Automated Analysis of Cohesion in Small Groups Interactions

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Introduction

Humans are *ultra* social animals

- Interactions happen in different groups and contexts

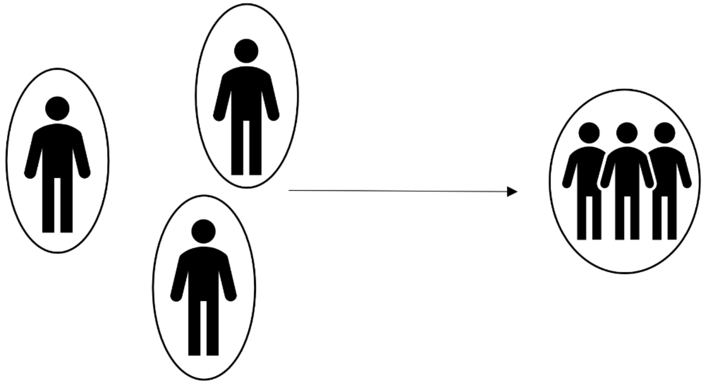
Social Signal Processing (SSP) & Affective Computing (AC)

- Develop machines that are **socially** and **emotionnaly** aware
- Automatically **analyze**, **detect** and **reproduce** social and affective skills
- **Enhance** group **processes**

Applications

- Robotics / Virtual agents
- Smart surveilance
- Human-computer interaction

Emergent states



Social group processes resulting from micro-level affective, cognitive, behavioral, and motivational interactions among group members (e.g., Marks, 2001)

3 - 4 families (e.g., Kozlowski & Ilgen, 2006, Rapp 2021):

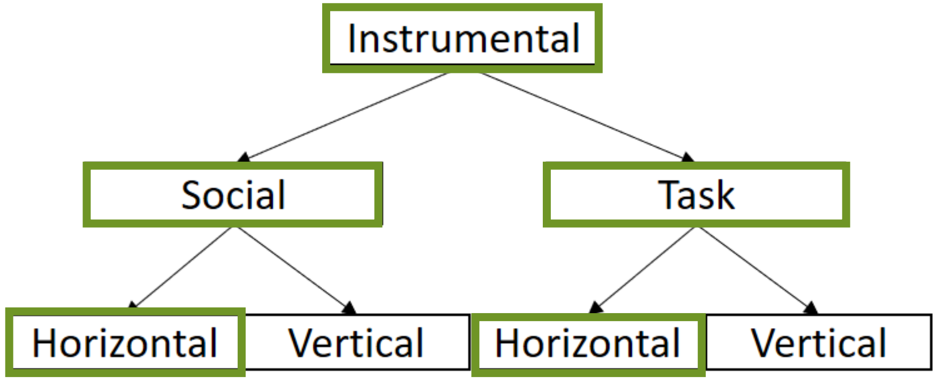
- *Affective:* what the members feel
- *Cognitive:* what the members think
- *Behavioral:* what the members do
- *Motivational:* what the members believe

Focus on **cohesion**
A group affective emergent state

Aim of the Thesis & Theoretical Background

Develop automated methods to study cohesion

Cohesion, an **affective** emergent state: "***dynamic*** *process that is reflected in the tendency for a* ***group*** *to stick together and remain united in the pursuit of its* ***instrumental*** *objectives and/or for the satisfaction of member* ***affective*** *needs*" (Carron & Brawley, 2000)



(Severt & Estrada, 2015)

4 Research Axes

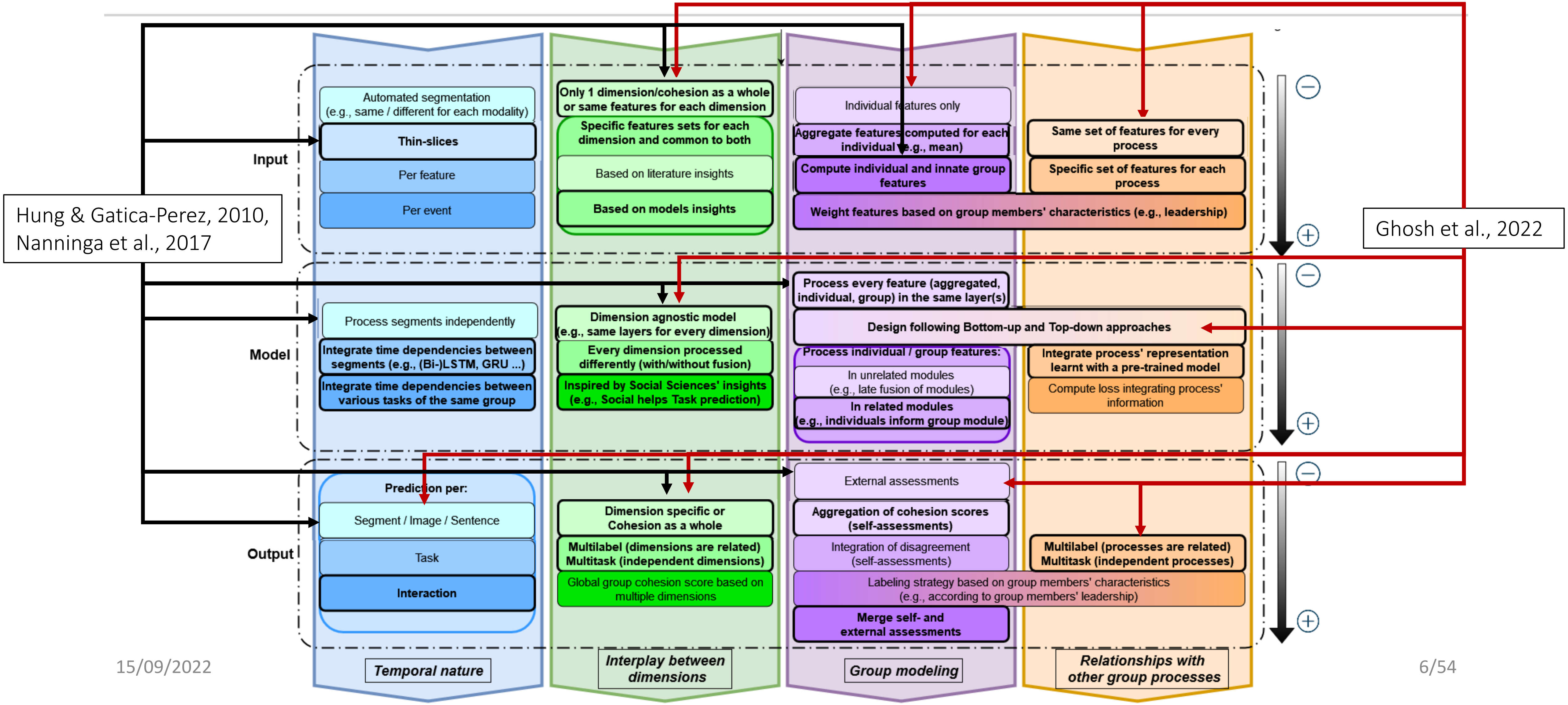
Temporal nature of cohesion (RA1)

Group modeling (RA2)

Interplay between cohesion's dimensions (RA3)

Relationships with other group processes (RA4)

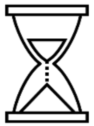
Structured survey for supporting the automated analysis of cohesion in small groups interactions



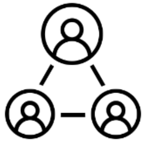
Research Questions (RQs)

RQ1: What computational architectures can be implemented to automatically predict cohesion and its dynamics?

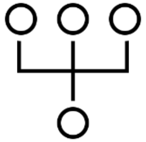
- How to integrate the temporal nature inherent to cohesion?



- How to take into account both individuals and group behaviors that result from, and are influenced by, the group members' interactions?



- How to model the interplay between the Social and Task dimensions of cohesion over time?



RQ2: How other group processes can inform the modeling of cohesion?

Contributions of the Thesis

1. A structured survey for supporting the automated analysis of cohesion in small groups interactions.
2. A multimodal dataset for the automated cohesion analysis.
3. Design and implementation of 10 computational models of cohesion

- 8 publications (1 journal, 3 conferences, 3 workshops & 1 doctoral consortium)
- 1 paper under review (1 journal)

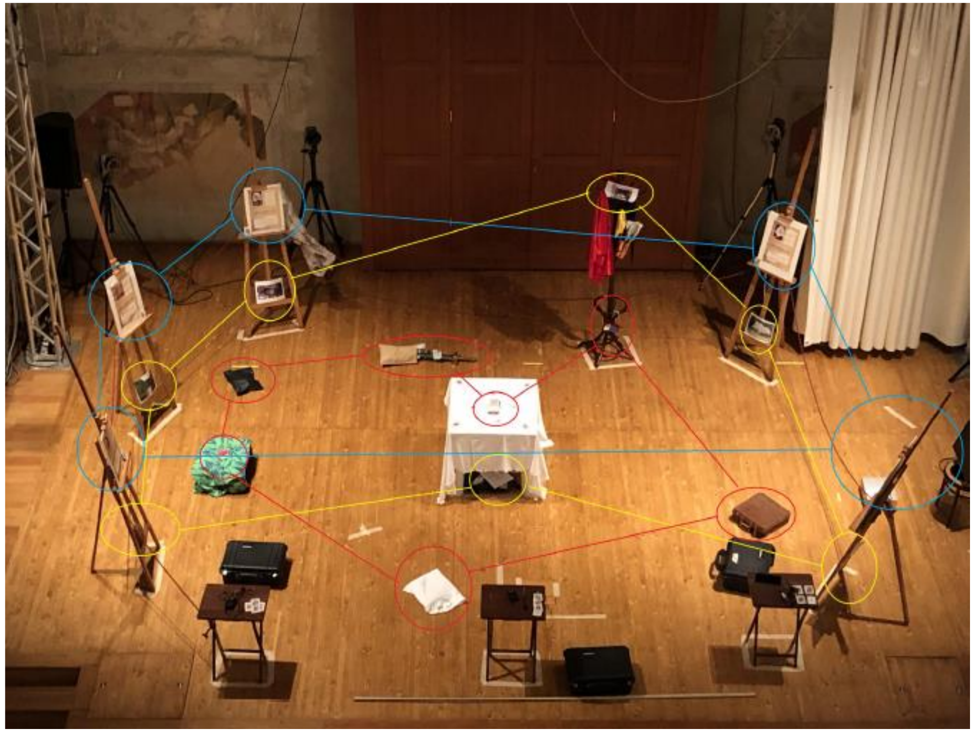
Outline

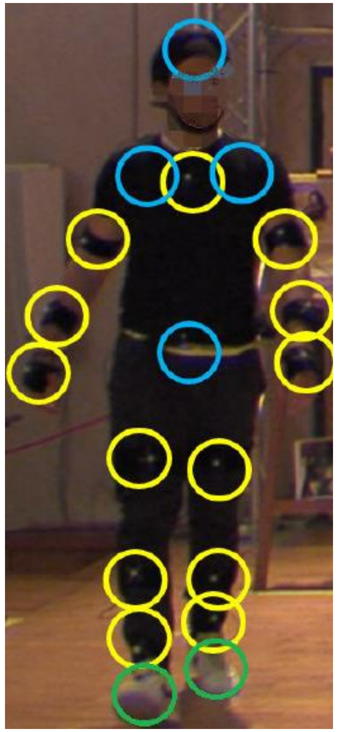
- The GAME-ON dataset
- Labeling strategy
- Multimodal nonverbal features
- Training & evaluation methodologies
- Computational models of cohesion (RQ1)
- Integrating relationships with other group processes (RQ2)
- Conclusions and perspectives

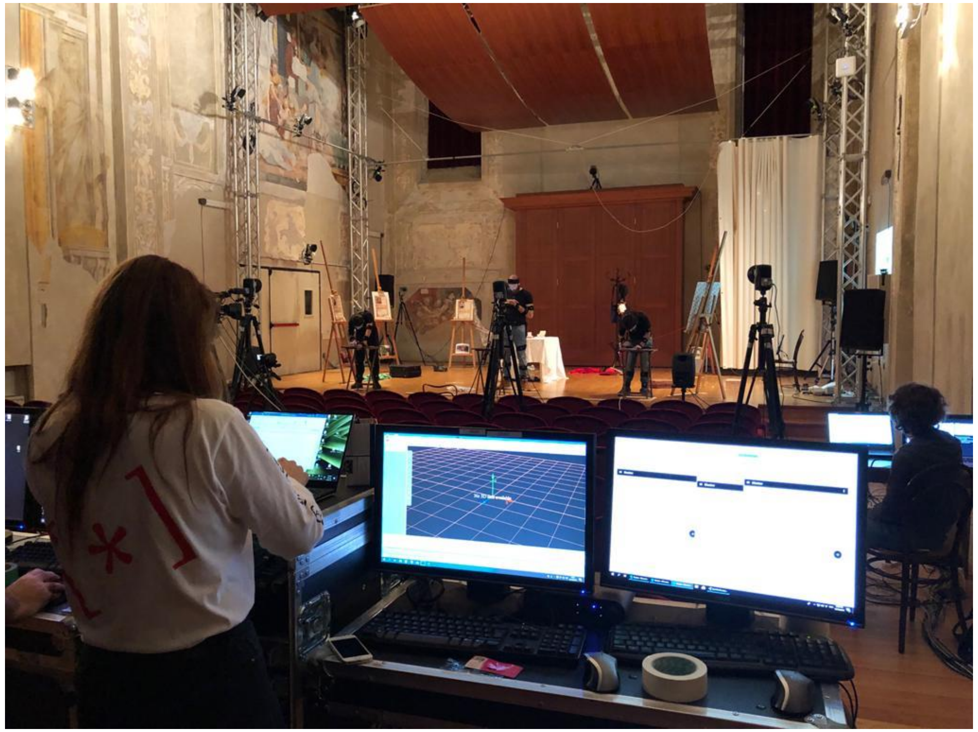
Outline

GAME-ON

- **11h+** of multimodal data (video, motion capture and audio) from **17 groups** of 3 friends
- SMPTE and EyesWeb based multimodal sync
- Hybrid motion capture solution

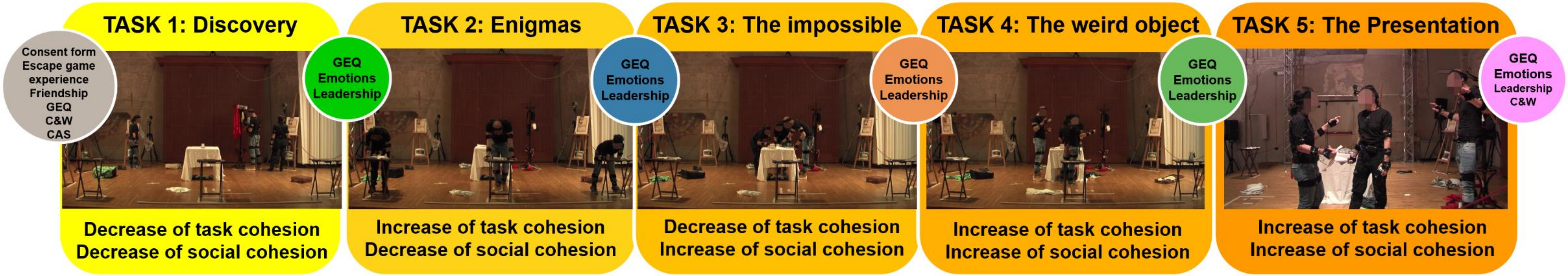






GAME-ON

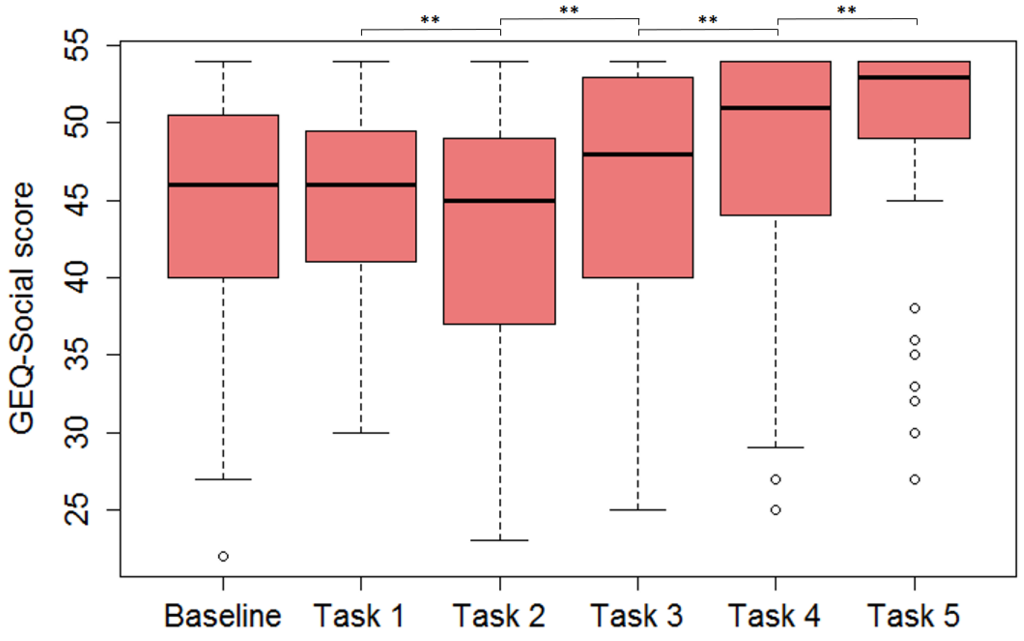
- **Social game scenario** (escape game)
- Focus on cohesion's dynamics (decrease vs increase)
- Self- and external assessments on cohesion
- Self-assessments on emotions, emergent leadership, and warmth and competence

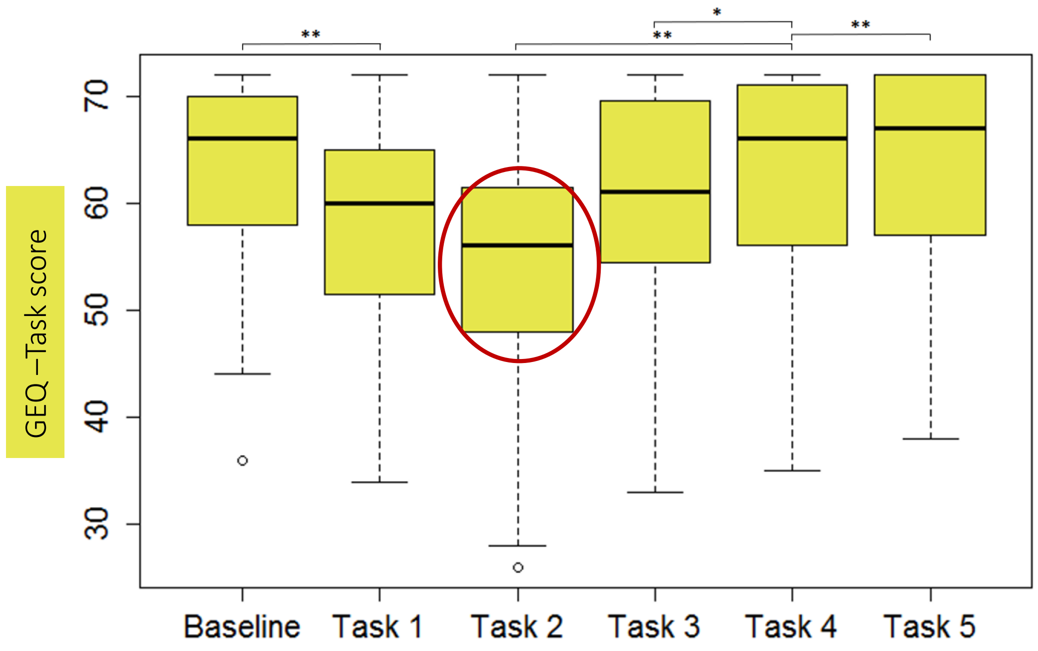


GEQ - scores from self-assessments

- Adapted version of the Group Environment Questionnaire (Carron et al., 1985):
  - 6 items for Social cohesion, 8 items for Task cohesion
  - Items on a 9-point Likert scale
- **Shapiro-Wilk test**: Significant departure from normality for both the Social dimension (W=0.87, p<.001) and the Task (W=0.90, p<.001) dimension
- **Non parametric Friedman tests** of differences for both the Social ($X^2(5)=68.86$, p<.001) and the Task ($X^2(5)=43.66$, p<.001) dimensions
- **Post-hoc Conover's tests** with a Bonferroni-adjusted α

Significance level α<.05





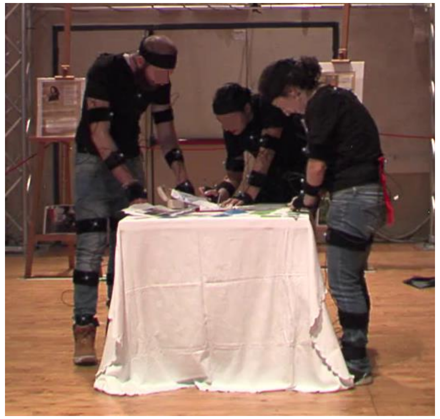
Outline

Labels

- What type of assessment should we use?
  - ➢ Based on self-assessments: true internal state (Uleman et al., 2008)
- How to get a cohesion ground-truth for the group?
  - ➢ Mean rank difference of scores between 2 consecutive tasks
- 1 binary label for each dimension (i.e., Social and Task cohesion)
  - ➢ decrease / not decrease

⋮

T2



p1 → 34
p2 → 24
p3 → 23

p1 → …
p2 → …
p3 → …

T1

p1 → 41
p2 → 45
p3 → 48

p1 → …
p2 → …
p3 → …

$$GS_{T_x} = \frac{1}{n}\sum_{i=1}^{n}\left(rank^{(i)}_{T_x} - rank^{(i)}_{T_x-1}\right)$$

	GEQ Score		Rank		Ranks
	Task 1	Task 2	Task 1	Task 2	difference
p_1	41	34	4	3	-1
p_2	45	24	5	2	-3
p_3	48	23	6	1	-5

→ Mean →

$$\Theta\,(mrd) = \begin{cases} 0\,, mrd < 0 \\ 1, mrd \geq 0 \end{cases}$$

Labels

- What type of assessment should we use?
  - ➢ Based on self-assessments: true internal state (Uleman et al., 2008)
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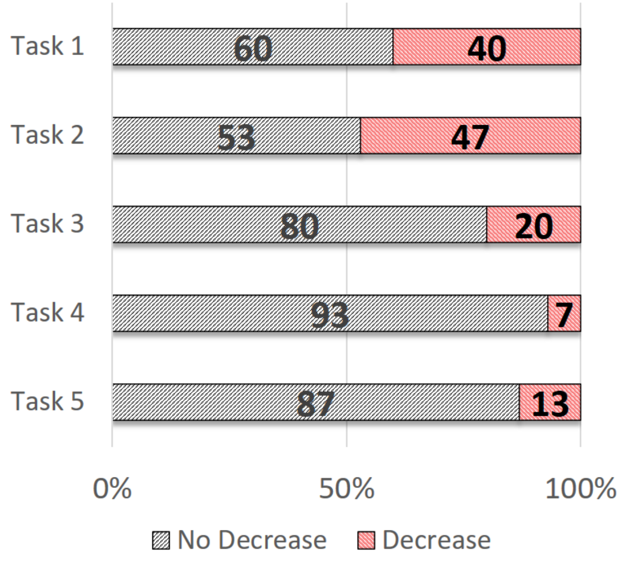
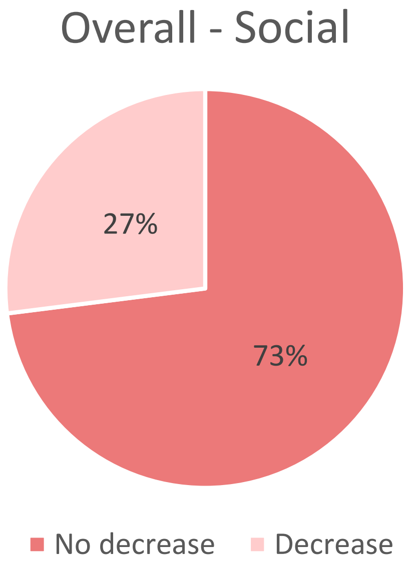
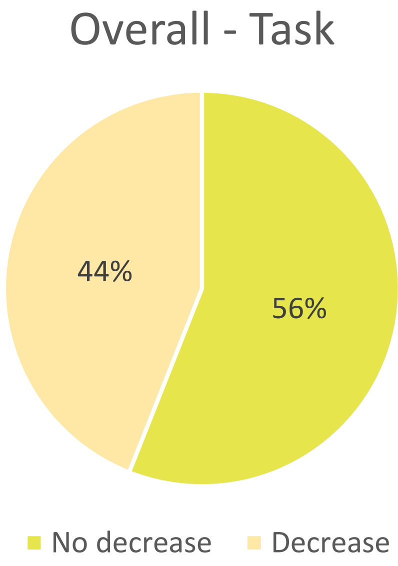
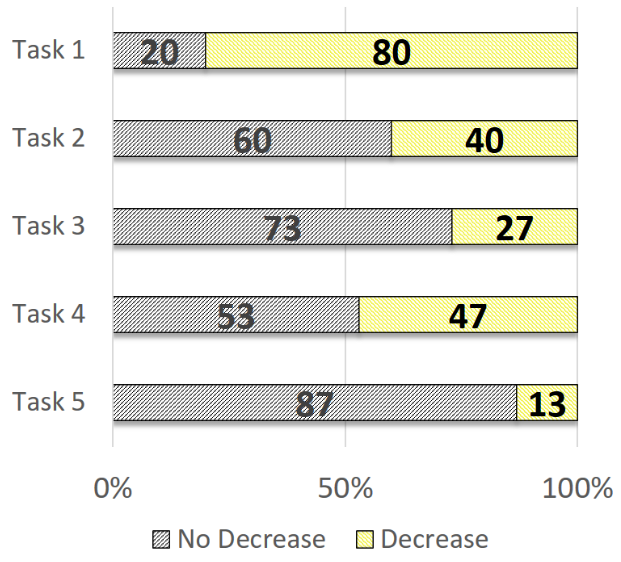
  - ➢ decrease / not decrease









Outline

Feature Extraction

Motion Capture

- Proxemics related features
  (Hall, 1966; Kendon, 1990)
- Kinesics related features
  (Hans & Hans, 2015)

Auditory

- Geneva Minimalistic Acoustic Parameter Set (GeMAPS)
  (Eyben et al., 2015)
- Turn-taking related features
  (Hung & Gatica-Perez, 2010)

		Individual	Group
Motion capture	Proxemics	Distance from group barycenter ⋆ Total distance traveled	Histogram of the interpersonal distances ⋆ Maximum of the interpersonal distances ⋆ Time in F-formation ⋆
	Kinesics	Longitudinal posture expansion ⋆ Lateral posture expansion ⋆ Occupied volume ⋆ Kinetic energy ⋆	Average amount of motion ⋆ Difference ratio of motion ⋆ Touches' duration ⋆ Synchrony among kinetic energies Average amount of hands movements while not moving ⋆ Difference ratio of hands movements while not moving ⋆
Auditory	Turn-taking	Laughter duration Total speaking time	Time of overlapping speech Average turn duration
		Individual	
	GeMAPS	Pitch Jitter Shimmer Loudness HNR F1, F2, F3 frequencies and F1 bandwidth	F1, F2, F3 relative energies H1-H2 H1-A3 Spectral slope (0-500Hz and 500-1500Hz) Alpha ratio (50-1000Hz and 1-5kHz) Hammarberg Index (0-2kHz and 2-5kHz)

Individual **and** group features

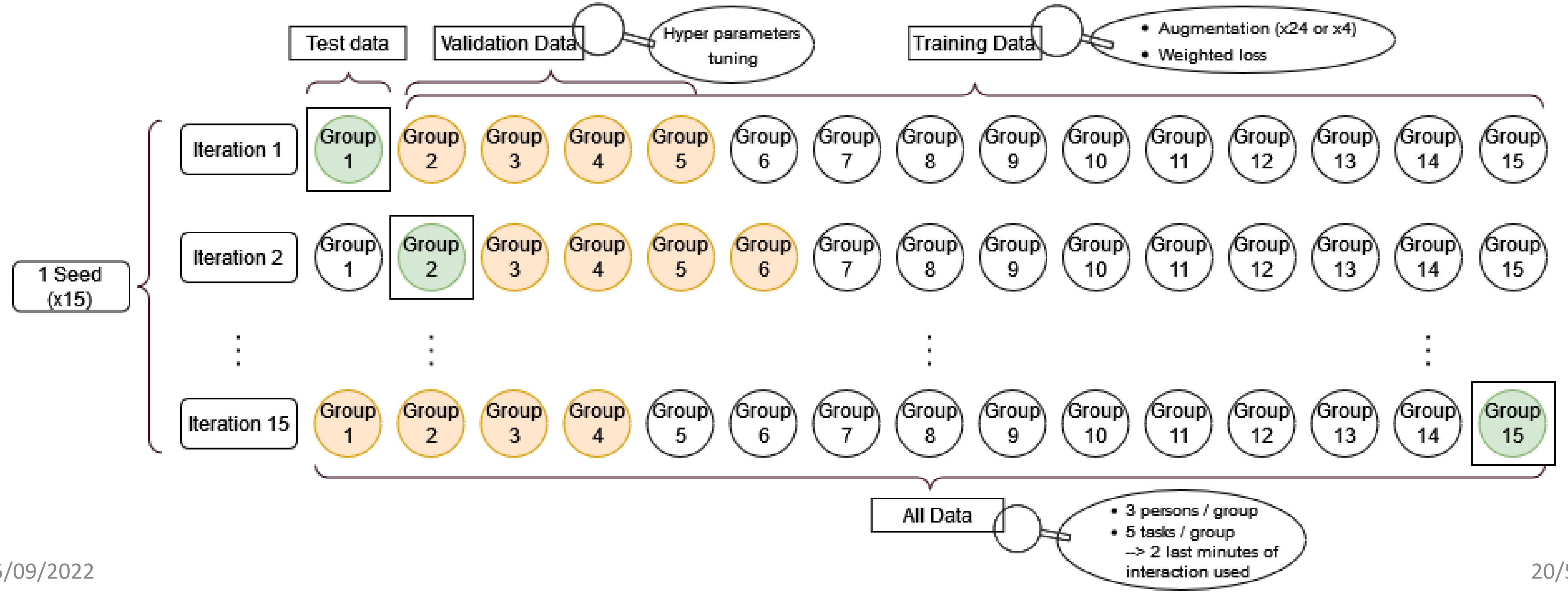
Functionals are applied
(mean, std, min, max, skewness)

- 20s time windows
- 91 values extracted for each window

Outline

Methodology

- Leave One Group Out (LOGO) Cross-validation
- 10/4/1 group(s) in train/val/test sets
- Data augmentation on train set (x24 or x4)
- 15 seeds
- 2 last mn of each of the 5 tasks is used as input for the models (i.e., 6 windows of 20s)



Comparing the models

- Average F1-score over 15 rounds of the LOGO
- k-sample permutation test with performances on the 15 seeds
- Postoc analysis pairwise permutation with a FDR adjusted p-value (α = 0.05)

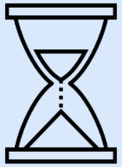
Outline

Collection of computational models

Full Interaction LSTM (FI-LSTM)	From Individual to Group (fItG)	Transfer Between Dimensions (TBD)	TBD Reciprocal Impact (TBD-RI)
Random Forest Classifier (RFC)	Specific To Entwined (STE)	Common to Specific (CTS)	RQ1
fItG Bottom-up (fItG_Bu)	fItG Top-down (fItG_Td)	fItG Leadership (fItG_Leadership)	RQ2

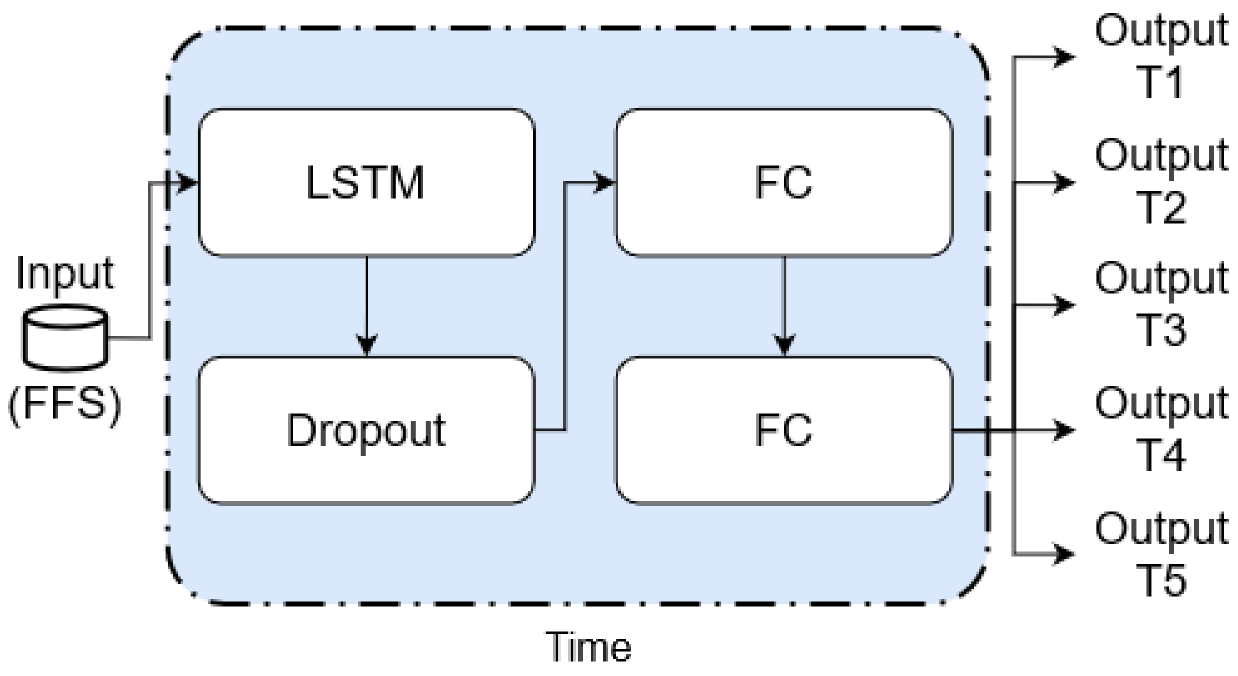
Axis

Temporal nature of cohesion (RA1)



The Full Interaction LSTM (FI-LSTM)

- Models dependencies between windows and between tasks
- Does not model a group
- Averaged F1-score:
  - Social: 0.66 +/- 0.06
  - Task: 0.56 +/- 0.04



Axes

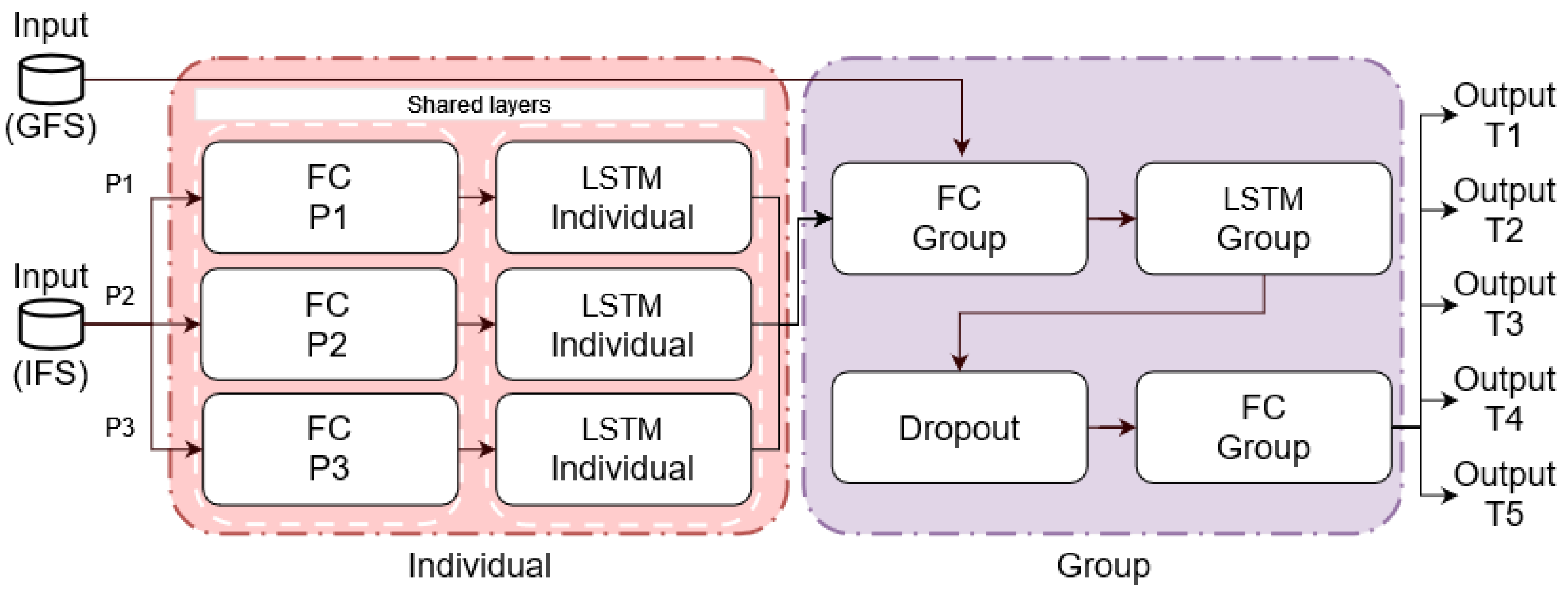
Temporal nature of cohesion (RA1)

Group modeling (RA2)

The from Individual to Group (fItG)

Integrating time (RA1) and group modeling (RA2)

- Models dependencies between windows and between tasks
- Models a group
- Averaged F1-score:
  - Social: 0.67 +/- 0.04
  - Task: 0.61 +/- 0.05



Best multilabel model

- Potential significant differences assessed using randomization tests (α = 0.05)
- FI-LSTM and fItG outperform RFC for both dimensions
- fItG is better than FI-LSTM for the Task dimension
- fItG is the most performing baseline

	F1-score ±std					
	RFC		FI-LSTM		fItG	
	Social	Task	Social	Task	Social	Task
T1	0.47 ±0.06	0.42 ±0.06	0.50 ±0.11	0.56 ±0.08	0.52 ±0.10	0.65 ±0.07
T2	0.23 ±0.04	0.35 ±0.03	0.41 ±0.11	0.46 ±0.12	0.51 ±0.13	0.56 ±0.12
T3	0.70 ±0.02	0.54 ±0.03	0.69 ±0.08	0.54 ±0.11	0.65 ±0.07	0.57 ±0.13
T4	0.86 ±0.00	0.61 ±0.02	0.84 ±0.07	0.50 ±0.13	0.87 ±0.04	0.66 ±0.14
T5	0.83 ±0.05	0.73 ±0.00	0.78 ±0.05	0.76 ±0.09	0.80 ±0.04	0.74 ±0.07
Average	**0.62 ±0.02**	**0.53 ±0.02**	**0.64 ±0.04**	**0.56 ±0.06**	**0.67 ±0.03**	**0.64 ±0.02**

Take-away

1. Integrating time in computational models of cohesion improves performances
   ➢ FI-LSTM > RFC

2. Integrating both individual and group contributions improves performances
   ➢ fItG > FI-LSTM > RFC

3. fItG in a multilabel setting is the most performing baseline

Axes

Temporal nature of cohesion (RA1)

Group modeling (RA2)

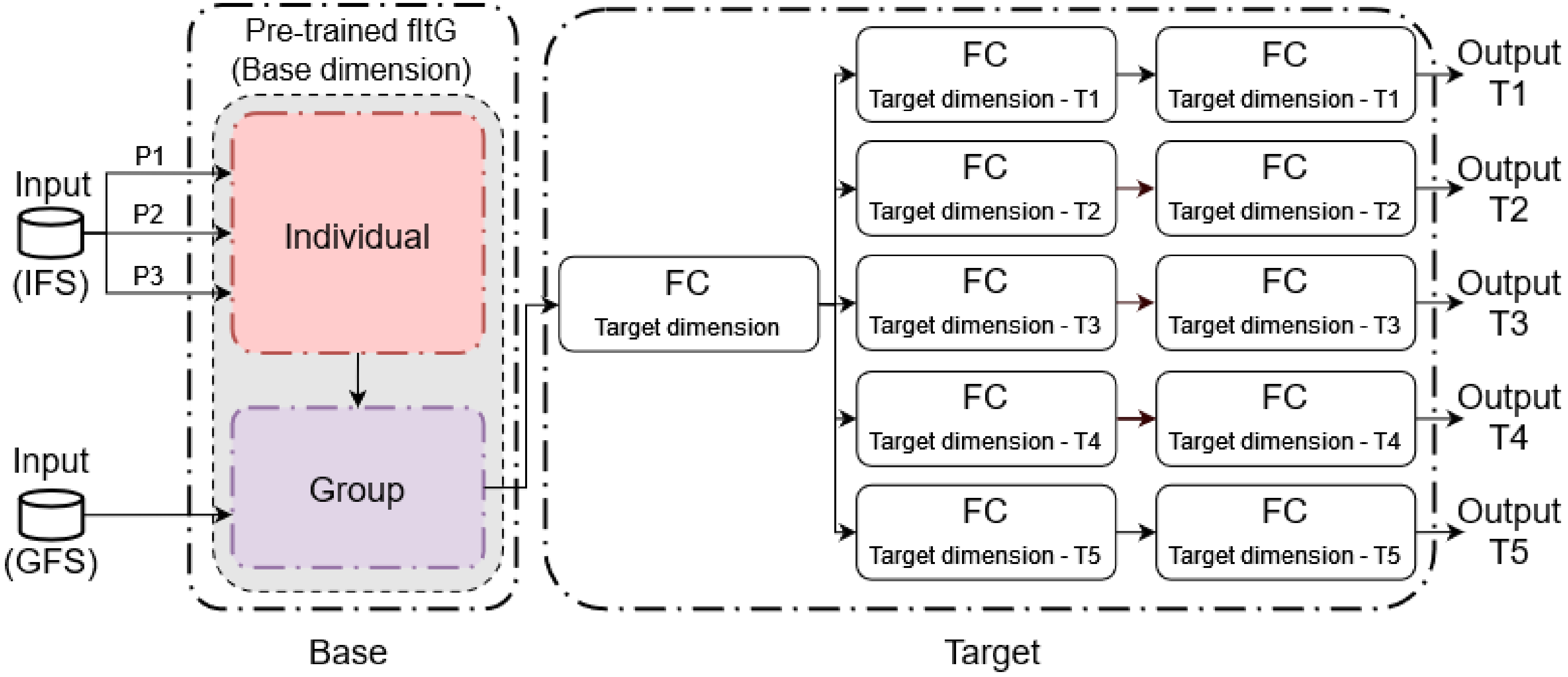
Interplay between cohesion's dimensions (RA3)

The Transfer between Dimensions (TBD)

Integrating time (RA1), group modeling (RA2) and the interplay between dimensions (RA3)

- Same architecture to integrate 2 Social Sciences' insights
- Leverages a transfer learning approach
- Averaged F1-score:
  - Social: 0.67 +/- 0.04
  - Task: 0.61 +/- 0.05

TBD-T: Social cohesion informs Task cohesion (Grossman et al., 2015)

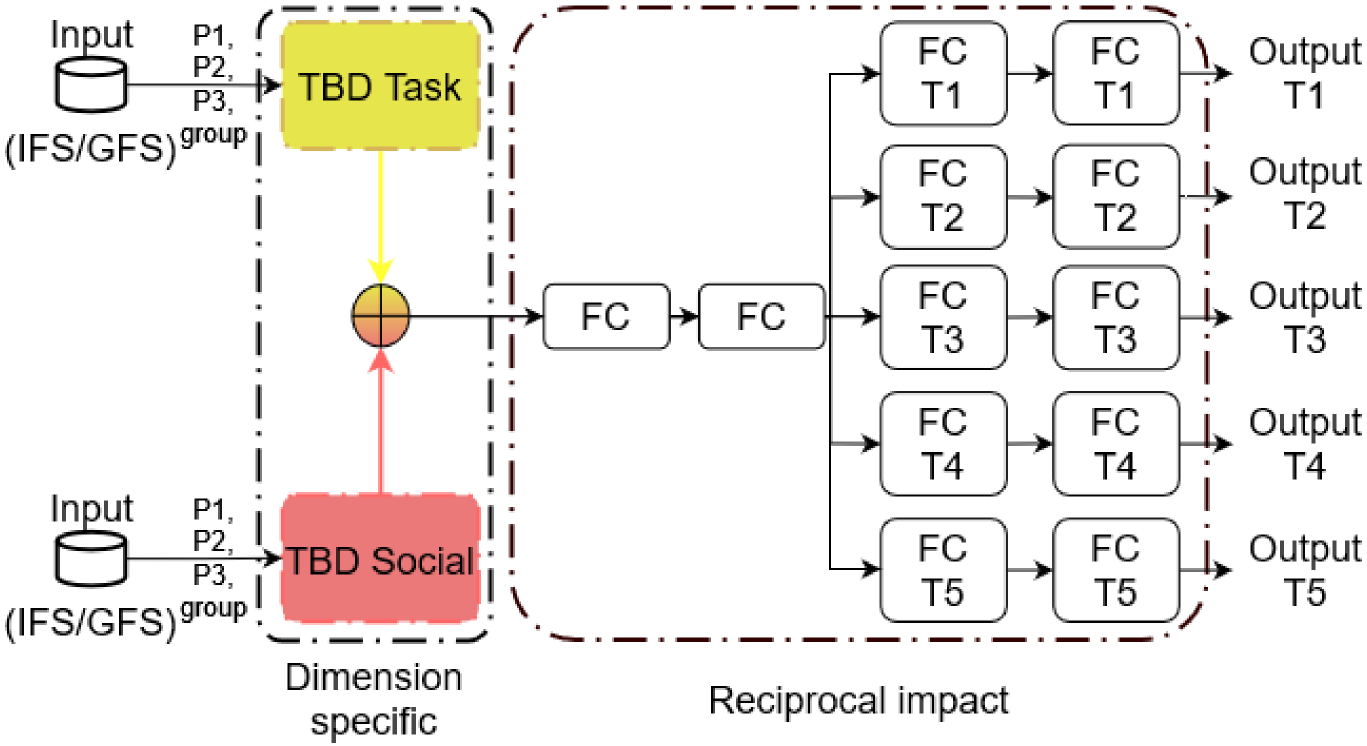


TBD-S: Task cohesion informs Social cohesion (Kozlowski et al., 1999)

The Transfer between Dimensions-Reciprocal Impact (TBD-RI)

Integrating time (RA1), group modeling (RA2) and the interplay between dimensions (RA3)

- A reciprocal interplay between both dimensions exists (Siebold, 2006)
- Leverages a transfer learning approach
- Averaged F1-score:
  - Social: 0.70 +/- 0.03
  - Task: 0.64 +/- 0.03



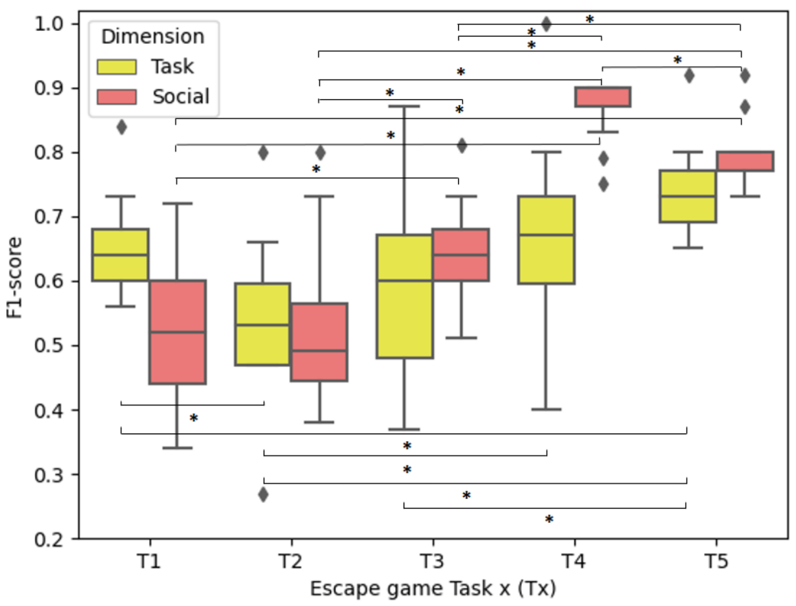
Comparing TBDs, TBD-RI and the fItG

- TBD-RI outperforms fItG and TBD-S, for the Social dimension
- TBD-T is the most performing model for the Task dimension

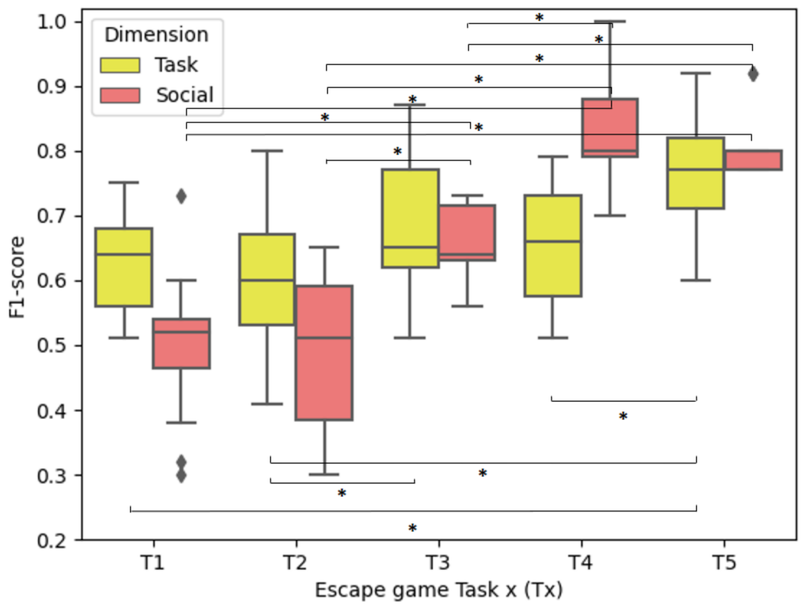
	F1-score ±std					
	fItG		TBD-S/T		TBD-RI	
	Social	Task	Social	Task	Social	Task
T1	0.52 ±0.10	0.65 ±0.07	0.50 ±0.11	0.63 ±0.07	0.56 ±0.10	0.64 ±0.09
T2	0.51 ±0.13	0.56 ±0.12	0.49 ±0.11	0.59 ±0.09	0.61 ±0.08	0.61 ±0.09
T3	0.65 ±0.07	0.57 ±0.13	0.66 ±0.06	0.69 ±0.10	0.69 ±0.06	0.62 ±0.11
T4	0.87 ±0.04	0.66 ±0.14	0.83 ±0.09	0.65 ±0.09	0.85 ±0.05	0.57 ±0.10
T5	0.80 ±0.04	0.74 ±0.07	0.80 ±0.05	0.76 ±0.09	0.79 ±0.05	0.78 ±0.05
Average	**0.67 ±0.03**	**0.64 ±0.02**	**0.66 ±0.04**	**0.66 ±0.02**	**0.70 ±0.03**	**0.64 ±0.03**

Comparing TBDs, TBD-RI and the fItG

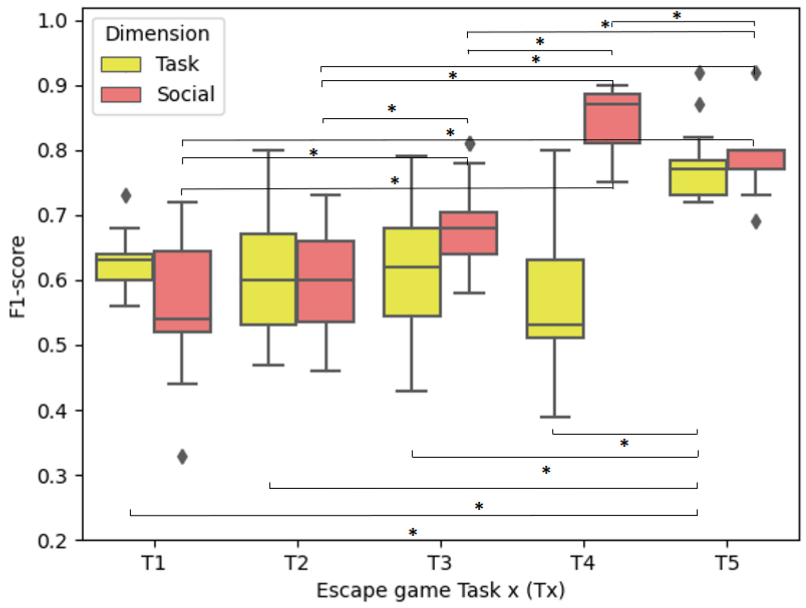
- For the Social dimension:
  - Task 1 and Task 2 are the worst predicted
  - Task 3 is better than Task 1 and Task 2
  - Task 4 and Task 5 outperform the others
- For the Task dimension:
  - T2 is among the worst predicted
  - T5 outperforms other tasks.



fItG



TBDs



TBD-RI

Take-away

1. There is an interplay between the Social and Task cohesion over time
   - ➢ Multiple Social Sciences theories exist depending on many factors (e.g., relationships between group members)

2. TBD-T (i.e., Social cohesion informs Task cohesion) is the most performing model for predicting **Task cohesion**

3. TBD-RI (i.e., a reciprocal interplay between the 2 dimensions exists) is the most performing model for predicting **Social cohesion**

4. There is a similar pattern in tasks' performances across all the models

Outline

Axes

Temporal nature of cohesion (RA1)

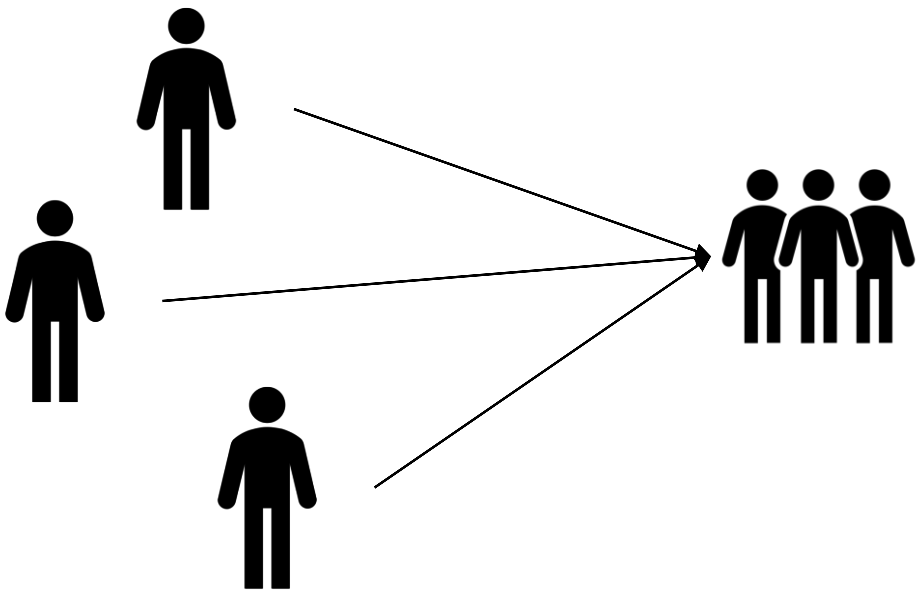
Group modeling (RA2)

Interplay between cohesion's dimensions (RA3)

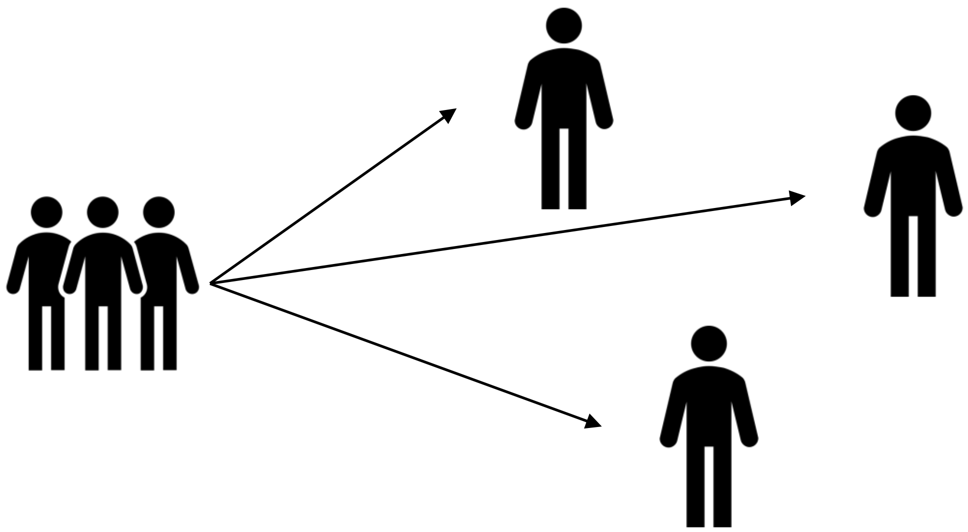
Relationships with other group processes (RA4)

Integrating group emotion (RA4)

Bottom-up
« From the individuals to the group »



Top-down
« From the group to the individuals »



(Barsade & Gibson, 1998)

Integrating group emotion

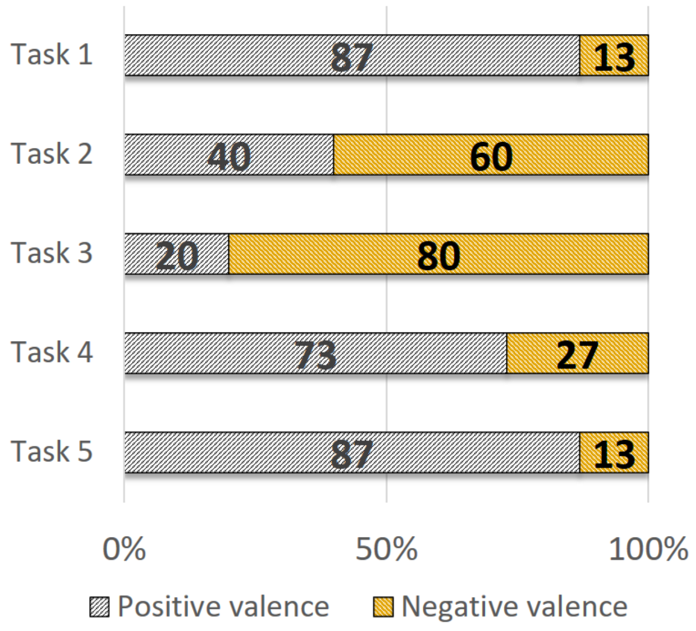
- Emotion labels collected with GAME-ON
- Each group member could pick **multiple** labels per task
- Emotions addressed in terms of their valence (+1 if positive / -1 if negative)
- Sum of all the valence within the group

How do you feel?

- Admiring
- Angry
- Proud
- Ashamed
- Happy
- Frustrated
- Other (to specify)

	Label(s)	Valence score
p_1	Admiring	+1
p_2	Happy, Proud	+2
p_3	Frustrated	-1
	Total	+2

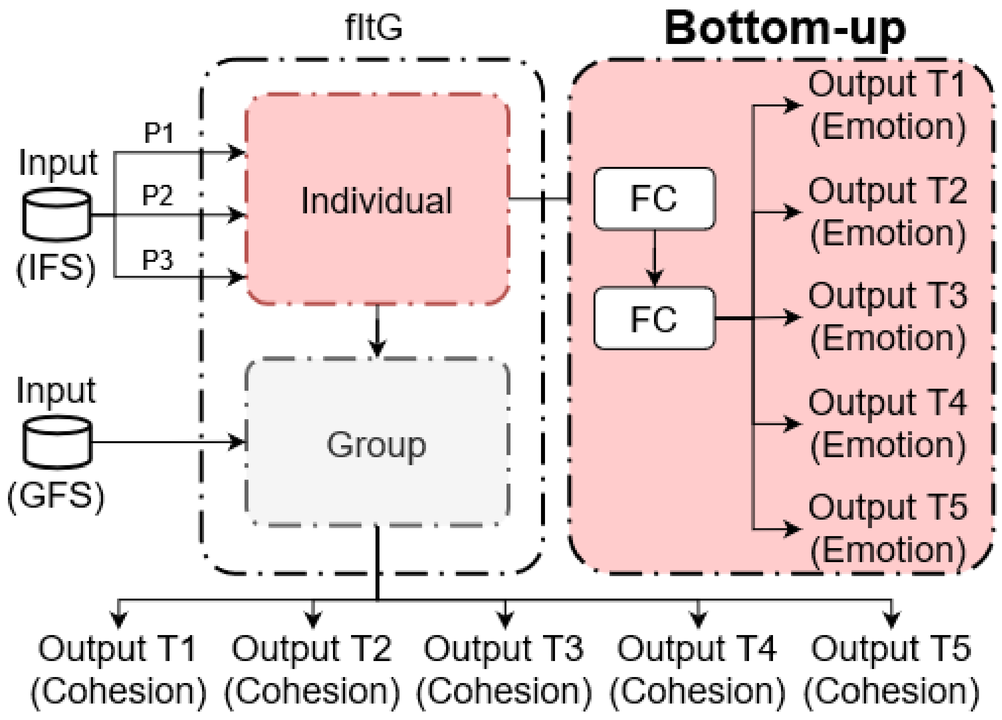
If ≥ 0 : Positive valence
if < 0 : Negative Valence

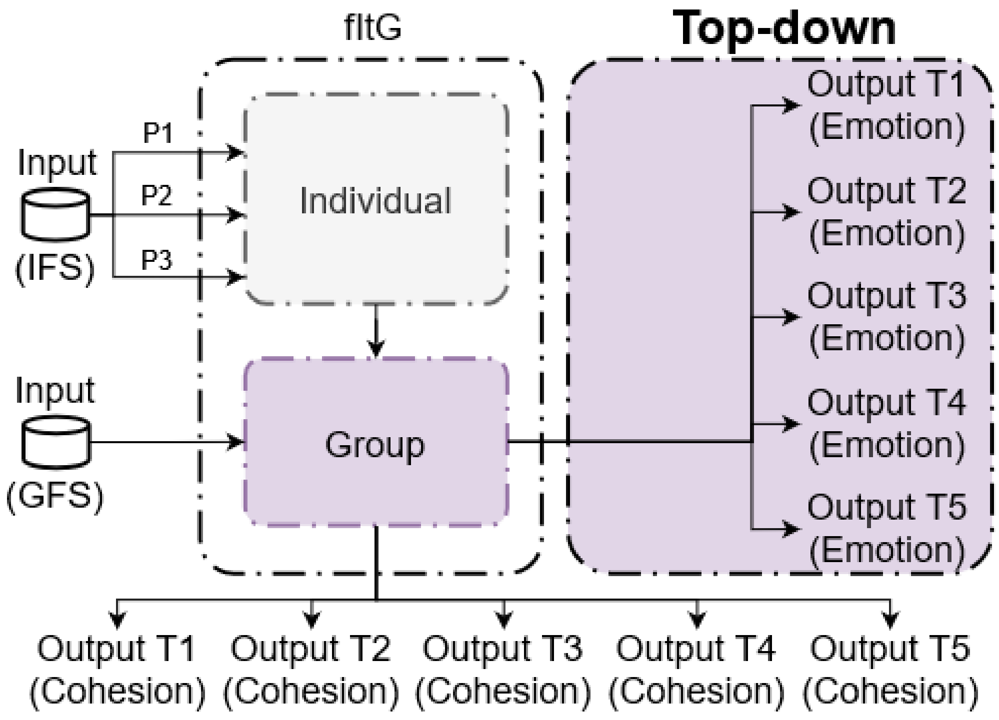


Integrating group emotion

Integrating time (RA1), group modeling (RA2), the interplay between dimensions (RA3), and relationships with other group processes (RA4)

- fItG as baseline
- Cohesion and group emotion in a multi-task setting
- Cohesion = primary task / Group emotion = secondary task

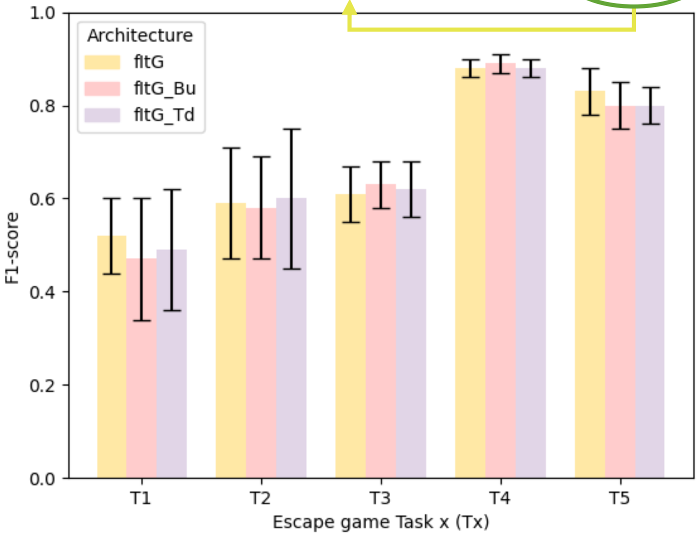




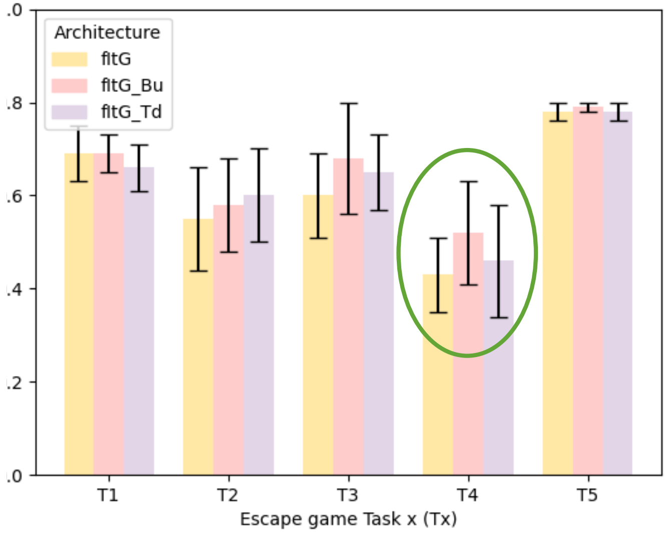
Comparing fltG, fltG_Bu and fltG_Td

- No significant difference between Top-down and fltG for both dimensions
- Bottom-up significantly improved Task cohesion prediction

	F1-scores ±std							
	fltG		fltG_Bu			fltG_Td		
	Social	Task	Social	Task	Valence of emotion	Social	Task	Valence of emotion
T1	0.52 ±0.08	0.69 ±0.06	0.47 ±0.13	0.69 ±0.04	0.76 ±0.05	0.49 ±0.13	0.66 ±0.06	0.78 ±0.07
T2	0.59 ±0.12	0.55 ±0.11	0.58 ±0.11	0.58 ±0.10	0.55 ±0.10	0.60 ±0.15	0.60 ±0.10	0.40 ±0.13
T3	0.61 ±0.06	0.60 ±0.09	0.63 ±0.05	0.67 ±0.12	0.66 ±0.03	0.62 ±0.06	0.65 ±0.08	0.67 ±0.05
T4	0.88 ±0.03	0.43 ±0.08	0.88 ±0.02	0.52 ±0.10	0.47 ±0.08	0.88 ±0.02	0.46 ±0.12	0.57 ±0.08
T5	0.84 ±0.05	0.78 ±0.02	0.81 ±0.05	0.79 ±0.02	0.79 ±0.02	0.80 ±0.04	0.78 ±0.02	0.78 ±0.02
Average	**0.69 ±0.03**	**0.61 ±0.03**	**0.67 ±0.03**	**0.65 ±0.04**	**0.65 ±0.03**	**0.68 ±0.03**	**0.63 ±0.03**	**0.64 ±0.04**



Social



Task

Take-away

1. There are 2 main approaches for characterizing group emotion
   - Bottom-up: from the individuals to the group
   - Top-down: from the group to the individuals

2. Only the fItG_BU (i.e., implementing a Bottom-up approach) improves Task performances, especially for the Task 4

3. Predicting cohesion and group emotion within the same model requires a trade-off in terms of performances

Integrating emergent leadership (RA4)

Features based leadership

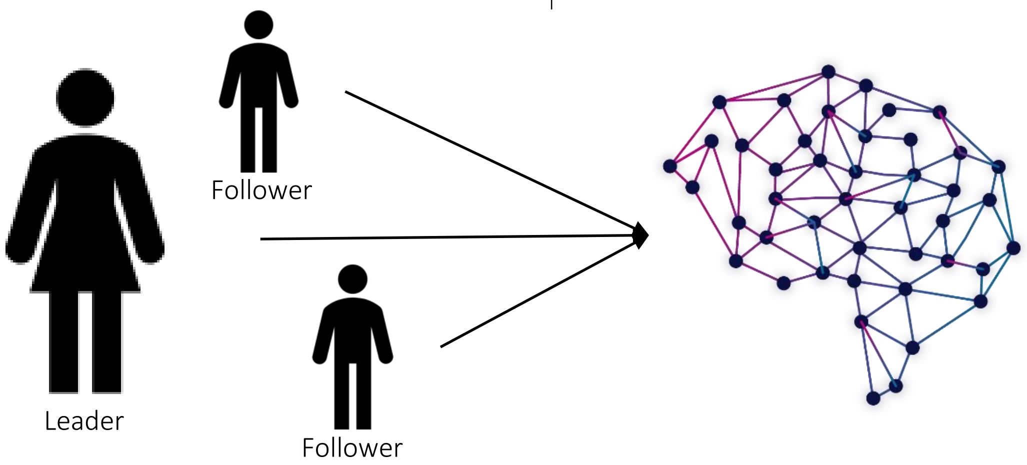
- Amplifying emergent leaders' features –

- 2 approaches:
  - ➢ Weighting
  - ➢ Normalization

Representation based leadership

- Injecting leadership representation –

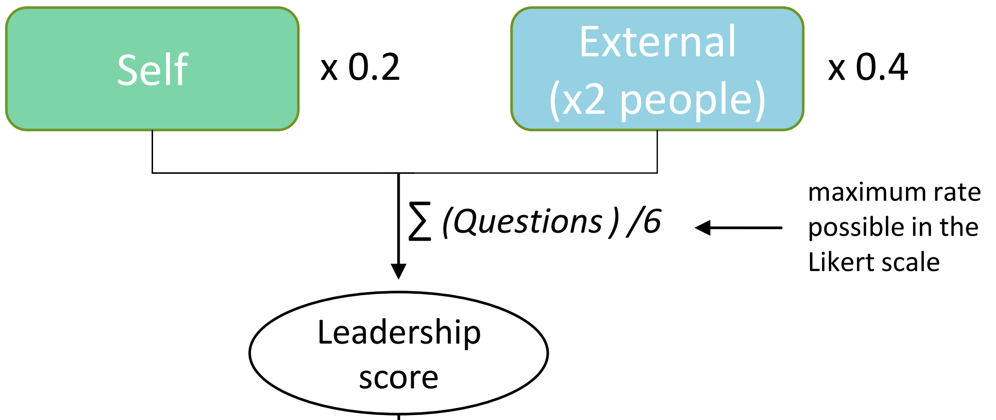
- 2 approaches:
  - ➢ Extracted from assessments
  - ➢ Automatically learned

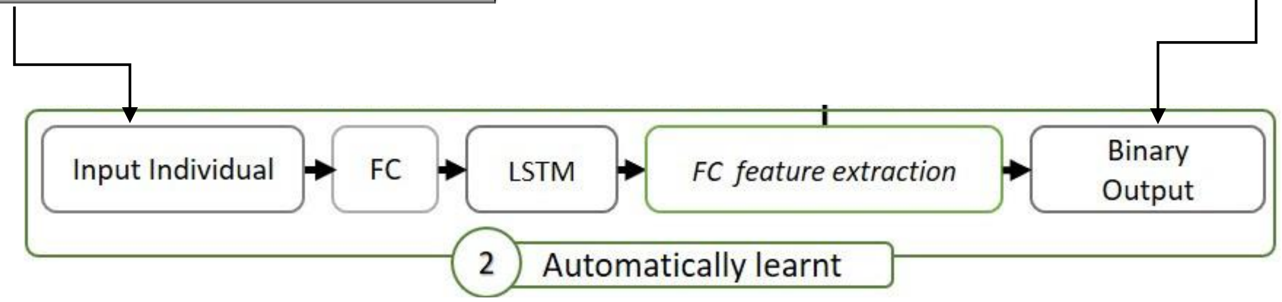


Representation Based Leadership
- Automatically learned -

- Model used as a feature extractor
- Features related to emergent leadership as input for the model: Speaking activity (SpeakAct) and Visual Focus Of Attention (VFOA)
- Best performing model (over 1000 seeds) was chosen, obtaining a F1-score of 0.72.
- More than 1 person can exhibit leadership in small groups
  → 0, 1 or 2 in groups of 3 persons
- Emergent leadership detection as **binary classification task**
- Labels based on **both** self and external assessments
- Slightly imbalanced labels' distribution: 60% leader vs 40% not a leader

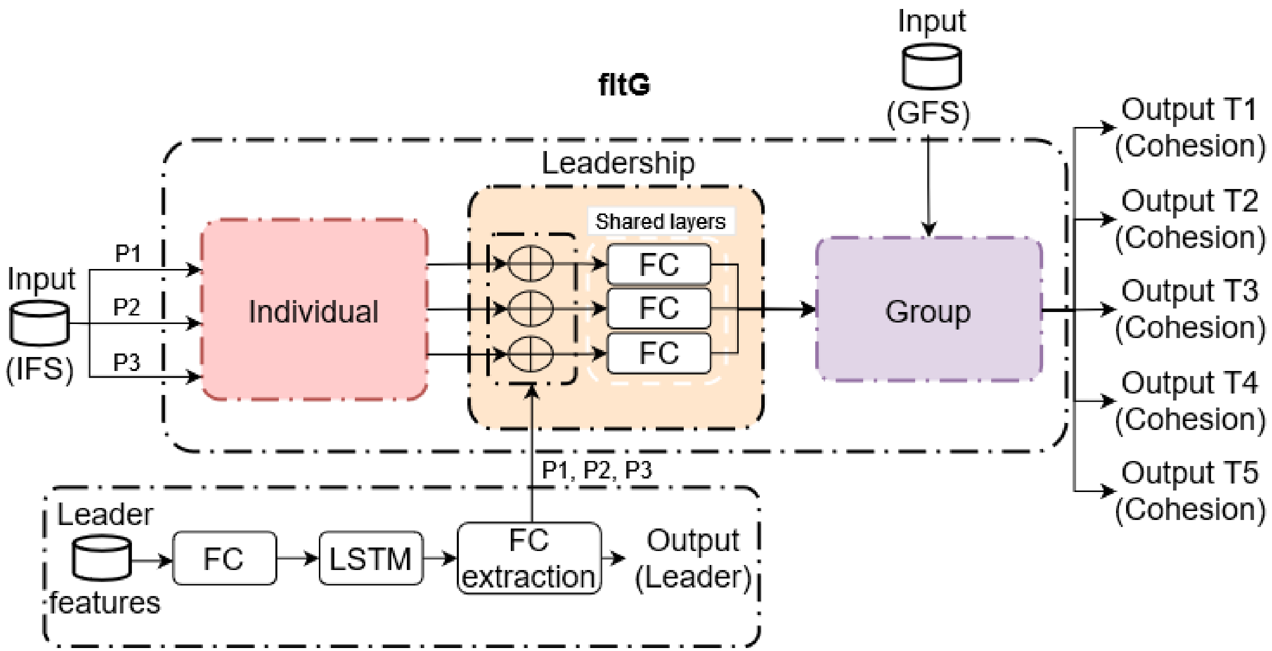
Features	
Speaking activity	
Total speaking time when at least one group member is speaking (Tss)	Average of speaking turns duration
Total speaking time when no one is speaking (Tsn)	Total number of time being un/successfully interrupted (TIunsuc/TIsuc)
Total number of times a person speaks first right after another one	Total number of time un/successfully interrupting other turns (TIOunsuc/TIOsuc)
Ratio between Tss and Tsn	Total number of speaking turns (Tst)
Total time of silence (Tsil)	Ratio between TIOsuc and TIsuc
Ratio between total speaking time (Tss+Tsn) and Tsil	Ratio between TIOsuc and Tst
	Ratio between TIunsuc and Tst
Visual focus of attention	
Looking someone with no ME (LnoME)	Total time being looked at
Being looked with no ME (BLnoME)	Number of times one initiates a ME
ME with any member	Ratio between BLnoME and LnoME





Integrating emergent leadership

- Focus on **altering the individual module** of the fItG model
- Adding leadership representation for each group member into shared fully connected layers
- Benefits of adding extra information for learning a representation of individuals
- Helps cohesion model learning new patterns that improve the prediction of the **Task** dimension of cohesion



Methods	Social F1-score (± std)	Task F1-score (± std)
Baseline (fItG)	**0.69 ±0.03**	0.61 ±0.03
Weighting (by 1.5)	0.68 ±0.03	0.64 ±0.04
Automatically Learnt	0.67 ±0.03	**0.67 ±0.04**

ns

Take-away

1. We implemented 2 families of approaches
   - ➢ Features based
   - ➢ Representation based

2. Adding extra information for learning a representation of individuals is beneficial for the model

3. Altering the model's architecture at the individual helps improving Task cohesion predictions

Outline

Summary of contributions

A structured survey on cohesion for supporting its automated analysis

A multimodal dataset for the automated cohesion analysis

Design and implementation of computational models of cohesion

Limitations

At Input level

- Other dataset could be used with different groups or environment settings (e.g., VR)
- More signals to extract features could be investigated (e.g., video)

At Model level

- Models designed for a fixed number of persons
- Models not designed for “real-time “ applications

At Output level

- Simple labeling strategies for all group processes
- Self- and external assessments could be combined

The self- vs external assessment's dilemma

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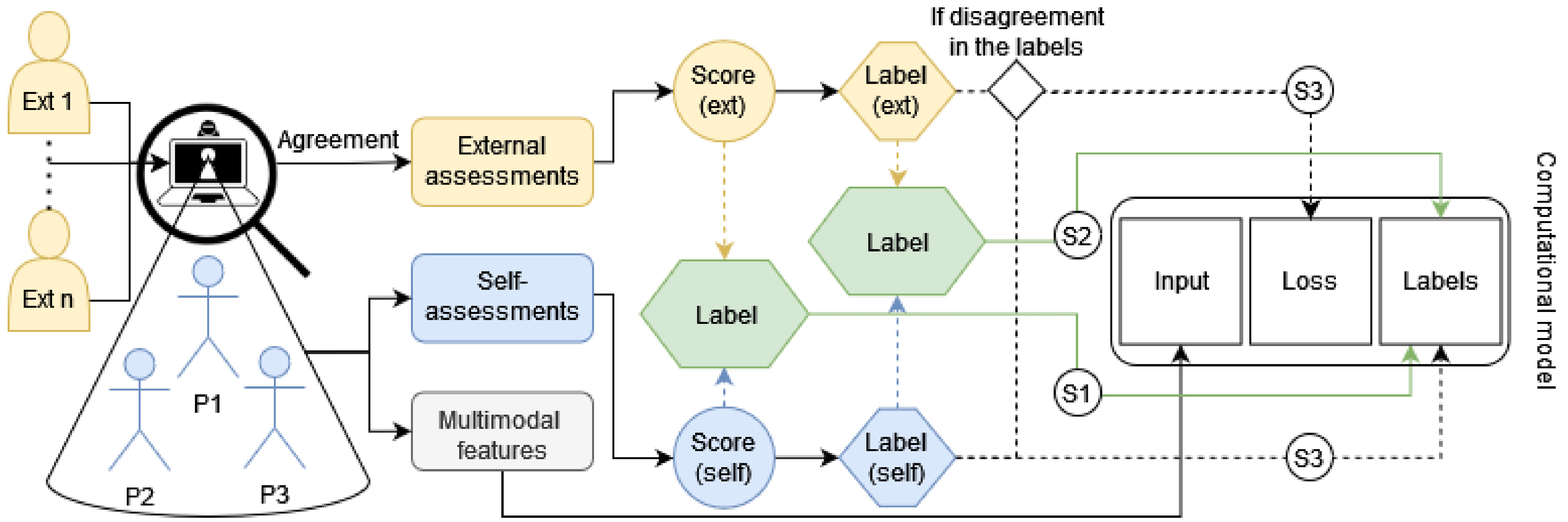
- Collecting labels is a long and costly process
- **Self-assessments** might be over-optimistic (Vinciarelli & Mohammadi, 2014)
- **External assessments**: do not necessarily correspond to the true internal state (Uleman et al., 2008)
- 3 strategies to take both assessments into account



Data and code distribution

- The GAME-ON dataset is available on the GRACE website:
  - ➢ Motion capture data
  - ➢ Audio features
  - ➢ Self-assessment through questionnaires

- Code of the computational models' architecture is available on the GRACE github

- GRACE github will be displayed on the Center for Open Software Innovation (COSI) platform

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Journal

- Maman, L., Ceccaldi, E., Lehmann-Willenbrock, N., Likforman-Sulem, L., Chetouani, M., Volpe, G., and Varni, G. (2020). Game-on: A multimodal dataset for cohesion and group analysis. IEEE Access 8, 124185–124203

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- Maman, L., Volpe, G., Varni, G. (2022). Training Computational Models of Group Processes without Groundtruth: the Self- vs External Assessment's Dilemma. To appear in Companion Publication of the 24th International Conference on Multimodal Interaction (LBR).
- Maman, L., Likforman-Sulem, L., Chetouani, M., and Varni, G. (2021). Exploiting the interplay between social and task dimensions of cohesion to predict its dynamics leveraging social sciences. In Proceedings of the 23rd International Conference on Multimodal Interaction. 16–24
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- Sabry, S., Maman, L., and Varni, G. (2021). An exploratory computational study on the effect of emergent leadership on social and task cohesion. In Companion Publication of the 23rd International Conference on Multimodal Interaction. 263–272
- Walocha, F., Maman, L., Chetouani, M., and Varni, G. (2020). Modeling dynamics of task and social cohesion from the group perspective using nonverbal motion capture- based features. In Companion Publication of the 22nd International Conference on Multimodal Interaction. 182–190

Thank you for your attention

Questions?