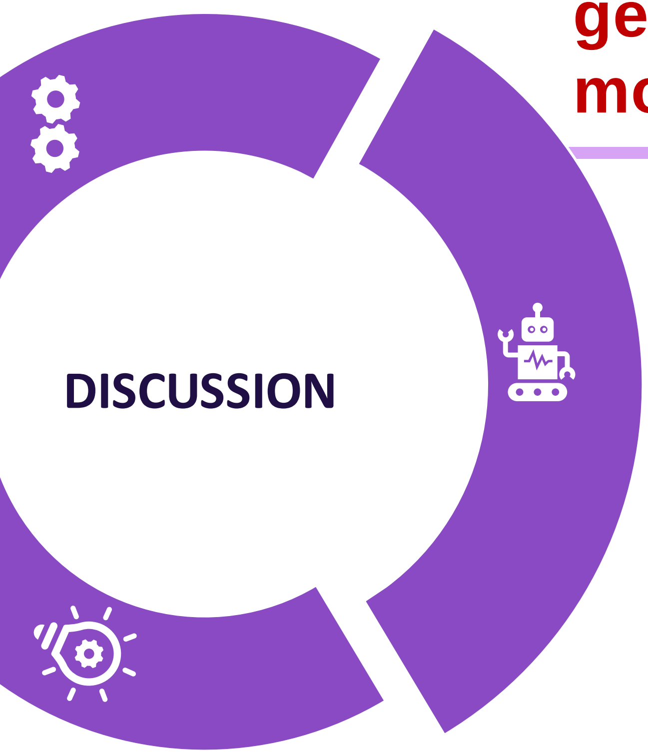
GAP #2: Lack of knowledge over building generalizable collaboration quality estimation models

G-MET

- … suggests 60s time window for building models for collaboration quality
- … illustrates that contextual data improves performance across contexts
- … recommends the use of Random Forest for modeling

Chounta et al., 2015

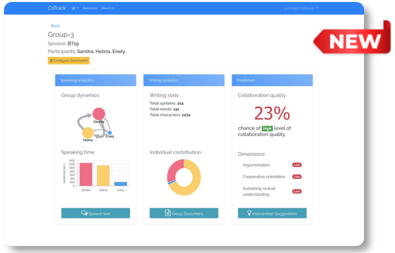
GAP #3: Lack of knowledge over extent of generalizability of collaboration estimation models in classroom settings



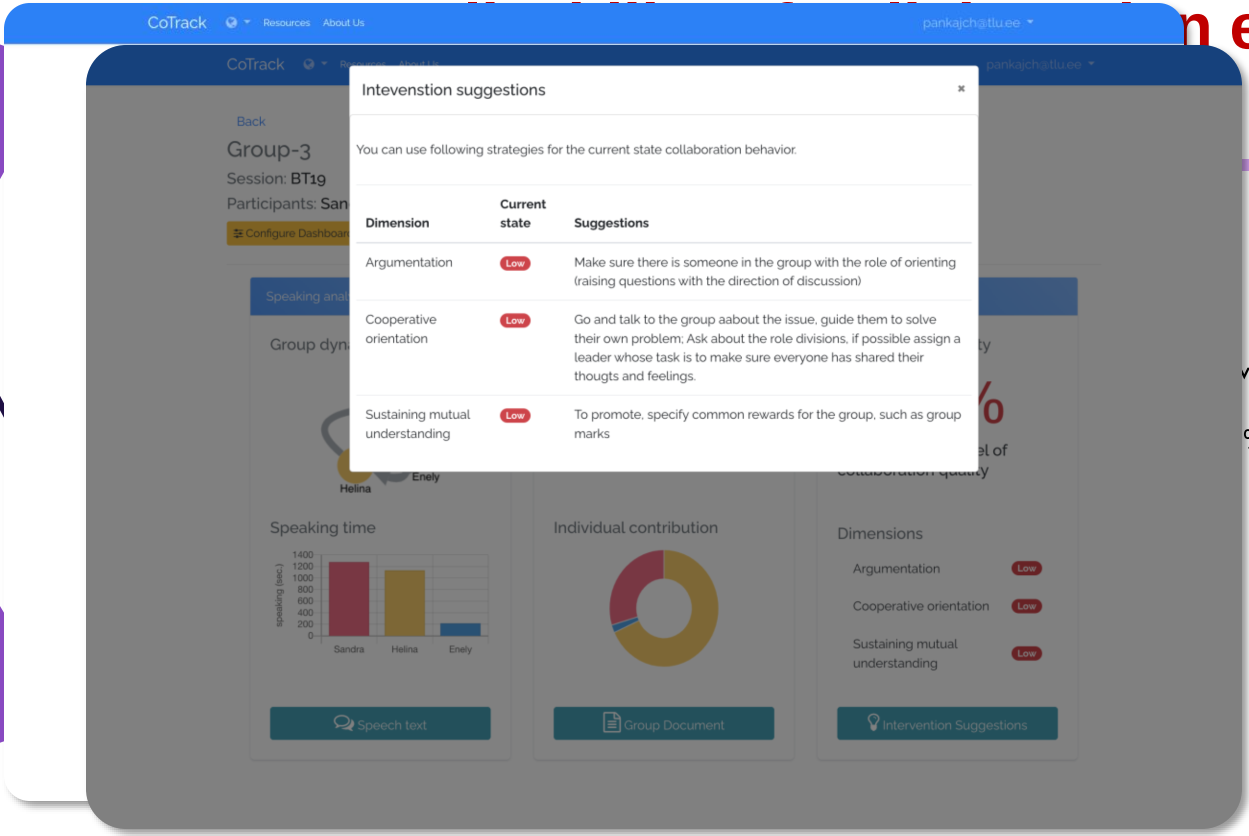
CO-MODELS

- … identify indicators for collaboration quality in authentic settings (e.g., verticle head movement)
- … achieve across-context generalizability in authentic settings with ~25% degradation
- … can help with closing the learning analytics loop

Pugh et al., 2022



GAP #3: Lack of knowledge over extent of … n estimation



DISCUSSION

verticle head movement)

% degradation

DISCUSSION

GAP #3: Lack of knowledge over extent of generalizability of collaboration estimation models in classroom settings

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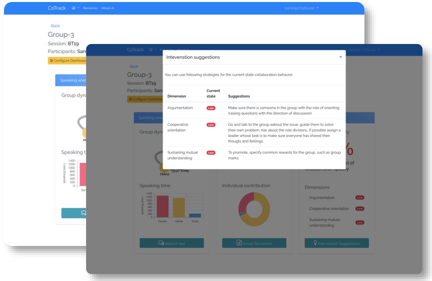
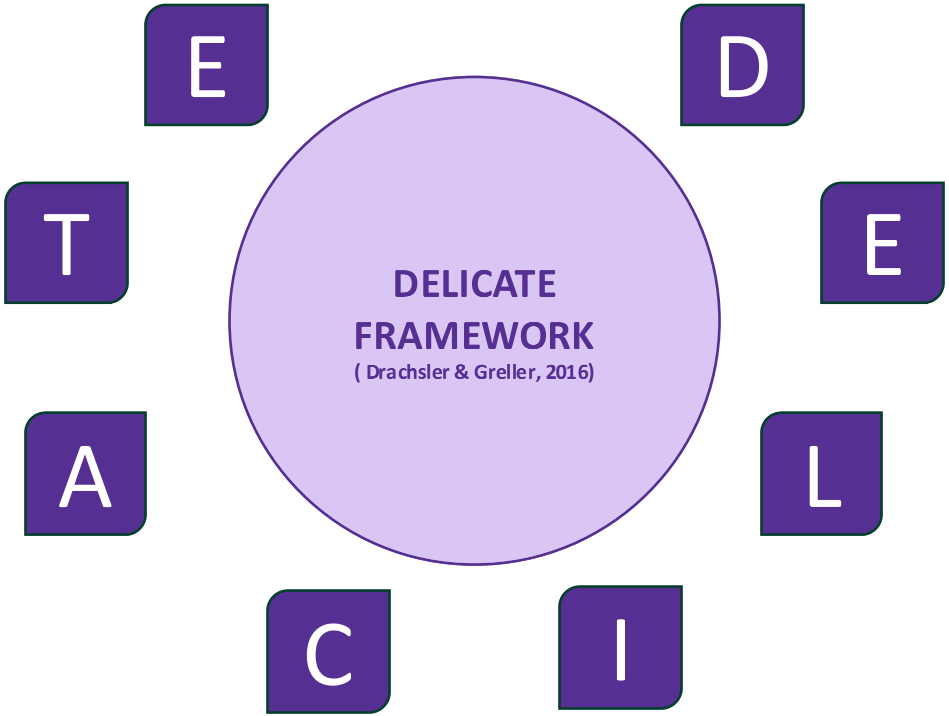


ETHICAL CONCERNS

NEW



ETHICAL CONCERNS

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Determination

Why do you want to apply learning analytics?

Voluntary participation

DELICATE FRAMEWORK

(Drachsler & Greller, 2016)

ETHICAL CONCERNS

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DELICATE FRAMEWORK

(Drachsler & Greller, 2016)

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Why do you want to apply learning analytics?

Voluntary participation

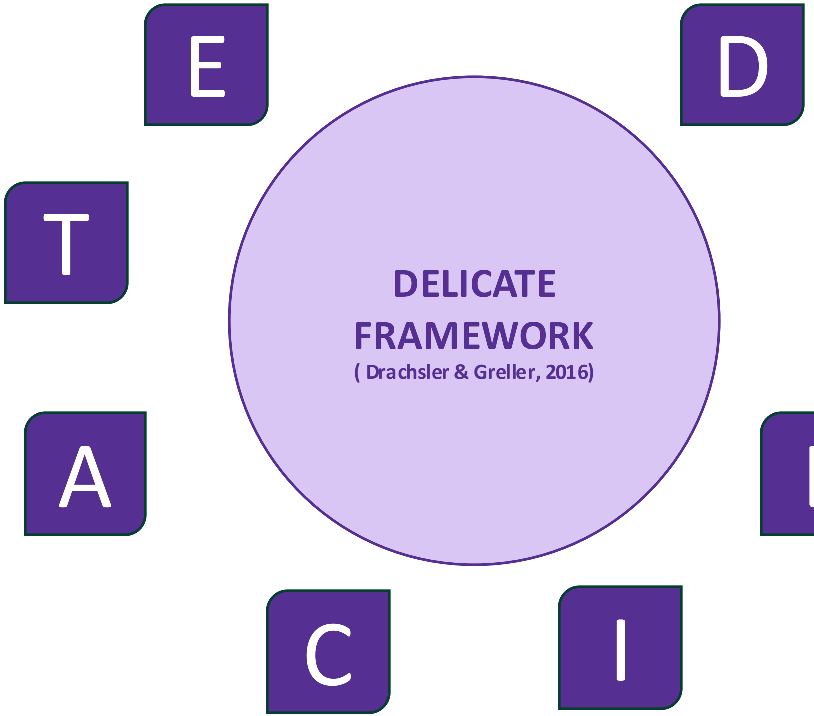
Explain

Be open about your intentions and objectives

Research introducation

ETHICAL CONCERNS

NEW



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Legitimate

Why are you allowed to have data?

Prior research evidence

Students' well-being

ETHICAL CONCERNS

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D — Determination
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E — Explain
Be open about your intentions and objectives
Research introducation

L — Legitimate
Why are you allowed to have data?
Prior research evidence | Students' well-being

I — Involve
Involve all stakeholders and data subjects

ETHICAL CONCERNS

NEW

DELICATE FRAMEWORK
(Drachsler & Greller, 2016)

D — **Determination**
Why do you want to apply learning analytics?
- Voluntary participation

E — **Explain**
Be open about your intentions and objectives
- Research introducation

L — **Legitimate**
Why are you allowed to have data?
- Prior research evidence
- Students' well-being

I — **Involve**
Involve all stakeholders and data subjects

C — **Consent**
Make a contract with data subjects
- Understanding of risks
- Integrated consent form

A

T

E

NEW

ETHICAL CONCERNS

DELICATE FRAMEWORK
(Drachsler & Greller, 2016)

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A — **Anonymize**
Make the individuals non retrievable
Feature-level anonymity

T

E

ETHICAL CONCERNS

NEW

DELICATE FRAMEWORK
(Drachsler & Greller, 2016)

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Make the individuals non retrievable
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T – **Technical**
Procedures to guarantee privacy
- Restricted access

E

ETHICAL CONCERNS

NEW

DELICATE FRAMEWORK
(Drachsler & Greller, 2016)

D – Determination
Why do you want to apply learning analytics?
- Voluntary participation

E – Explain
Be open about your intentions and objectives
- Research introduction

L – Legitimate
Why are you allowed to have data?
- Prior research evidence
- Students' well-being

I – Involve
Involve all stakeholders and data subjects

C – Consent
Make a contract with data subjects
- Integrated consent form
- Understanding of risks

A – Anonymize
Make the individuals non retrievable
- Feature-level anonymity

T – Technical
Procedures to guarantee privacy
- Restricted access

E – External
Regulation for external service providers

“SOME” LIMITATIONS & FUTURE WORK

➔ Limitations

- Narrow educational context
- Non-temporal analysis
- Use of low-level features (content free)

➔ Future work addressing limitations

- Research in wider range of contexts

➔ Future work opened up by research

- Closing the loop (feedback)
- Teacher’s response

CONCLUSION

How to build and assess across-context generalizable machine learning models for the estimation of collaboration quality and its dimensions in small groups in authentic classroom face-to-face settings?

Guidelines

1. Use of **RF** and **60 seconds time window** for modeling collaboration quality

CONCLUSION

How to build and assess across-context generalizable machine learning models for the estimation of collaboration quality and its dimensions in small groups in authentic classroom face-to-face settings?

Guidelines

1. Use of **RF** and **60 seconds time window** for modeling collaboration quality

2. Use of **contextual data to** build context **generalizable models for estimating collaboration quality**

CONCLUSION

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1. Use of **RF** and **60 seconds time window** for modeling collaboration quality
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3. Use of **audio data alone** enable development **of across-context generalizable collaboration quality estimation models**

CONCLUSION

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Final remarks

1. **Community efforts** needed to address issues relataed to dataset size, annnotation, modeling

CONCLUSION

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Guidelines

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Final remarks

1. **Community efforts** needed to address issues relataed to dataset size, annnotation, modeling
2. **Human-AI parternship** to bring together the power of AI and Teacher's knowledge and expertise

ACKNOWLEDGEMENT

TALLINN UNIVERSITY

Eesti hariduse ja teaduse heaks
ARCHIMEDES

DoRa

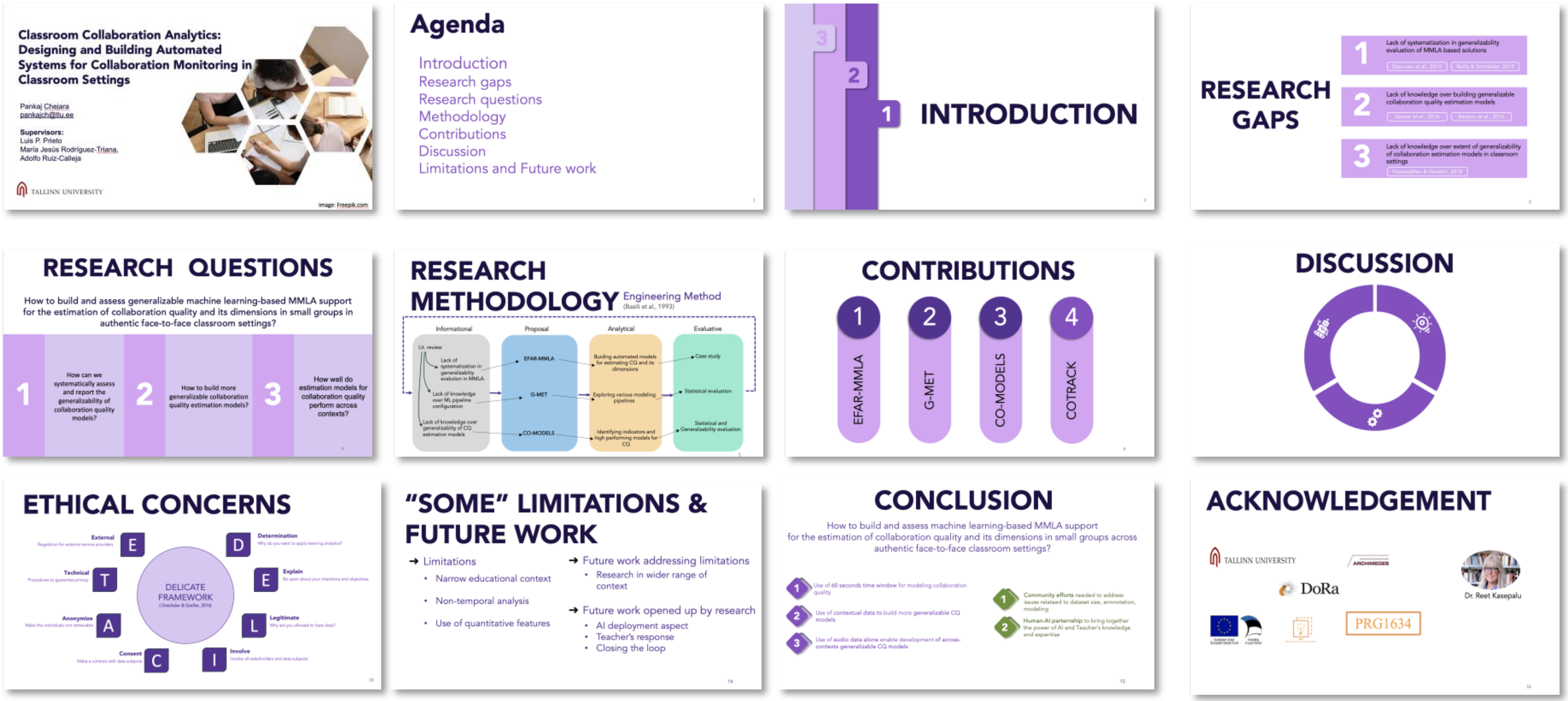
European Union
European Social Fund

Investing
in your future

SEIS
Scaling Up Educational Innovations in Schools

PRG1634

Dr. Reet Kasepalu



THANK YOU

QUESTIONS?

References

1. Chounta, I. A., & Avouris, N. (2016). Towards the real-time evaluation of collaborative activities: Integration of an automatic rater of collaboration quality in the classroom from the teacher's perspective. *Education and Information Technologies*, *21*(4), 815–835. https://doi.org/10.1007/s10639-014-9355-3
2. Rummel, N., Deiglmayr, A., Spada, H., Kahrimanis, G., & Avouris, N. (2011). Analyzing Interactions in CSCL. *Analyzing Interactions in CSCL*, 367–390. https://doi.org/10.1007/978-1-4419-7710-6
3. Ochoa, X., & Worsley, M. (2016). Augmenting Learning Analytics with Multimodal Sensory Data. *Journal of Learning Analytics*, 3(2), 213–219. https://doi.org/10.18608/jla.2016.32.10
4. Mercer, N., Littleton, K., & Wegerif, R. (2009). Methods for studying the processes of interaction and collaborative activity in computer-based educational activities. In *Investigating classroom interaction* (pp. 27-42). Brill.
5. Raschka, S. Model Evaluation, Model Selection, and Algorithm Selection in Machine Learning. arXiv 2018, arXiv:1811.12808.
6. Ezen-Can, A.; Grafsgaard, J.F.; Lester, J.C.; Boyer, K.E. Classifying Student Dialogue Acts with Multimodal Learning Analytics. In Proceedings of the Fifth International Conference on Learning Analytics And Knowledge (LAK '15), Poughkeepsie, NY, USA, March 2015; Association for Computing Machinery: New York, NY, USA, 2015; pp. 280–289.
7. Reilly, J. M., & Schneider, B. (2019). Predicting the Quality of Collaborative Problem Solving Through Linguistic Analysis of Discourse. *Educational Data Mining*, 149–157.
8. Shuchi Grover, Marie A. Bienkowski, Amir Tamrakar, Behjat Siddiquie, David A. Salter, and Ajay Divakaran. 2016. Multimodal analytics to study collaborative problem solving in pair programming. In Proceedings of the 6th International Conference on Learning Analytics & Knowledge, LAK 2016, Dragan Gasevic, Grace Lynch, Shane Dawson, Hendrik Drachsler, and Carolyn Penstein Rosé (Eds.). ACM, Edinburgh, United Kingdom, 516–517.
9. Nikoletta Bassiou, Andreas Tsiartas, Jennifer Smith, Harry Bratt, Colleen Richey, Elizabeth Shriberg, Cynthia D'Angelo, and Nonye Alozie. 2016. Privacy-Preserving Speech Analytics for Automatic Assessment of Student Collaboration. In Interspeech 2016, 17th Annual Conference of the International Speech Communication Association, Nelson Morgan (Ed.). ISCA, San Francisco, CA, USA, 888–892. https://doi.org/10.21437/Interspeech.2016-1569
10. Viswanathan, S. A., & Vanlehn, K. (2018). Using the Tablet Gestures and Speech of Pairs of Students to Classify Their Collaboration. *IEEE Transactions on Learning Technologies*, *11*(2), 230–242. https://doi.org/10.1109/TLT.2017.2704099
11. Basili, V. R. (1993). The experimental paradigm in software engineering. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 706 LNCS* (pp. 3–12). https://doi.org/10.1007/3-540-57092-6_91
12. Di Mitri, D., Schneider, J., Specht, M., & Drachsler, H. (2018). From signals to knowledge: A conceptual model for multimodal learning analytics. *Journal of Computer Assisted Learning*, *34*(4), 338–349. https://doi.org/10.1111/jcal.12288
13. Shankar, S. K., Rodríguez-Triana, M. J., Ruiz-Calleja, A., Prieto, L. P., Chejara, P., & Martínez-Monés, A. (2020). Multimodal data value chain (m-dvc): A conceptual tool to support the development of multimodal learning analytics solutions. *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje*, *15*(2), 113-122.
14. Chounta, I. A., & Avouris, N. (2015). Towards a time series approach for the classification and evaluation of collaborative activities. *Computing and Informatics*, *34*(3), 588–614.
15. Martínez-maldonado, R. (2011). Modelling and Identifying Collaborative Situations in a Collocated Multi- display Groupware Setting. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *6738*(June), 39–46. https://doi.org/10.1007/978-3-642-21869-9
16. Pugh, S. L., Rao, A., Stewart, A. E. B., & D'Mello, S. K. (2022). Do Speech-Based Collaboration Analytics Generalize Across Task Contexts? *ACM International Conference Proceeding Series*, 208–218. https://doi.org/10.1145/3506860.3506894
17. Drachsler, H., & Greller, W. (2016, April). Privacy and analytics: it's a DELICATE issue a checklist for trusted learning analytics. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 89-98).

CLASSROOM COLLABORATION ANALYTICS: DESIGNING AND BUILDING AUTOMATED SYSTEMS FOR MONITORING COLLABORATION IN CLASSROOM

Research Gaps	Research Questions	Research Objectives	Data	Analysis	Publications
RG #1: There is a lack of **systematization** for the **evaluation** of automated machine learning models in MMLA and specifically MMLA for collaboration.	**RQ #1:** How to **systematically assess** and **report generalizability** of automated estimation models of collaboration quality and its dimensions in small groups in class?	**OB #1.** *To **systematically assess** and **report generalizability** of machine learning-based MMLA solutions of collaboration quality.*	Audio Log data	Supervised machine learning	III
RG #2. There is a lack of knowledge over building generalizable collaboration quality estimation models for classroom settings.	**RQ #2:** How to build **more generalizable automated estimation models of collaboration quality** and its dimensions in small groups in classroom collaborative learning?	**OB #2.** *To identify machine learning pipeline configurations that enable the **building of more generalizable** collaboration quality estimation models.*	Audio Log data	Dimensionality reduction Supervised machine learning Statistical analysis	I II IV V
RG #3. The field lacks knowledge on to what extent automated collaboration models can generalize in classroom settings.	**RQ #3:** How well do automated estimation models for collaboration quality and its dimensions **perform across contexts** (e.g., task contexts, task type contexts, school contexts) in **authentic classroom settings**?	**OB #3.** *To investigate the **impact of attribute noise** on the performance of collaboration quality models in **authentic settings**.*	Audio Log data	Supervised machine learning	IX
		OB #4. *To investigate **generalizability** of automated estimation models of collaboration quality at **different levels** (across different tasks, task-types, schools).*	Audio Log data Video data	Unsupervised machine learning Supervised machine learning Statistical analysis	VII VIII

Publication category 1.1

Publication category 3.1

EU AI Act: Educational & Vocational Training as High Risk Industry

DIGITAL EDUCATION COUNCIL

Risk Classification

Unacceptable Risk

High Risk
8 areas including **Educational & Vocational Training**

Limited Risk

Low and Minimal Risk

High Risk AI Systems

1. **AI for Admissions**
   Determine access or admission or to assign to educational and vocational training institutions
2. **AI for Evaluation**
   Evaluate learning outcomes, including when those are used to steer the learning process
3. **AI for Assessment**
   Assessing the appropriate level of education that individual will receive or will be able to access
4. **AI for Proctoring**
   Monitoring and detecting prohibited behaviour of students during tests

Requirements for High Risk Providers*


Risk and Quality Management System


Conduct Data Governance


Technical Documentation & Record Keeping


Instruction Guide


Human Oversight


Appropriate level of Accuracy, Robustness, and Cybersecurity

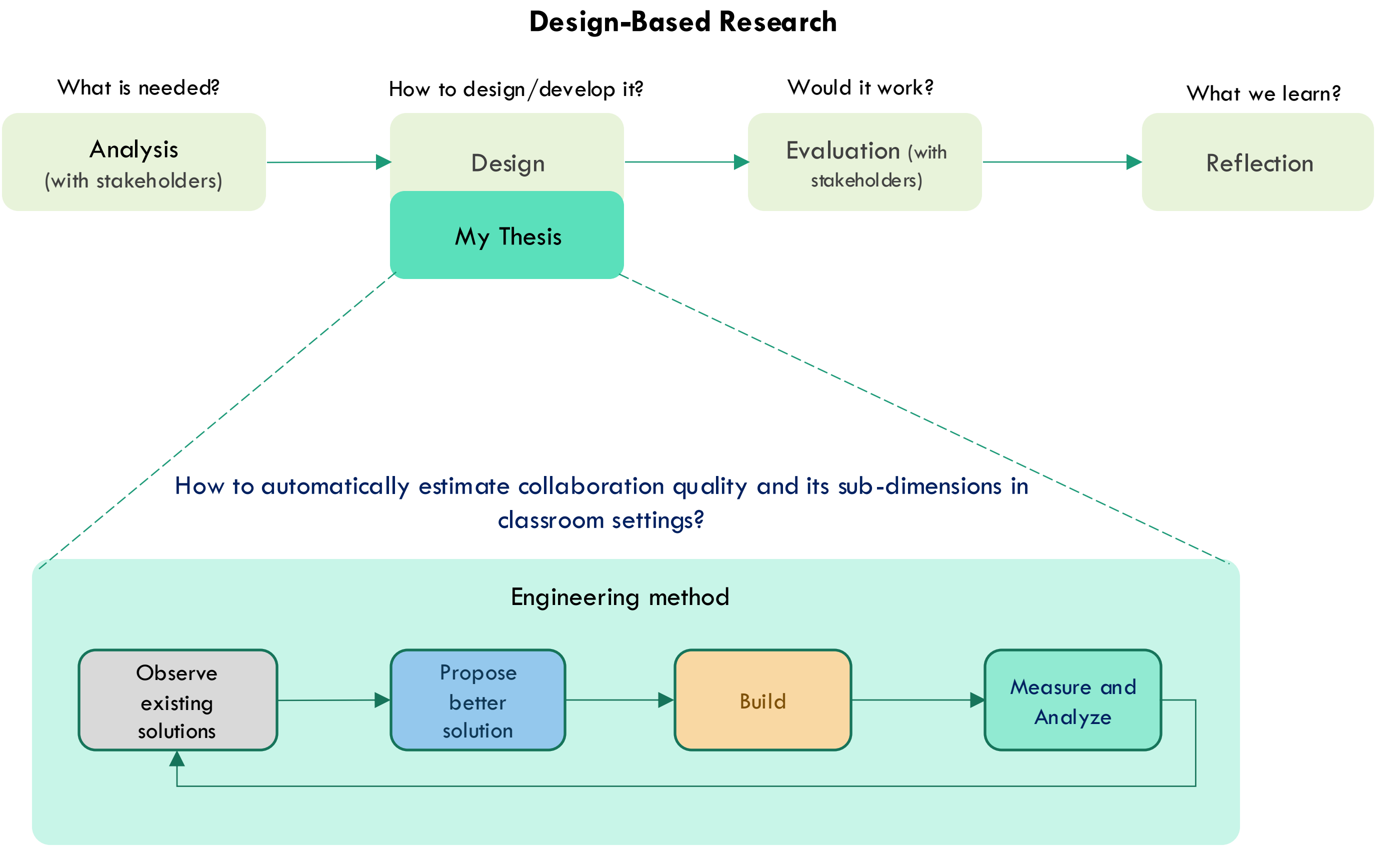
Predictions

- Compliance requirements may be too complex and resources-intensive for smaller companies, hindering their ability to compete and innovate
- Restrictions on how student data can be collected and used could limit the potential of personalised and adaptive tools, impeding the development of edtech solutions relying on customisation
- Complexity of regulation may induce fear of violation, discouraging companies from taking risks and innovating

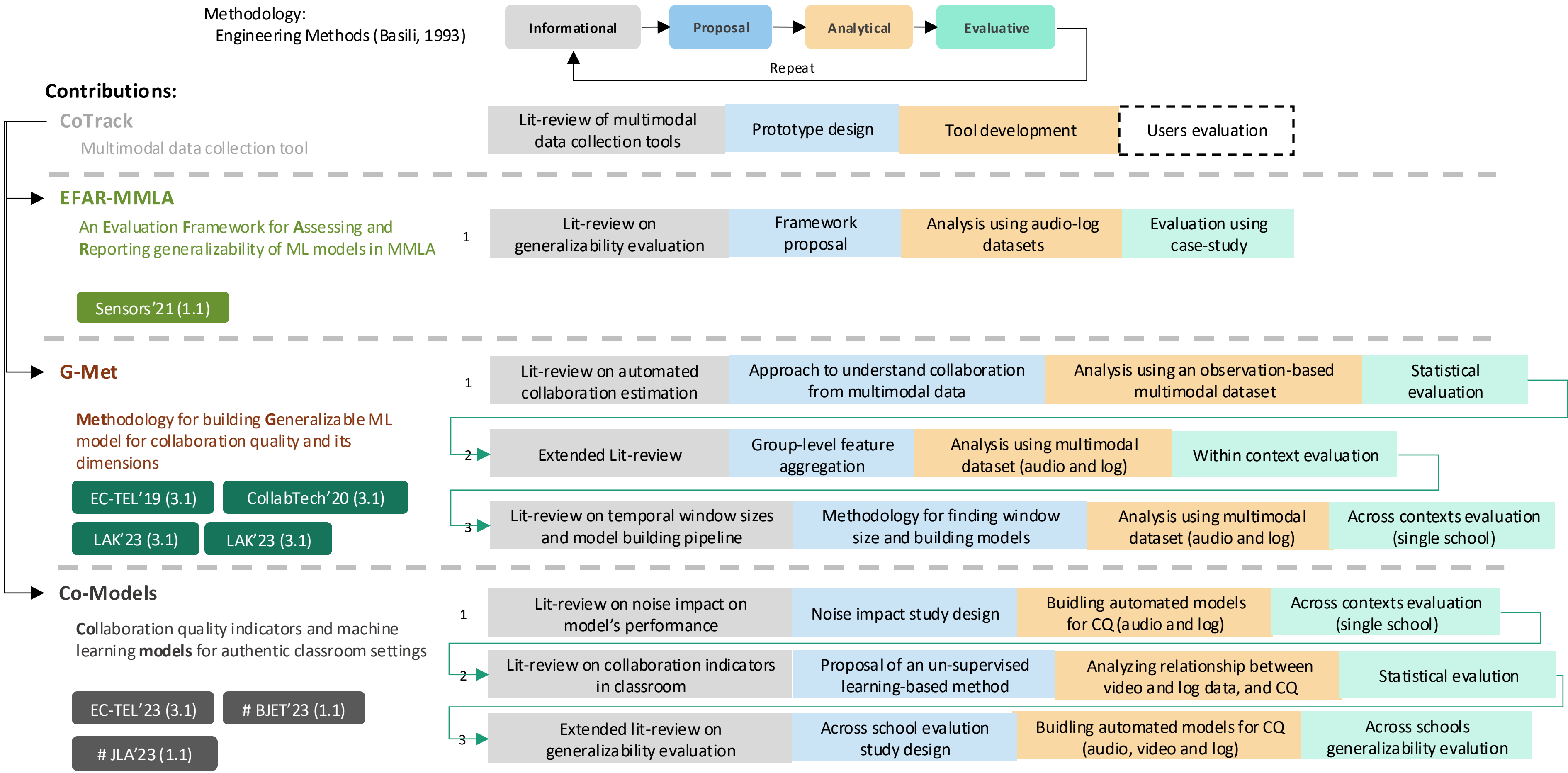
***Providers:** those intending to place on the market/put into service high-risk AI systems in the EU.

https://www.digitaleducationcouncil.com/post/eu-ai-act-what-it-means-for-universities

Supporting and guiding teachers during collaborative learning activities of small groups in classroom settings (Reet Kasepalu)



CLASSROOM COLLABORATION ANALYTICS: DESIGNING AND BUILDING AUTOMATED SYSTEMS FOR MONITORING COLLABORATION IN CLASSROOM



Dark-colored boxes: publications; #: Submitted

AUTHENTIC FACE-TO-FACE CLASSROOM SETTINGS

- Free-form collaboration
- Writing
- Synchronous interaction
- Laptop use

O 1.1: IMPORTANCE OF CONTEXT

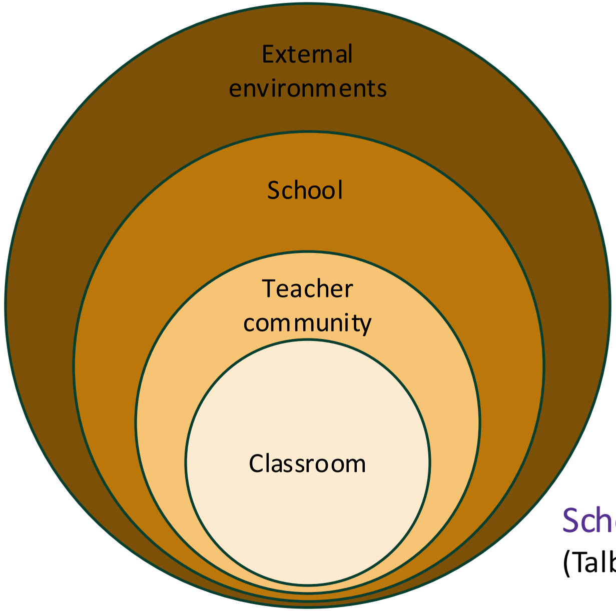
- The need to consider students as being nested within classrooms and schools while assessing generalizability of students' achivement (Cronbach et al.,1997)

- Generalizability might not be desirable in every case.

- For example, a model which is performing well for a certain type of collaborative learning activity will not loose its worth if failed to generalize to another type of activity.

Cronbach, L. J., Linn, R. L., Brennan, R. L., & Haertel, E. H. (1997). Generalizability analysis for performance assessments of student achievement or school effectiveness. *Educational and Psychological Measurement*, *57*(3), 373-399.

O 1.2: HOW TO PROVIDE CONTEXTUAL INFORMATION TO THE MODEL?



School context Model
(Talbert & McLaughlin, 1999)

Indicators Examples (Bascia, 2014)

Parental engagement in their children's education

Appropriate resources are available.

Teachers use data to support educational decision-making.

Social and emotional learning is valued.

Talbert, J. E., & McLaughlin, M. W. (1999). Assessing the school environment: Embedded contexts and bottom-up research strategies. In S. L. Friedman & T. D. Wachs (Eds.), *Measuring environment across the life span: Emerging methods and concepts* (pp. 197–227). American Psychological Association. https://doi.org/10.1037/10317-007

Bascia, N. (2014). The School Context Model: How School Environments Shape Students' Opportunities to Learn. In Measuring What Matters, People for Education. Toronto: November 8, 2014

O 1.5: CLARIFICATION OF SPEECH-TO-TEXT

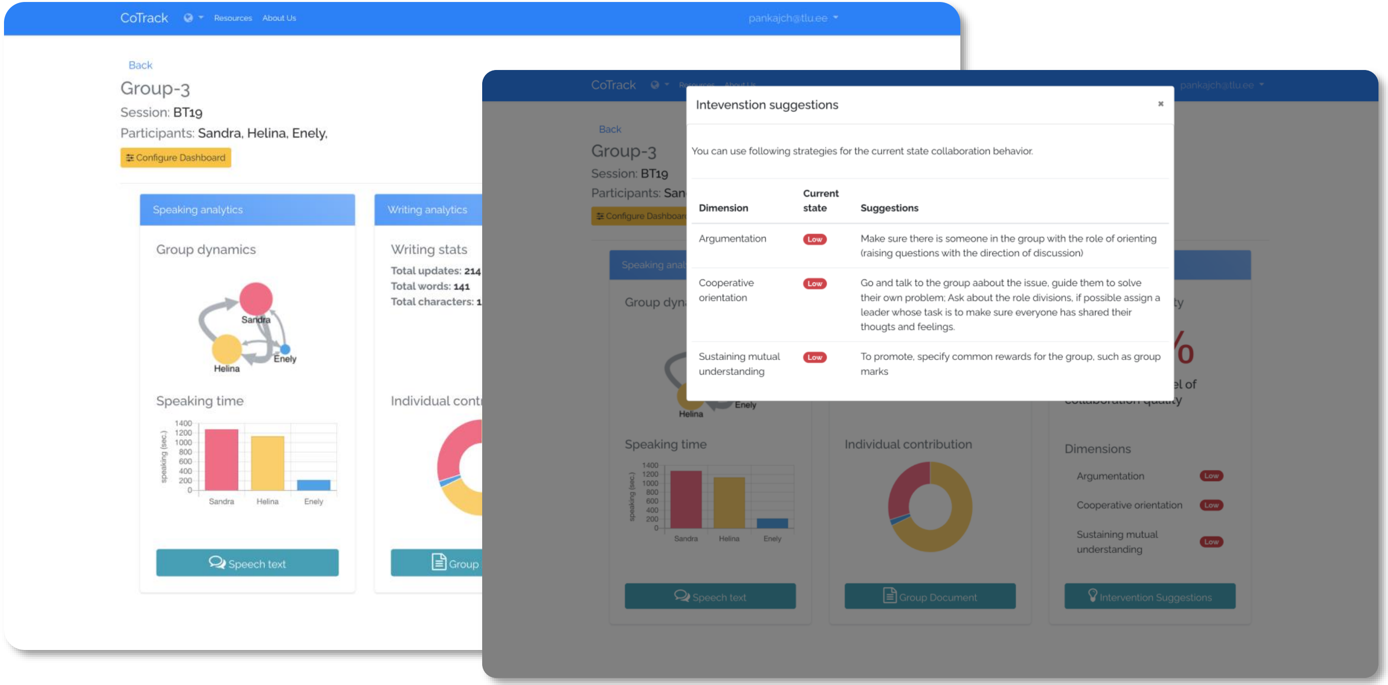
- Frequency of particular words (e.g., “I”, “WE”, “Wh-words”) (briefly mentioned in the paper V)

O 1.7: PRACTICALITY OF MMLA SOLUTIONS

- Techincal complexity
- Financial burden
- Noisy situations

Yan, L., Zhao, L., Gasevic, D., & Martinez-Maldonado, R. (2022, March). Scalability, sustainability, and ethicality of multimodal learning analytics. In *LAK22: 12th international learning analytics and knowledge conference* (pp. 13-23).

O 1.8: CLOSING THE LOOP



Kasepalu R, Prieto LP, Ley T and Chejara P (2022) Teacher Artificial Intelligence-Supported Pedagogical Actions in Collaborative Learning Coregulation: A Wizard-of-Oz Study. *Front. Educ.* 7:736194. doi: 10.3389/feduc.2022.736194