

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

Pankaj Chejara  
[pankajch@tlu.ee](mailto:pankajch@tlu.ee)



## Researcher

Center of Education Technology  
Tallinn University, Estonia



## Data Scientist

Applied Health Data Division  
Metroser AS, Estonia



# AGENDA

Introduction

Modeling collaboration

Generalizability

Multimodal data & Collaboration monitoring

Guidelines for building models

Challenges/Future directions

Conclusion

# INTRODUCTION

## COLLABORATION

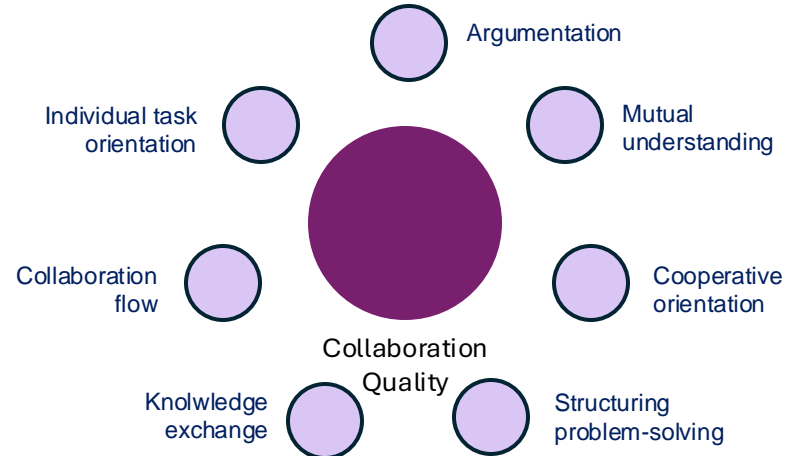
Collaboration is a complex construct (Rummel et al., 2011).



# INTRODUCTION

## COLLABORATION

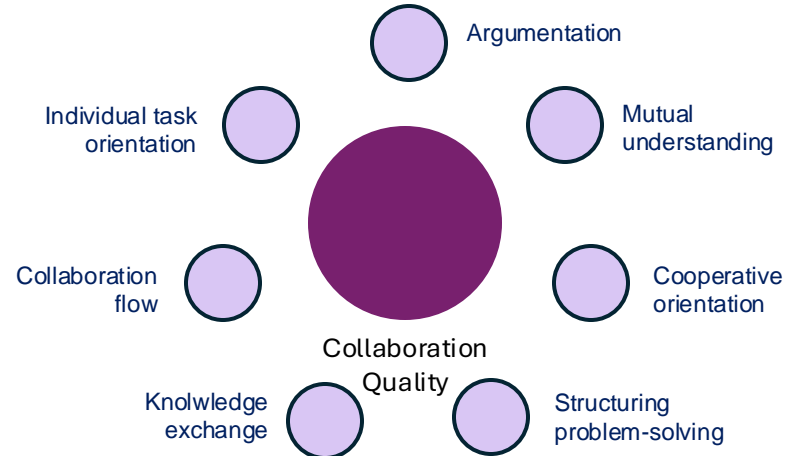
Collaboration is a complex construct (Rummel et al., 2011).



# INTRODUCTION

## COLLABORATION

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



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

# INTRODUCTION

## MULTIMODAL LEARNING ANALYTICS

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

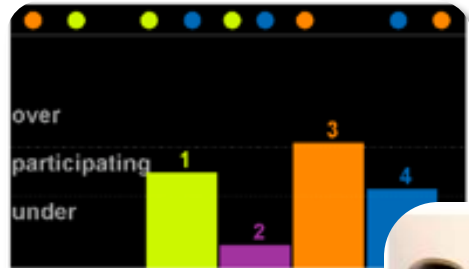


Captures multimodality of students' interactions.



# INTRODUCTION

## MULTIMODAL LEARNING ANALYTICS



Speaking participation  
(DiMicco et al., 2004)



LED matrix display  
(Bachour et al., 2010)

Visualization

Speaking time  
(collaboration quality)

(Martinez-Maldonado et al.,  
2011)

Distance between  
hands  
(Performance)

(Spikol et al., 2018)

Pattern

Collaboration  
quality

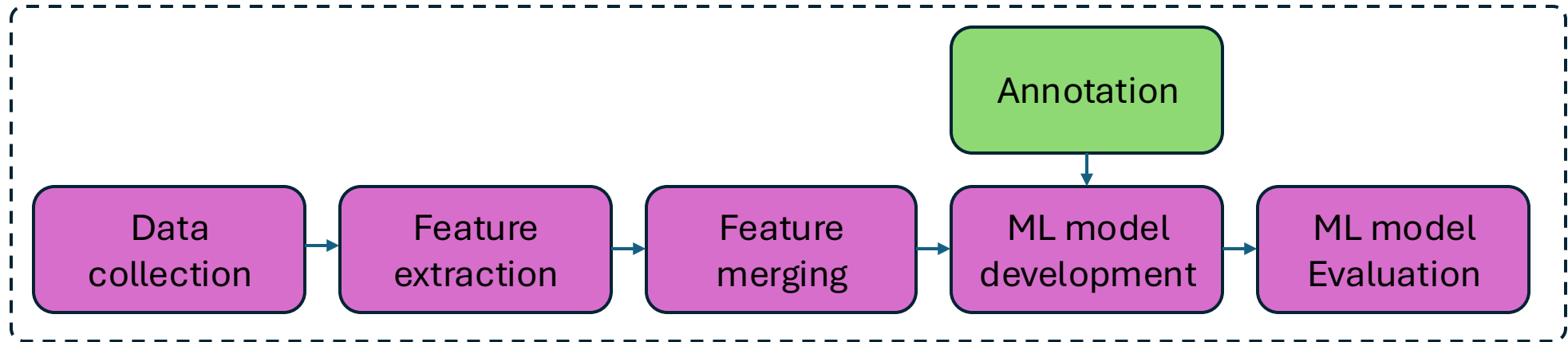
(Martinez-Maldonado et al.,  
2011)

Rapport

(Lubold et al., 2014)

Modeling

# MODELING COLLABORATION







# Multimodal data collection systems

- 1 iMotions Lab  
Commercialized
- 2 Multimodal Learning Hub  
Schneider et al., 2018
- 3 Social Signal Framework  
Wagner et al., 2013
- 4 Lab Streaming Layer  
Kothe et al., 2014
- 5 EZ-MMLA toolkit  
Schneider et al., 2022
- 6 CoTrack  
Chejara et al., 2024



# Feature extraction



Audio data

Voice activity detection (VAD, py-webrtcvad)

Speaking time  
Turn-taking

Acoustic feature extraction (OpenSmile tool)

Pitch  
Energy

Speech-to-Text (Google Speech-to-Text)

Speech data



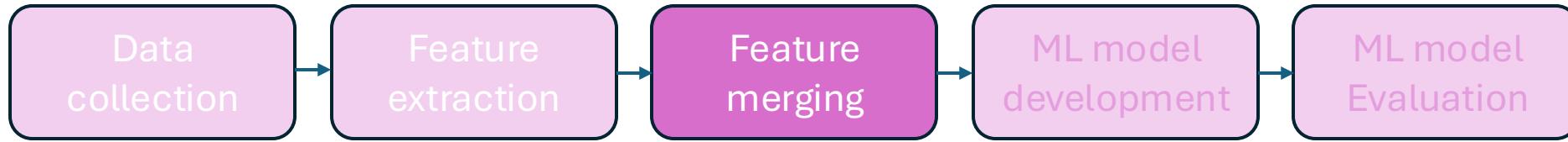
Video data

Facial expressions (OpenFace, Py-Feat)

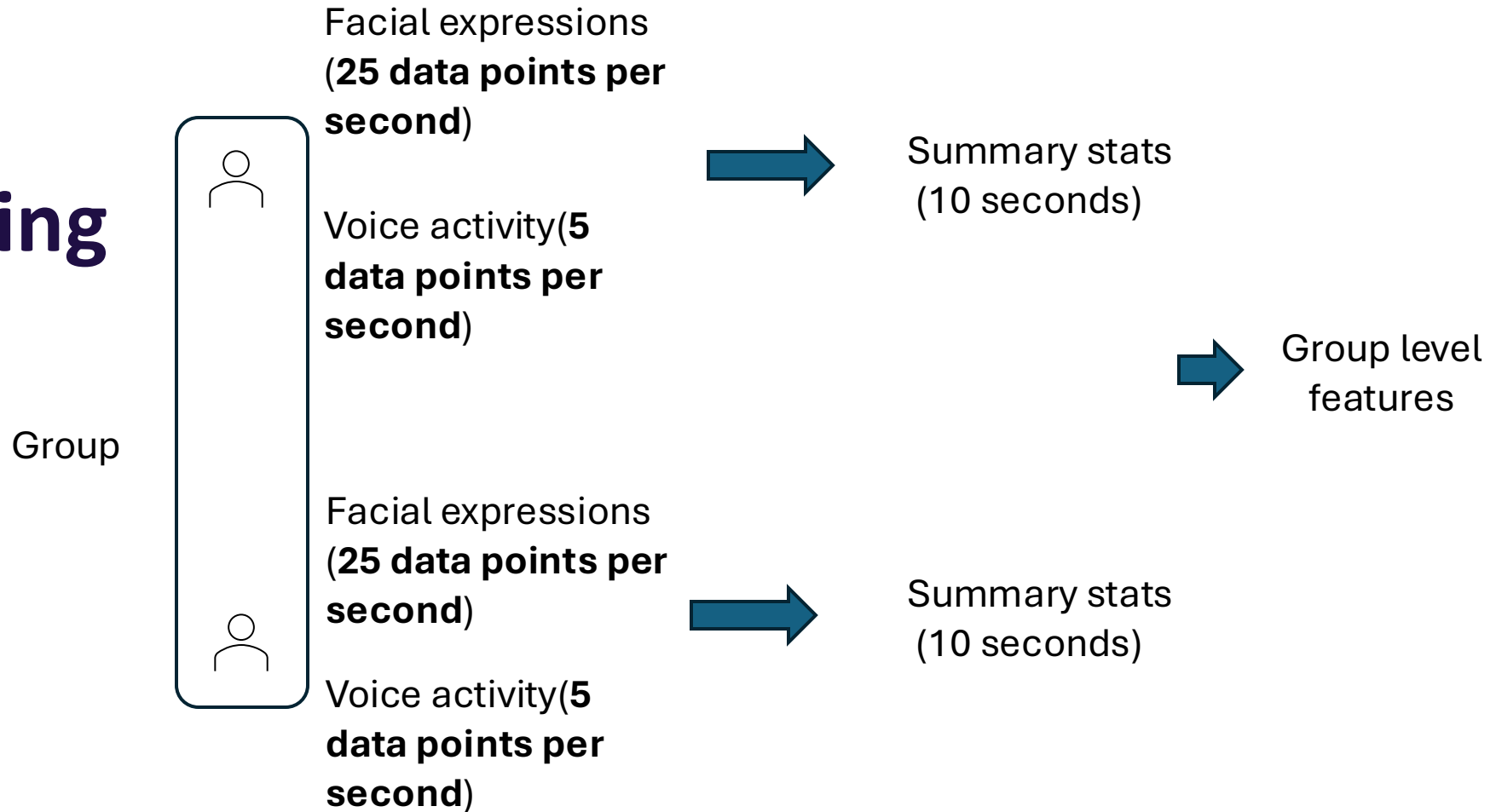
Facial action units  
Emotions

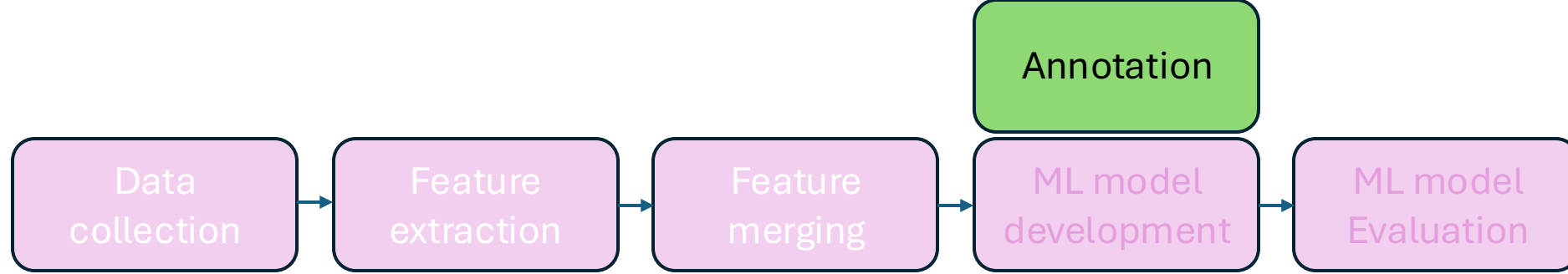
Body movement (OpenPose)

Head movement  
Hand movement



# Feature merging





# Annotation



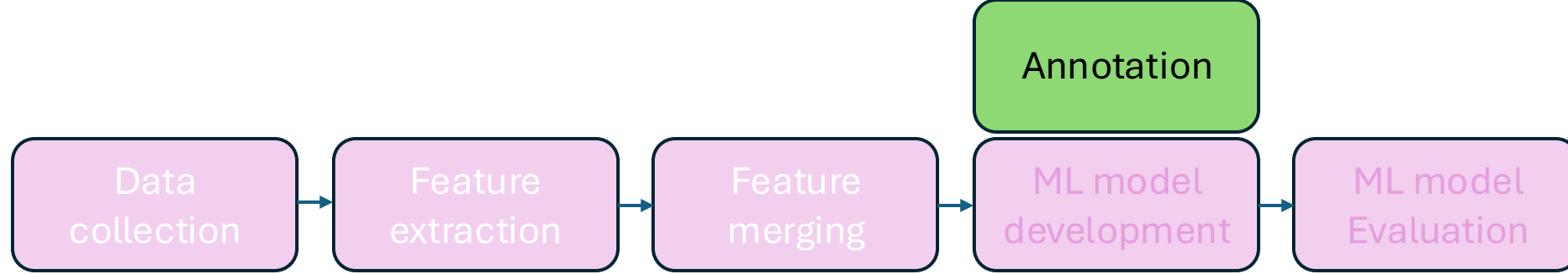
Expert  
evaluation



Artifact  
assessment



Self-reported  
survey



# Annotation



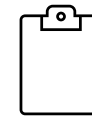
[Rating handbook](#)  
(Rummel et al., 2011)



Expert  
evaluation



Artifact  
assessment



Self-reported  
survey



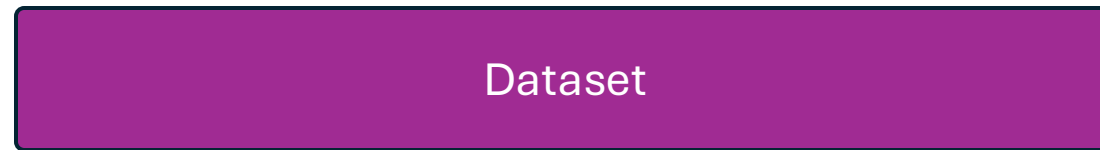
# ML model development

index	frame	group	user_speak_mean	user_speak_sd	user_turns_mean	user_turns_sd	write_text	user_wh_mean	user_self_mean	user_u
0	1	87_1	3.960666666666667	1.095701398901888	2	0.4714045207910317	0	1	0	
1	2	87_1	2.578333333333333	1.208881117213580	1	0.4714045207910317	*The Growth	0	0	
2	3	87_1	5.400333333333332	3.269392638124429	2	1.24721912892464	*The Growth	0	0	
3	4	87_1	Feb.56	2.222851022148508	1	0.942809041582064	*The Growth	0	0	
4	5	87_1	3.168333333333333	2.292290024310963	1	0.4714045207910317	*The Growth	0	0	
5	6	87_1	4.741333333333333	1.288999956900266	2	0.4714045207910317	*The Growth	0	0	
6	7	87_1	3.965333333333333	3.169162069415546	1	0.942809041582064	*The Growth	0	0	
7	8	87_1	4.828	2.568189634742730	1	0.4714045207910317	*The Growth	0	0	
8	9	87_1	3.239000000000000	2.962571293094339	1	0.816496580927774	*The Growth	0	0	
9	10	87_1	5.597	0.44648925183303	2	0.0	*The Growth	0	0	
10	11	87_1	3.986666666666667	1.102041842319166	2	0.816496580927774	*The Growth	0	0	
11	12	87_1	7.578	2.561475746518011	2	0.4714045207910317	*The Growth	0	0	
12	13	87_1	7.608000000000000	2.735462422821169	2	0.0	*The Growth	0	0	
13	14	87_1	1.529666666666667	2.163275345910044	0	0.4714045207910317	*The Growth	0	0	
14	15	87_1	8.931333333333333	0.962386732152009	5	0.816496580927774	0	0	0	
15	16	87_1	5.556333333333334	2.261789900843037	2	0.4714045207910317	*The Growth	0	0	
16	17	87_1	6.727	1.017153216908183	3	0.0	*The Growth	1	1	
17	18	87_1	10.116666666666667	0.788052592717573	2	0.4714045207910317	*The Growth	0	0	
18	19	87_1	4.003333333333333	2.393908148242580	1	0.4714045207910317	*The Growth	1	2	
19	20	87_1	2.688333333333333	1.207213412045369	1	0.4714045207910317	*The Growth	0	0	
20	21	87_1	3.849666666666666	2.990847854520334	2	1.6996731711975	*The Growth	1	0	
21	22	87_1	3.414333333333333	2.844651160023355	1	1.24721912892464	*The Growth	0	0	
22	23	87_1	2.529666666666667	2.335577349512440	1	0.4714045207910317	*The Growth	0	0	
23	24	87_1	3.084333333333333	2.186550759123195	2	1.4142135623730	*The Growth	0	0	
24	25	87_1	5.055000000000001	4.149196629067688	1	0.942809041582064	*The Growth	0	0	
25	26	87_1	5.559333333333332	4.346422385773793	1	0.816496580927774	*The Growth	0	0	
26	27	87_1	7.597333333333332	3.063529808715575	2	0.816496580927774	*The Growth	0	0	
27	28	87_1	3.507333333333333	3.013227984884132	1	0.4714045207910317	*The Growth	2	0	
28	29	87_1	4.020000000000000	2.012179581117616	1	0.4714045207910317	*The Growth	1	0	
29	30	87_1	7.004666666666666	4.640425650974511	2	1.24721912892464	*The Growth	0	0	
30	31	87_1	6.007666666666666	1.914539863489107	2	0.4714045207910317	*The Growth	0	0	
31	32	87_1	6.849	0.687692276142945	1	0.0	*The Growth	0	0	
32	33	87_1	2.880000000000000	2.347438320098457	1	0.816496580927774	*The Growth	0	0	
33	34	87_1	3.532	2.464377135640295	2	0.816496580927774	*The Growth	0	1	
34	35	87_1	2.981666666666667	3.437058076643777	0	0.4714045207910317	*The Growth	0	0	

Dataset



# ML model development



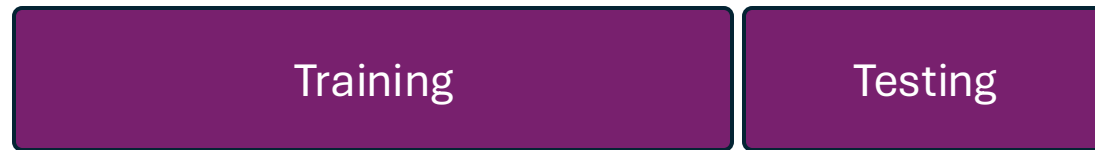
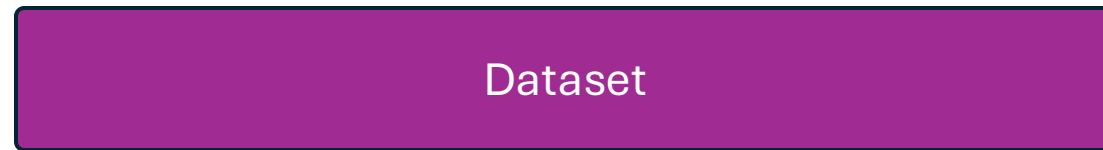
ML model development



ML model



# ML model Evaluation



ML model



# WHAT NEXT?

Would our model  
work well in  
authentic classroom  
settings?

NOISE ISSUE

VARYING CONTEXT

Collaboration quality model

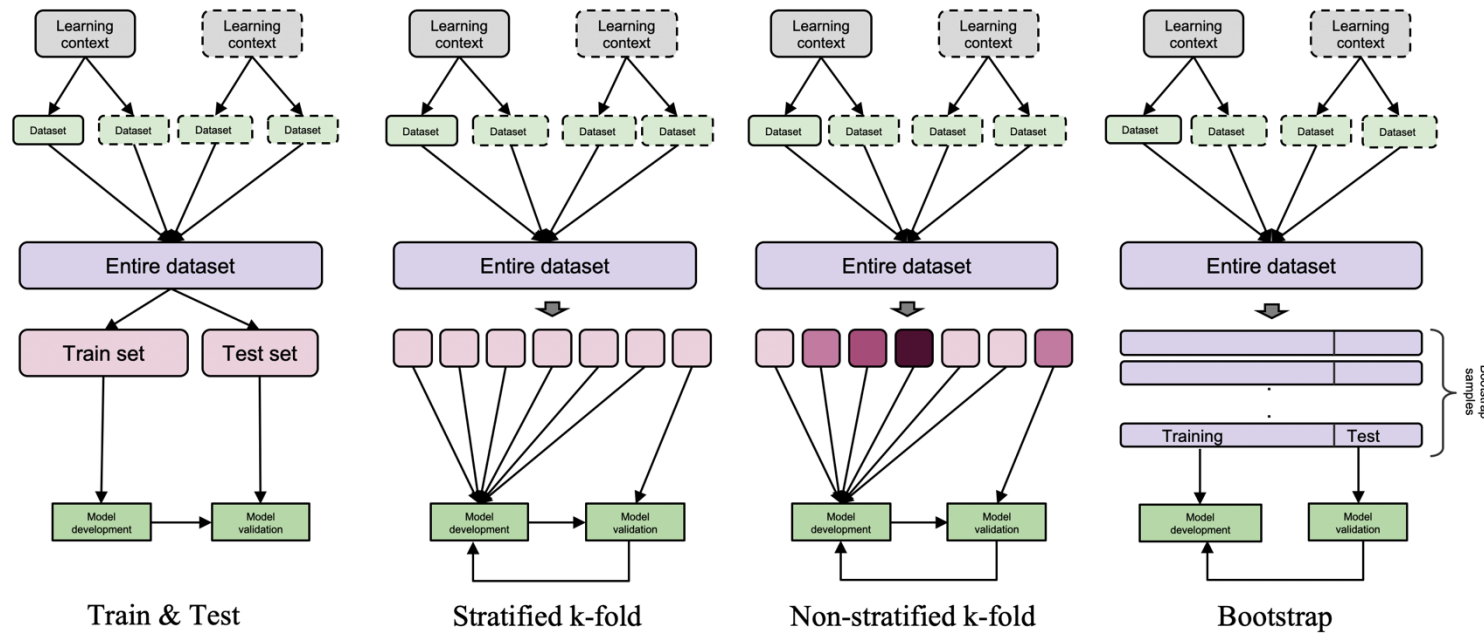


Transitioning from research to practice

# GENERALIZABILITY

1

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

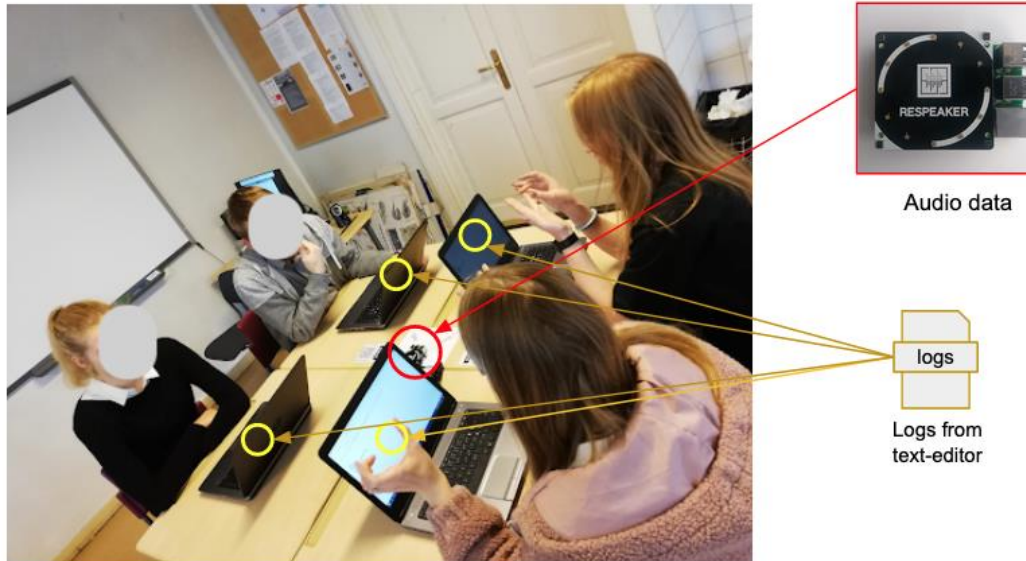


Model Evaluation Methods

1 Lack of systematization for generalizability evaluation & reporting

2 Do not consider educational nature of MMLA

# EXAMPLE



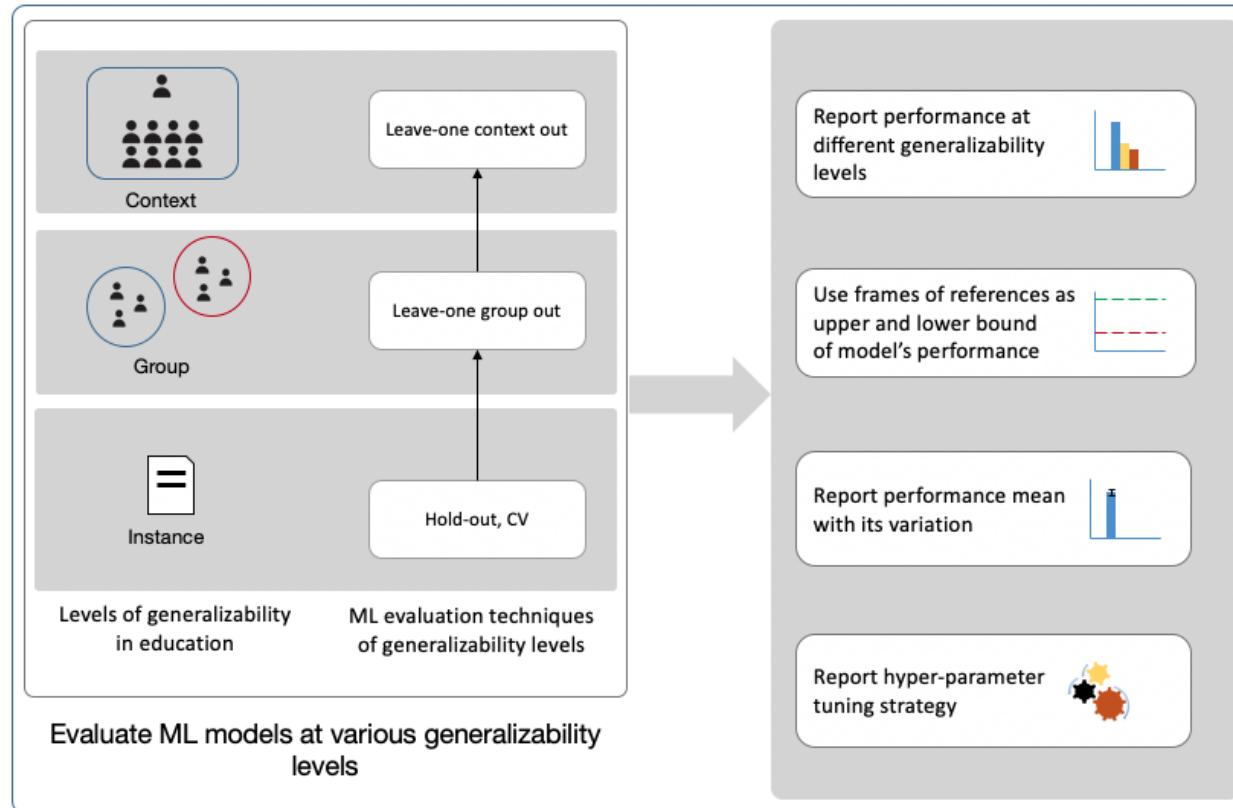
Features (30 sec)
Speaking time
number of char added
number of char deleted

<b>Group</b>	2
<b>Group-size</b>	4
<b>Duration</b>	30 mins
<b>Instances</b>	121

How to systematically assess and report generalizability in MMLA?

# EFAR-MMLA

## GENERALIZABILITY EVALUATION FRAMEWORK



# EFAR-MMLA

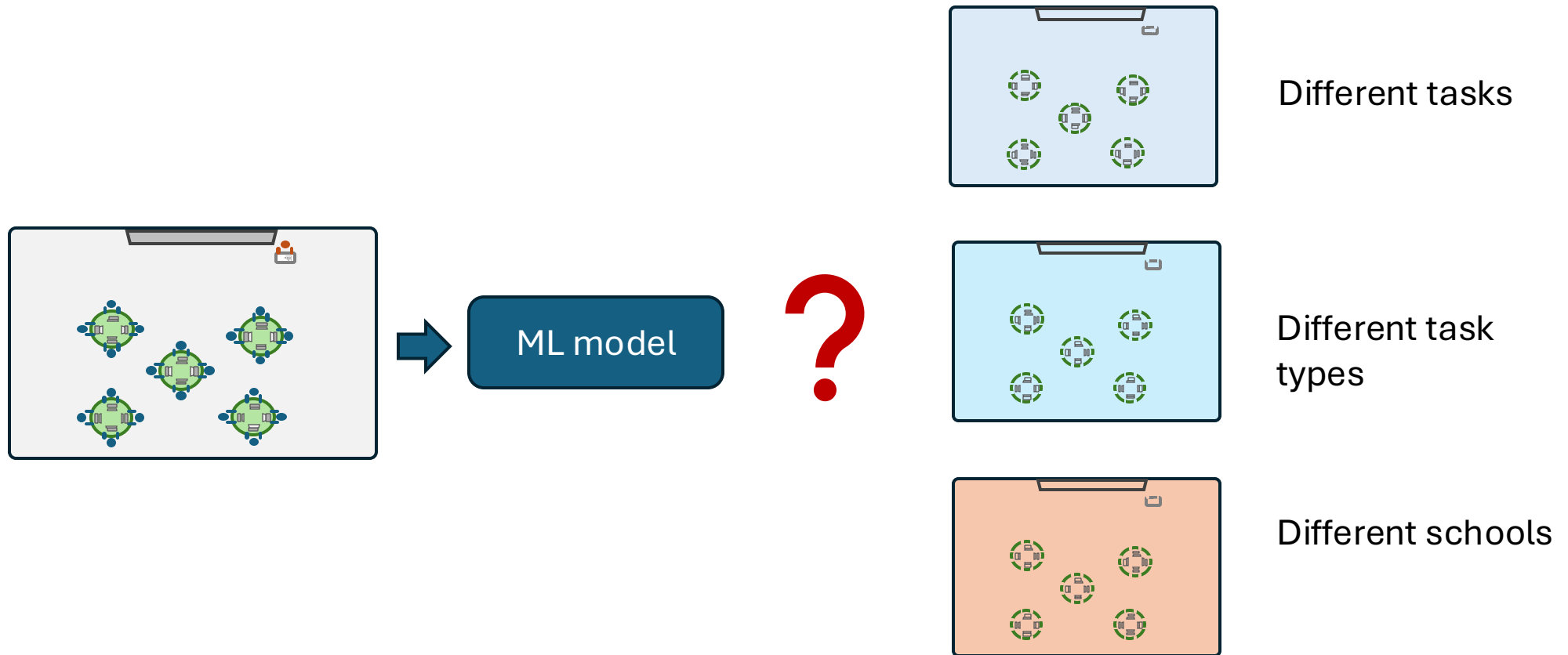
## GENERALIZABILITY EVALUATION FRAMEWORK

**1** Assessment of generalizability relevant to MMLA

**2** Bias identification

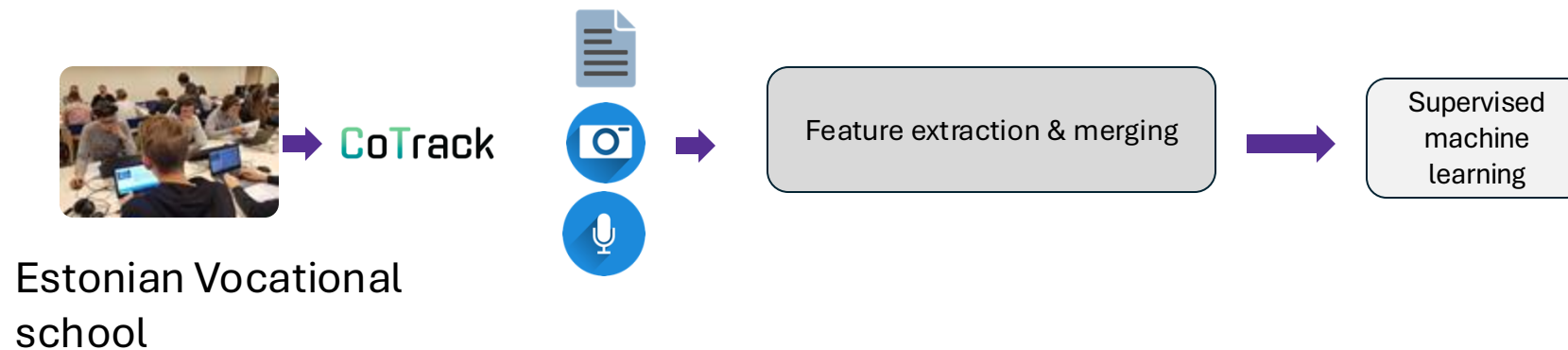
How well automated collaboration estimation models perform across different contexts varying on task, task type and school?

# CONTEXT GENERALIZABILITY

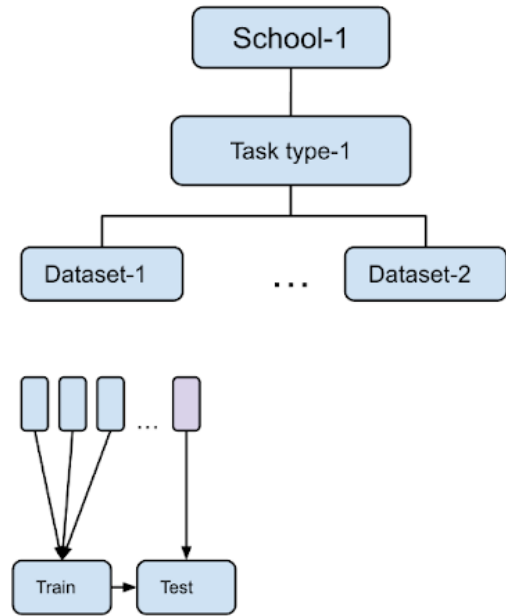




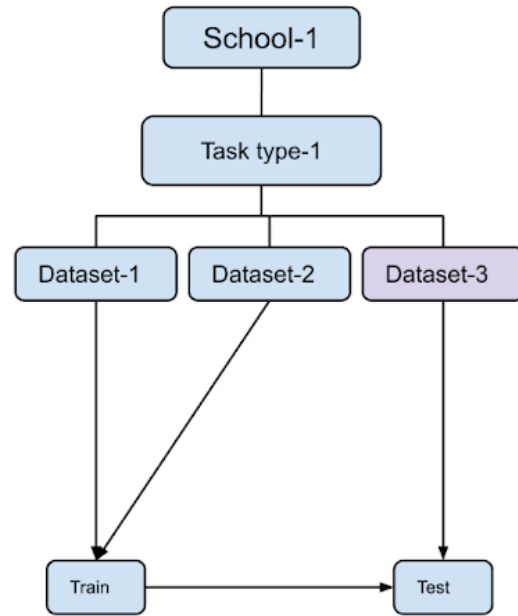
# CONTEXT GENERALIZABILITY



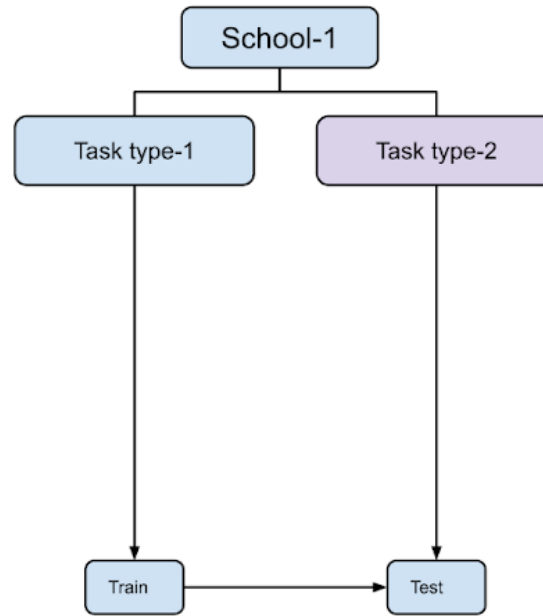
# EVALUATION



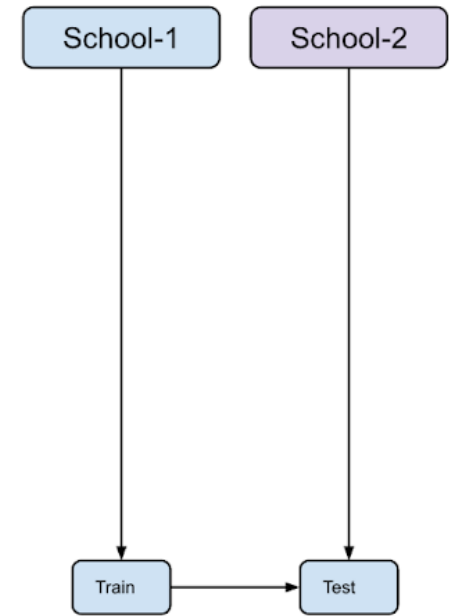
Within context  
generalizability



Across tasks  
generalizability



Across task-type  
generalizability

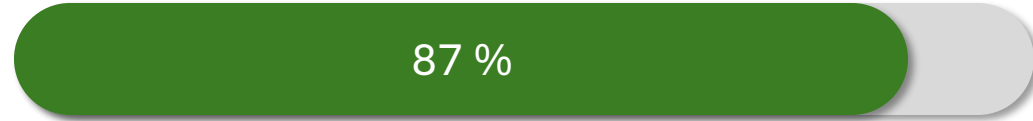


Across school  
generalizability

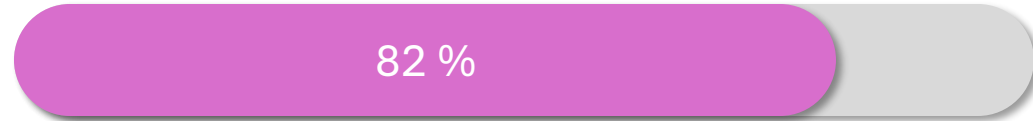
# RESULTS

## GENERALIZABILITY ACROSS CONTEXTS

HUMAN  
PERFORMANCE



MODEL  
PERFORMANCE



# RESULTS

## GENERALIZABILITY ACROSS CONTEXTS

HUMAN  
PERFORMANCE

87 %

MODEL  
PERFORMANCE

82 %

68 %

59 %

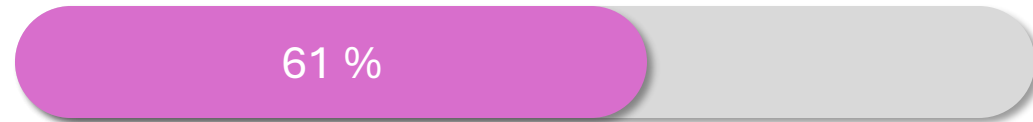
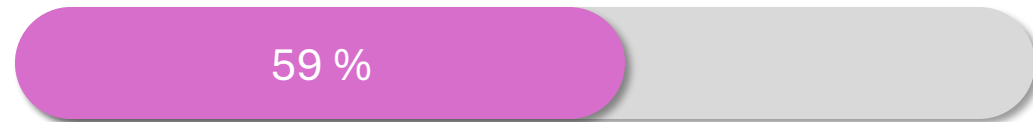
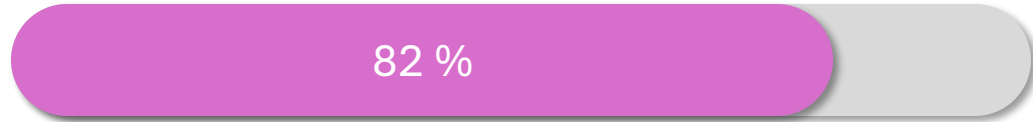
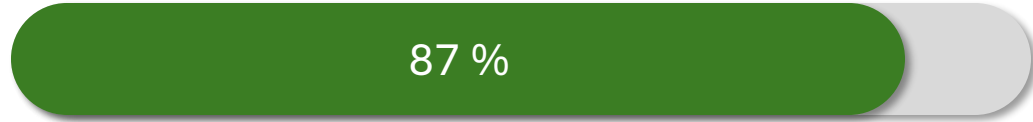
61 %

Within context

Across different tasks (group discussion)

Across different tasks types

Across schools (group discussion tasks)



# RESULTS

## GENERALIZABILITY ACROSS CONTEXTS

HUMAN  
PERFORMANCE

87 %

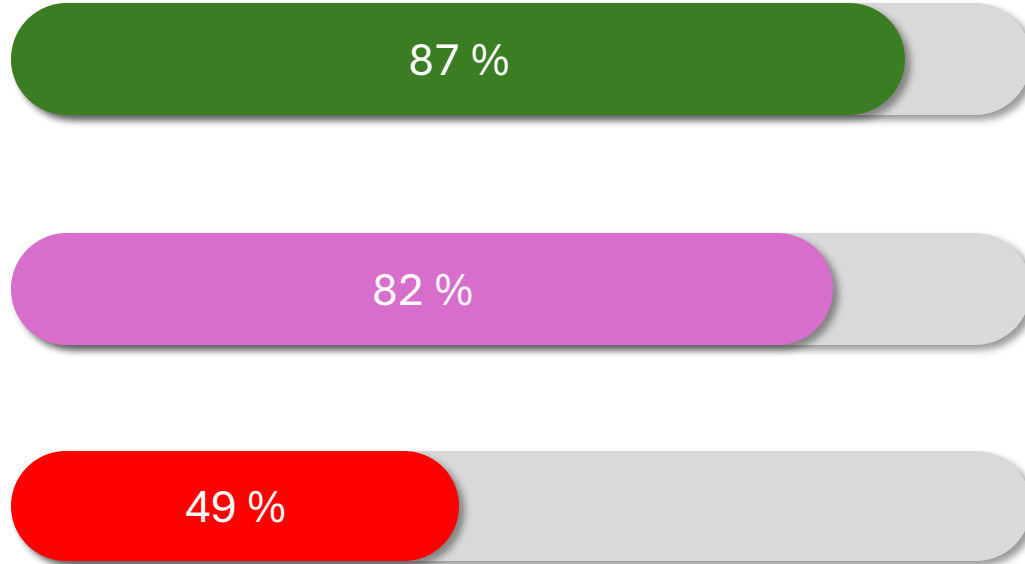
MODEL  
PERFORMANCE

82 %

49 %

Within context

Across different tasks  
(collaborative writing)

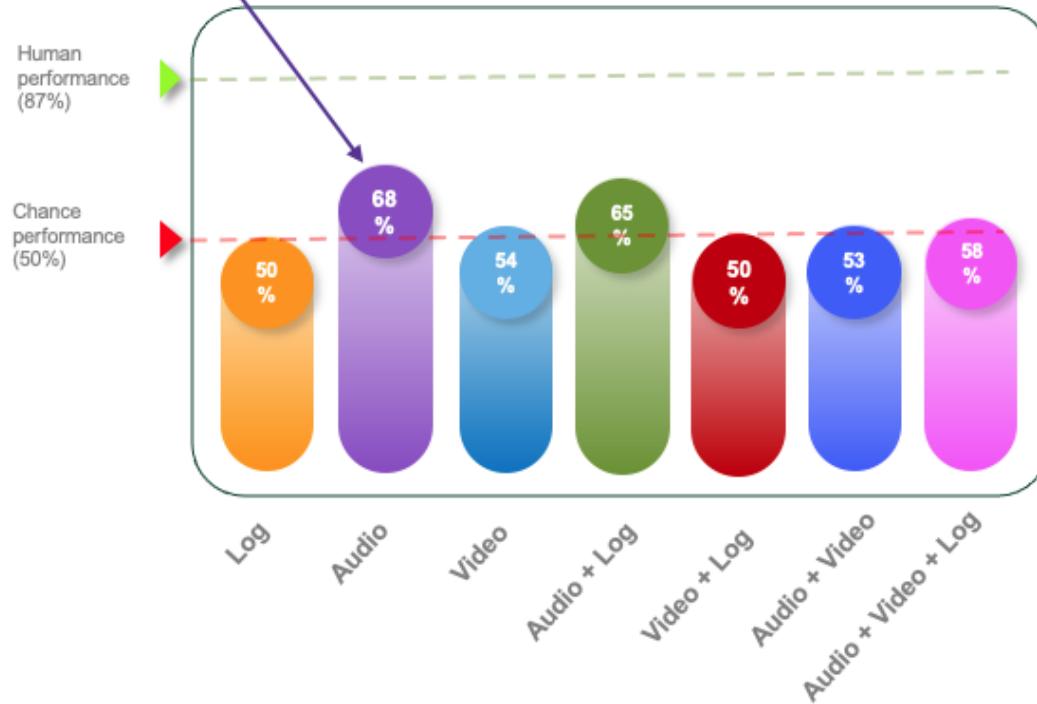


# RESULTS

## DATA IMPORTANCE

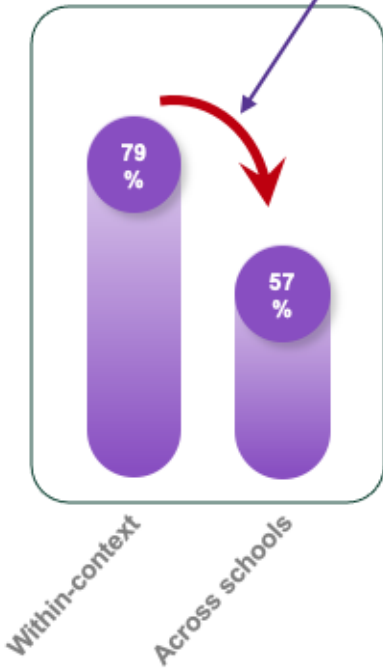
**Audio data** alone enabled the development of context generalizable models

Balanced accuracy of models built using different modalities across different group-discussion tasks



Model experienced a **loss of 22%** in balanced accuracy when performing across different schools

Balanced accuracy of models built using audio within and across contexts



# Multimodal Data Collection & Collaboration Monitoring

# CoTrack



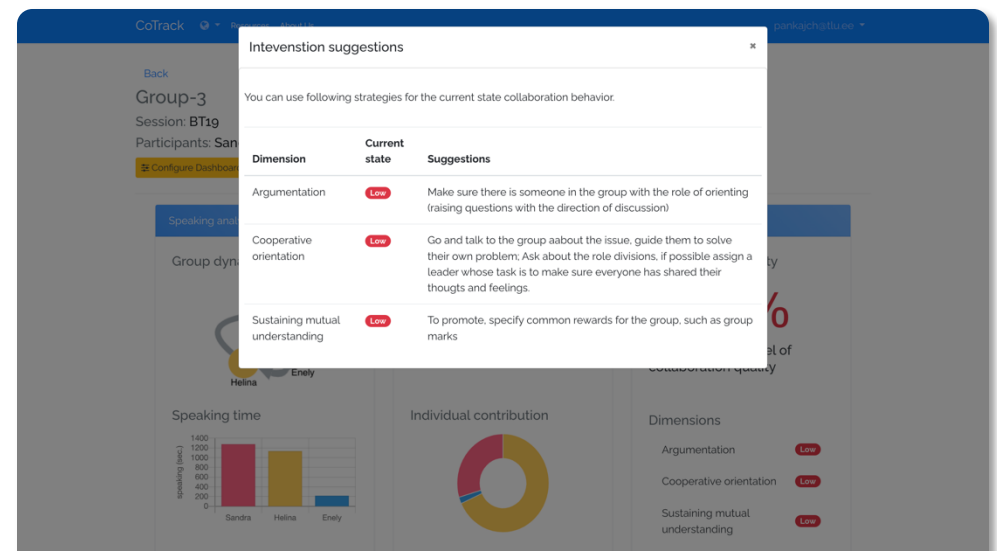
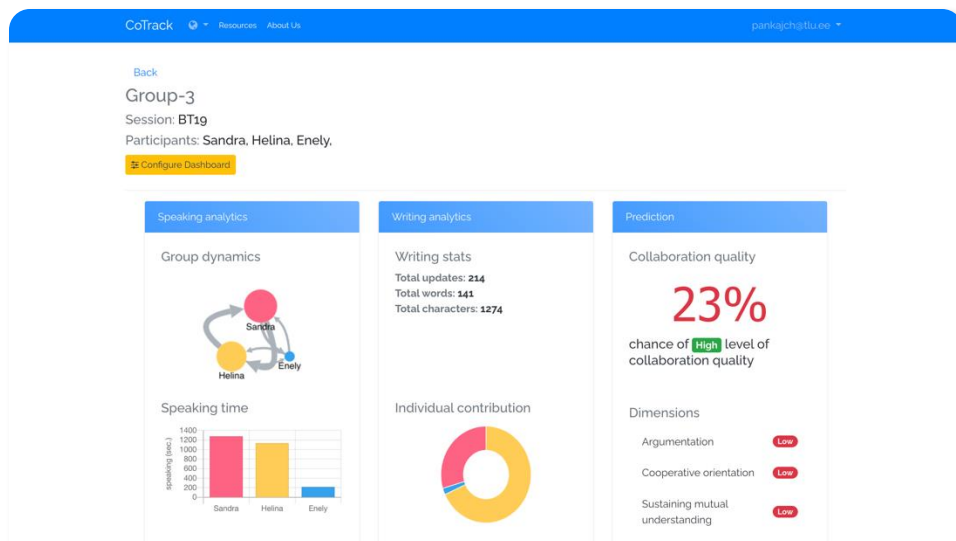
Tool Demo

<https://www.cotrack.website>

6 Researchers

58 Teachers

600 Students





# CLASSROOM VIEW

CoTrack Resources About Us pankajcha@tu.ee

BT19 Download Data

Total Groups 3 Activity Duration 1:30:00 Active Groups 2

Group	Social dynamics	Writing behavior	Collaboration quality	links
Group-1				Group analytics
Group-2				Group analytics
Group-3				Group analytics

Basic details

Showing how equally group participants are speaking (in this example, only three students are talking to each other more often)

It shows the size of text each group has produced in comparison with other groups.

This traffic system shows the predicted collaboration quality level of the group. (Green: High, Yellow: Medium, Red: Low)

# Group VIEW

Configure the dashboard.

Group dynamics in terms of who is talking to whom.

Speaking time of each group member.

It shows how much everyone in the group contributed to written text document.

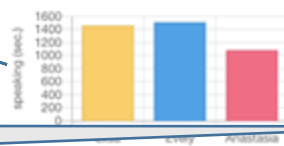
Back  
Group: Group-1  
Session: BT19  
Participants: Liisa, Evely, Anastasia.  
Configure Dashboard

### Speaking analytics

Group dynamics



Speaking time



Speech Text

To see the word cloud of group's conversation.

### Writing analytics

Writing stats

Total updates: 396  
Total words: 44  
Total characters: 407

Individual contribution



Group Document

To see group's written document.

### Prediction

Collaboration quality

83%

chance of High level of collaboration quality

Dimensions

- Argumentation: High
- Cooperative orientation: High
- Sustaining mutual understanding: Medium

Intervention Suggestions

To see suggestions on interventions.

Predicted chances of high collaboration quality. Higher is better.

Predicted level of three dimensions of collaboration quality.

Guidelines to build context  
generalizable collaboration  
estimation models

# GUIDELINES

1

Use **60 seconds time window** for data segmentation for modeling collaboration quality using multimodal data

2

Use **Random Forest** for building robust ML models for collaboration quality

3

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



[Thesis link](#)

# FUTURE DIRECTIONS



Small dataset size



Investigation using cross-modal features



Impact of choosing different choices of ML modeling step on generalizability



Privacy-preserving approaches for MMLA



Teacher's perception and response to AI-enabled systems

# CONCLUSION



Time to move research from laboratories to practice.



Teacher-AI hybrid partnership

“ Your reasoning for **WHY** you do **WHAT YOU DO** is more critical than **WHAT YOU DO**.  
Anonymous

# Thank you

Pankaj Chejara  
[pankajch@tlu.ee](mailto:pankajch@tlu.ee)

# 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. DiMicco, J. M., Pandolfo, A., & Bender, W. (2004). Influencing group participation with a shared display. *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work - CSCW '04*, 614. <https://doi.org/10.1145/1031607.1031713>
4. Bachour, K., Kaplan, F., & Dillenbourg, P. (2010). An interactive table for supporting participation balance in face-to-face collaborative learning. *IEEE Transactions on Learning Technologies*, 3(3), 203–213. <https://doi.org/10.1109/TLT.2010.18>
5. Lubold, N., & Pon-Barry, H. (2014). Acoustic-Prosodic Entrainment and Rapport in Collaborative Learning Dialogues. *Proceedings of the 2014 ACM Workshop on Multimodal Learning Analytics Workshop and Grand Challenge - MLA '14*, 5–12. <https://doi.org/10.1145/2666633.2666635>
5. 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. Raschka, S. Model Evaluation, Model Selection, and Algorithm Selection in Machine Learning. arXiv 2018, arXiv:1811.12808.
6. 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>
7. Spikol, D., Ruffaldi, E., Dabisias, G., & Cukurova, M. (2018). Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning*, 34(4), 366–377. <https://doi.org/10.1111/jcal.12263>
8. 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).