Unveiling the Power of Affect during Learning

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What is affect?

Affect

- Feeling, mood, or emotion
- Affect encompasses multiple systems at multiple levels and at multiple time scales
- Signaling functions (Schwarz, 2012), pointing out gaps in knowledge (confusion)
 - Appraising events in terms of their value, goal relevance, and goal congruence (Izard, 2010)

NEUROBIOLOGY AND CONSCIOUSNESS

PHYCHOPHYSIOLOGY AND BODILY SENSATIONS

COGNITIVE AND MOTIVATIONAL COMPONENTS

Component process model

Emotion episode

- *interrelated, synchronized changes* in all or most components
- in response to evaluation of an external or internal stimulus
- relevant to major concerns of the individual

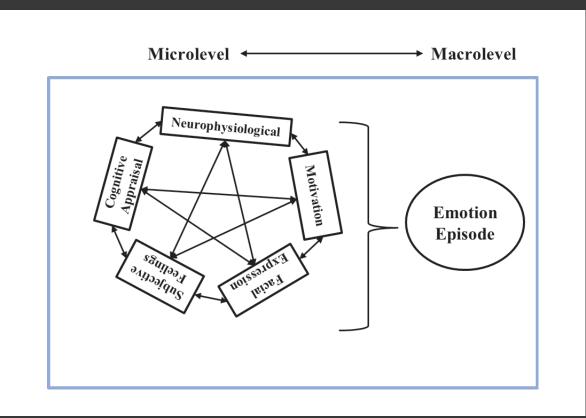
Relationships between organismic subsystems and the functions and components of emotion			
Emotion function	Organismic subsystem and major substrata	Emotion component	
Evaluation of objects and events	Information processing (CNS)	Cognitive component (appraisal)	
System regulation	Support (CNS, NES, ANS)	Neurophysiological component (bodily symptoms)	
Preparation and direction of action	Executive (CNS)	Motivational component (action tendencies)	
Communication of reaction and behavioral intention	Action (SNS)	Motor expression component (facial and vocal expression)	
Monitoring of internal state and organism– environment interaction	Monitor (CNS)	Subjective feeling component (emotional experience)	

Note: CNS = central nervous system; NES = neuro-endocrine system; ANS = autonomic nervous system; SNS = somatic nervous system.

Scherer, K. R., Schorr, A., & Johnstone, T. (Eds.). (2001). Appraisal processes in emotion: Theory, methods, research. Oxford University Press.

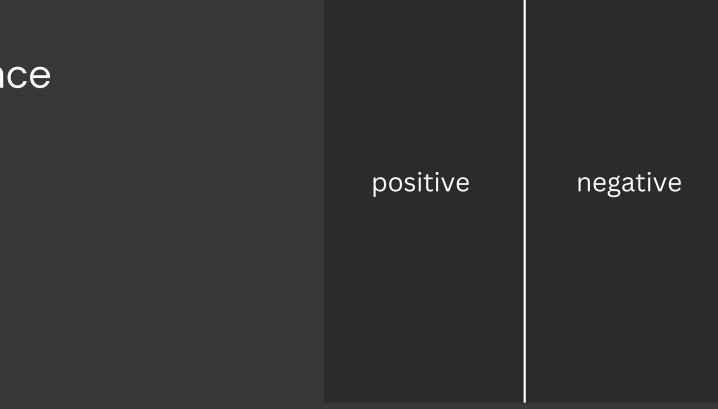
Component process model

The *process* consists of the coordinated changes over time



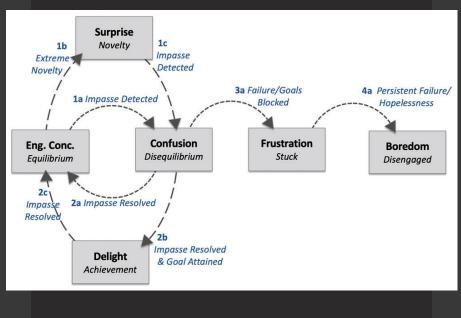
Scherer, K. R., Schorr, A., & Johnstone, T. (Eds.). (2001). Appraisal processes in emotion: Theory, methods, research. Oxford University Press.

UNIDIMENSIONAL



Valence

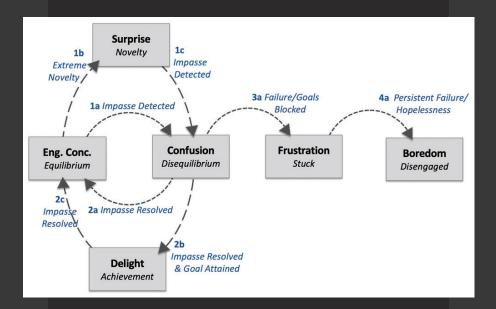
Model of Affective Dynamics



(D'Mello & Graesser, 2012)

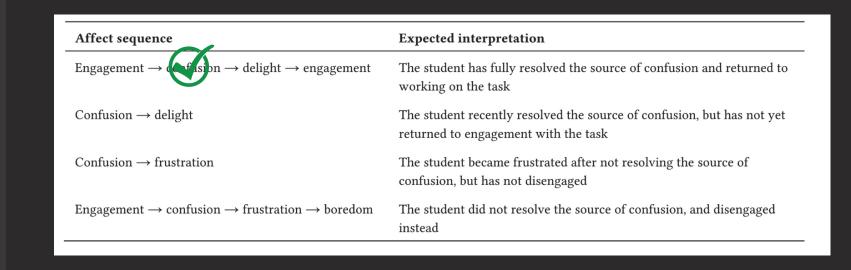
Model of Affective Dynamics

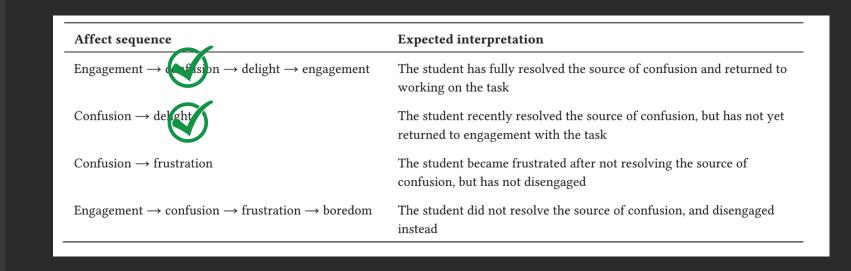
- Valence
- Temporal dimension

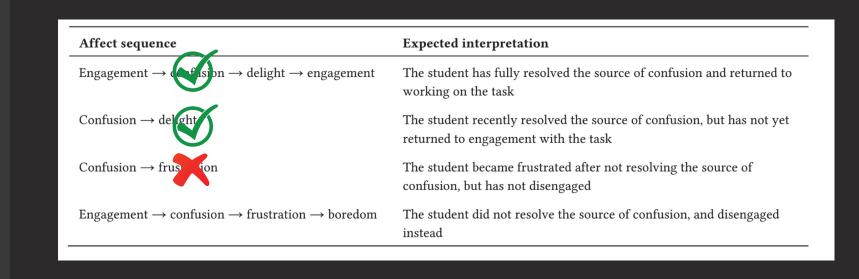


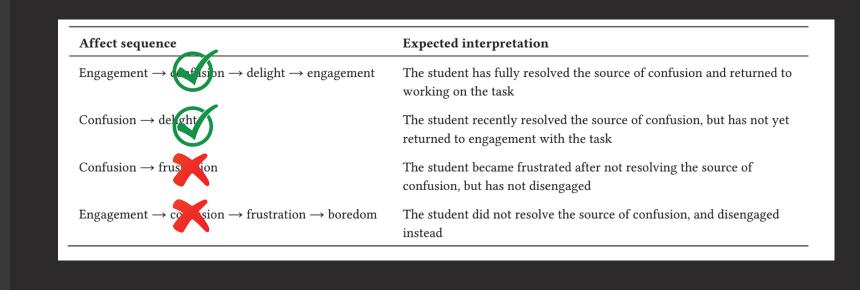
(D'Mello & Graesser, 2012)

Affect sequence	Expected interpretation
Engagement \rightarrow confusion \rightarrow delight \rightarrow engagement	The student has fully resolved the source of confusion and returned to working on the task
Confusion \rightarrow delight	The student recently resolved the source of confusion, but has not yet returned to engagement with the task
Confusion \rightarrow frustration	The student became frustrated after not resolving the source of confusion, but has not disengaged
${\rm Engagement} \rightarrow {\rm confusion} \rightarrow {\rm frustration} \rightarrow {\rm boredom}$	The student did not resolve the source of confusion, and disengaged instead



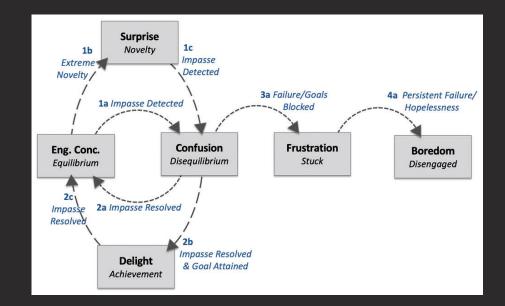






Empirical does not match theoretical

- Baker et al (2010)
- Lee et al (2011)
- Liu et al (2013)
- D'Mello et al. (2014)
- Andres et al. (2019)
- Karumbiah et al. (2022)



Challenges

• Methodological

- Typically rely on interval data
- Need for fine-grain and continuous data on multiple affective dimensions
- Analytical
 - Model dynamically



Leading Questions

How to measure affect as a dynamic process?

How to model affect as a dynamic process?

Affective Dynamics and Cognition with Crystal Island

Game-based learning environments foster emotional engagement via mechanics to enhance learning (Clark & Tanner-Smith, 2016; Plass et al., 2020)



RQ: Are there dynamic relationships between time expressing frustration, confusion, and neutral states and time engaging in scientifically reasoning?

Cloude, E. B., Dever, D. A., Hahs-Vaughn, D. L., Emerson, A. J., Azevedo, R., & Lester, J. (2022). Affective Dynamics and Cognition During Game-Based Learning. IEEE Transactions on Affective Computing, 13(4), 1705-1717.

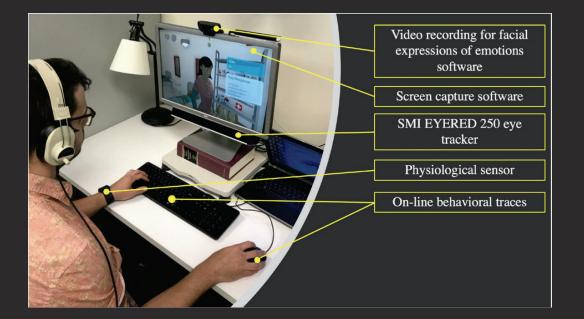
Methods

Sample of 78 Undergraduates (67% females)

- Age: 20 years
- 69% White
- 71% played 0-2 hrs of video games/week

Random assignment to the full (n=62), restricted (n=16), no agency

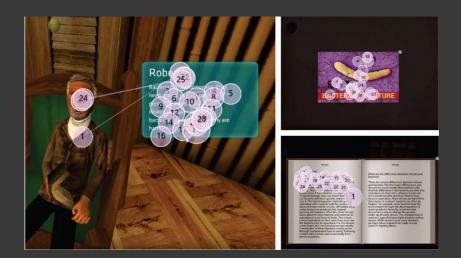
- Restricted agency: 78 mins
- Full agency: 81 mins



Data Coding and Scoring (1)

Scientific reasoning:

- Time engaging in scientific reasoning = overlap in
 - Eye gaze fixations using Areas of Interest
 - Log file interaction with game elements (Cloude et al., 2020)



Variables	Data channels	Game elements
Action 1: gathering information	Timestamped log files and eye fixations	Reading books, research articles, and posters; talking to NPCs.
Action 2: hypothesis generation	Timestamped log files and eye fixations	Backpack, food items, first field in the diagnosis worksheet.
Action 3: experimental testing	Timestamped log files and eye fixations	Final diagnosis field on the worksheet, concept matrix, and scanner.

Cloude, E. B., Dever, D. A., Wiedbusch, M. D., & Azevedo, R. (2020). Quantifying scientific thinking using multichannel data with crystal island: Implications for individualized game-learning analytics. Frontiers in Education, 572546.

Data Coding and Scoring (2)

Emotions:

- Time expressing confused, frustrated or neutral states
 - $\circ\,$ AUs via iMotions
 - Facial landmarks deviated from baseline (neutral)
- Confused
- Frustrated
- Neutral



Statistical Analysis

Multi-level Growth Model

- Fixed term between-subject variability
- Random term within-subject variability

Two-level growth models:

- Level 1: within-individuals (15,882)
- Level 2: between-individuals (78)
 - Pre-test scores
 - Agency condition
 - \circ Action

Unconditional Models:

$$Y_{ij} = \lambda_{00} + \lambda_{01}^{*} (Time)_{ij} + \sigma_{0j} + \sigma_{1j}^{*} (Time)_{ij} e_{ij}$$
(1)

View Source 🖗

where Y_{ij} describes the outcome variable (e.g., time scientific reasoning), lambda₀₀ and λ_{01} are, respectively, mean initial status and average growth rate. The symbols σ_{0j} , σ_{01} , and e represent, respectively, residual variance in initial status, residual variance in growth rate, and within-person residual variance.

Condition Models:

$$\begin{split} Y_{ij} &= \lambda_{00} + \lambda_{01}^* (Time) + \lambda_{02}^* (Action) \\ &+ \lambda_{03}^* (Facial Expression) \\ &+ \lambda_{04}^* (Facial Expression)^* (Time) \\ &+ \lambda_{05}^* (PreTestScore) + \lambda_{06}^* (Experimental Condition) \\ &+ \sigma_{0i} + \sigma_{1i} + e_{ii} \end{split}$$

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where Y_{ij} represents the outcome variable (e.g., time scientifically reasoning). λ_{0j} and λ_{1j} , respectively, represented the average initial status and average growth rate for predictors. Symbols σ_{0j} , σ_{1j} , and e_{ij} , represent, respectively, residual variance at initial status, residual variance in growth rate, as well as within-individual residual variance.

Are there dynamic relationships between time expressing frustrated, confused, and neutral states and scientifical reasoning?

Three separate models for each emotion

	Frustration	Confusion	Neutral
Variable	Estimate (SE)	Estimate (SE)	Estimate (SE)
Fixed effects			
Mean initial status	114.97 (27.13)	140.38 [*] (21.11)	92.59 [*] (29.43)
Mean growth rate	-0.05 [*] (0.01)	-0.05 [*] (0.01)	-0.05 [*] (0.01)
Emotion duration	0.32 [*] (0.05)	0.26 [*] (0.03)	0.40 [*] (0.05)
Action ₁	-115.30° (4.54)	-116.37 [*] (3.77)	-114.38 [*] (1.93)
Action ₂	-84.19 [*] (2.93)	-84.78 [*] (4.11)	-83.57 [*] (2.25)
Action ₃	-116.41 [*] (12.58)	-117.03 [*] (7.03)	-114.84 [*] (5.35)
Pre-test scores [Level 2]	-65.89 (50.04)	-93.00 [*] (38.86)	-53.84 (53.39)
Experimental condition ₁ [Level 2]	50.31° (15.26)	33.03° (12.03)	-4.94 (16.28)
Random effects			
Within-individual	53.41	53.55	53.31
Initial status	82.31	62.89	97.66
Growth rate	0.05*	0.04	0.05^{*}
Emotion duration	0.37*	0.27*	0.40^{*}
Action ₁	37.55	30.18	10.51
Action ₂	22.10	33.67*	14.53
Action ₃	110.29	60.68*	45.38
Deviance	172787	172672	172575
ICC	0.70	0.58	0.77
Pseudo-R ² (fixed effects)	0.25	0.30	0.35
Pseudo- R^2 (total effects)	0.90	0.85	0.91
Note $*n < 0.05$. Action $l = Information aathe$	ring Action?=Hypothesis generation	n: Action3=Experimental testing	

Note. *p < 0.05; Action1=Information gathering, Action2=Hypothesis generation; Action3=Experimental testing

Key Takeaways

- More frustrated and confused predicted more engagement in scientific reasoning
- Within-subject variability explained large portion of outcome variable
 Individual differences (e.g., values, goals)
- More prior knowledge predicted less engagment in scientific reasoning

 May be moderated by confusion

Case Study: Modeling Confusion as a Nonlinear Dynamical System

Adaptive Complex Systems theory



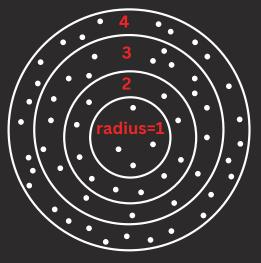
Nonlinear dynamical systems theory

Recurrence quantification analysis is a nonlinear time series analysis

• Sequential organization in a time-series

Embedding Parameters:

- Time delay = high-dimensional phase-space trajectory reconstruction (Takens, 1981)
- Radius = defines the window of recurrence plots



Sample

Sample of 80 participants

- Age = 20.12 (SD=1.57)
- 66% female
- Experimental design:
 - Random assignment: Full (n=51), Restricted (n=29)
 - Pre-test
 - Calibrated to Sensors
 - Gameplay
 - Post-test

Research Questions

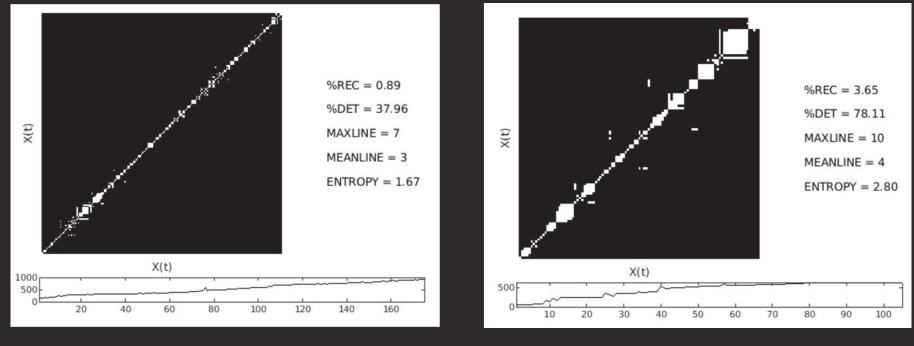
- Do repetitive instances of confused facial expressions differ between full and partial agency conditions during game-based learning?
- Do repetitive instances of confused facial expressions relate to posttest scores while controlling for agency and pre-test scores?

Do repetitive instances of confused facial expressions differ between full and restricted agency conditions during game-based learning?

- Radius of .01 = smallest window
- A *t*test revealed <u>no</u> significant differences in the rate of repetitive confused facial expressions between restricted (*M*=1.46) and full (*M*=1.50) agency conditions, *p*=.3106.

This suggests that learners expressed similiar repetitive rates of confused facial expressions during game-based learning regardless of agency

Do repetitive instances of confused facial expressions differ between full and restricted agency conditions during game-based learning?



Lowest RR%

Highest RR%

Do repetitive instances of confused facial expressions during scientific-reasoning actions relate to post-test scores while controlling for agency and pre-test scores?

Multiple linear regression

Regression estimates of associations with p	ost-test scores.	
	Beta	Std. Error
Intercept	1.096*	0.244
Condition ₁	-1.10*	0.335
Experimental Testing (Action 1)	0.558	0.299
Hypothesis Generation (Action 2)	0.622*	0.269
Information Gathering (Action 3)	0.347	0.296
Duration	0.002	0.001
Recurrence Rate of Confusion	-0.816*	0.165
Pre-test Scores	-0.551	0.430
Recurrence rate*Condition1	1.228*	0.234
F	68.91*	
Df	31,48	
Adjusted R ²	0.34	2
Note. *p < 0.05.		

Key Takeaways

- More recurring time expressing confusion was detrimenal to posttest scores
- Positive interaction between restricted agency and confusion on post-test scores
- How to best determine the parameters of RQA
 - 2-5% for human systems (Webber & Zbilut, 2005)
 - Increase radius
- Multiple signals of confusion

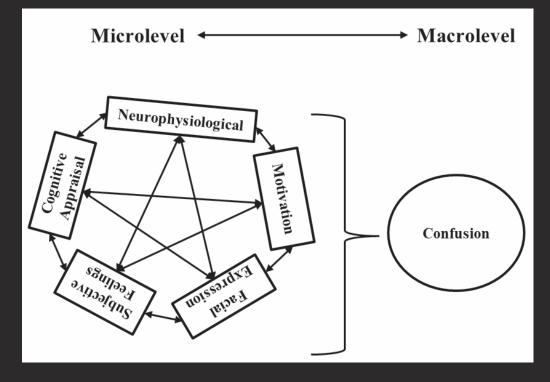
Future Work

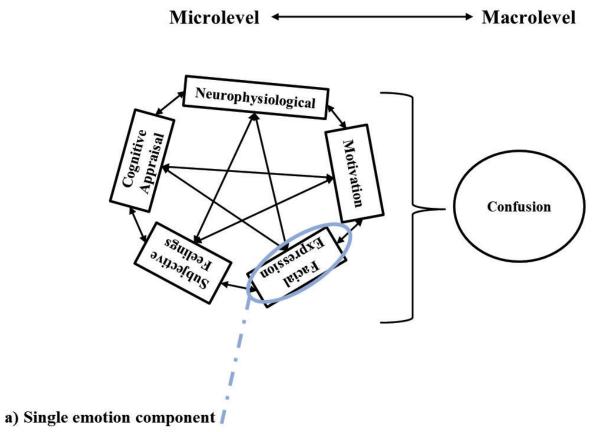
• Measure and model multiple dimensions of an emotion episode

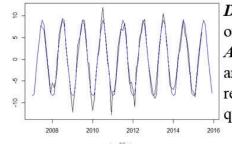
Future Work

• Measure and model multiple dimensions of an emotion

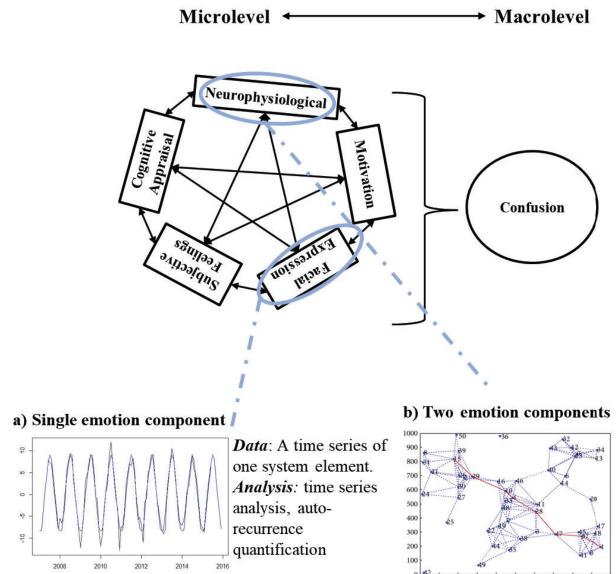
episode





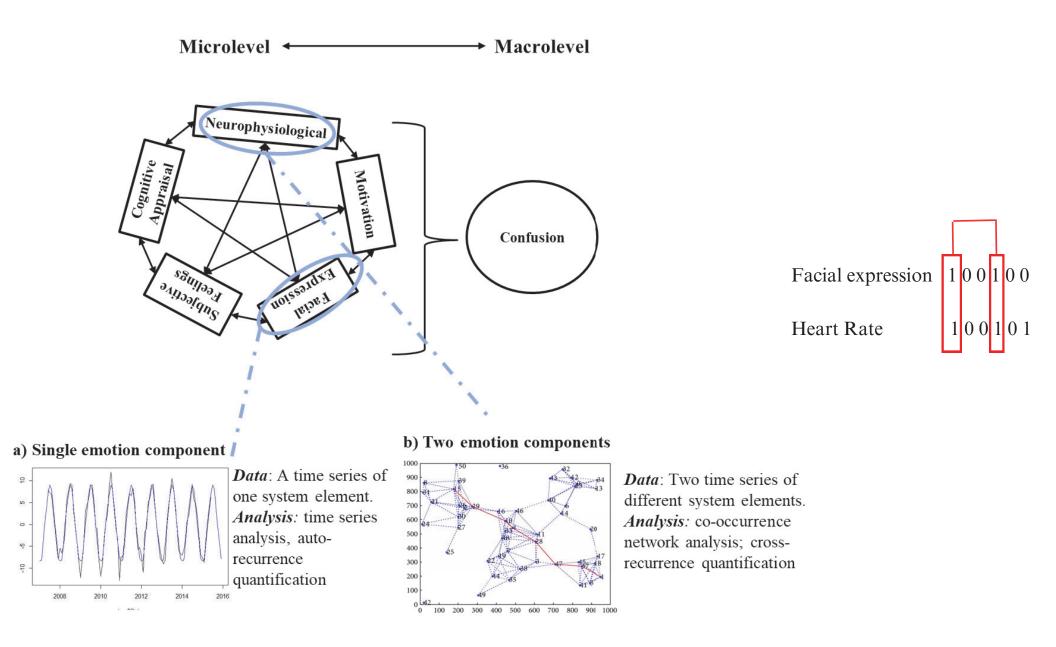


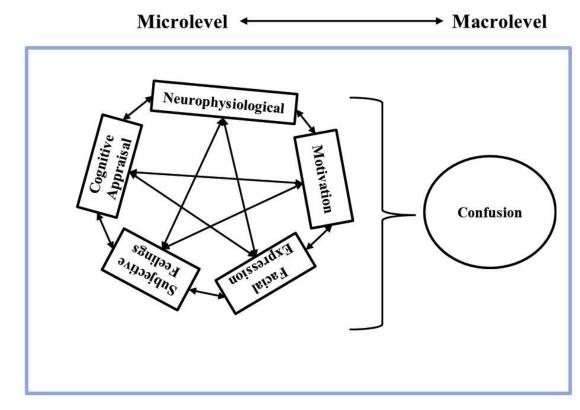
Data: A time series of one system element. *Analysis*: time series analysis, autorecurrence quantification



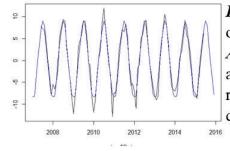
0 100 200 300 400 500 600 700 800 900 1000

Data: Two time series of different system elements. *Analysis:* co-occurrence network analysis; cross-recurrence quantification



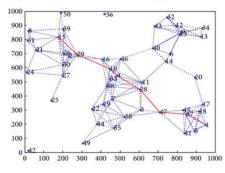


a) Single emotion component

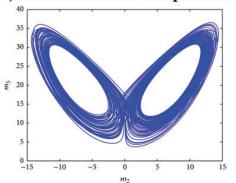


Data: A time series of one system element. *Analysis:* time series analysis, autorecurrence quantification

b) Two emotion components

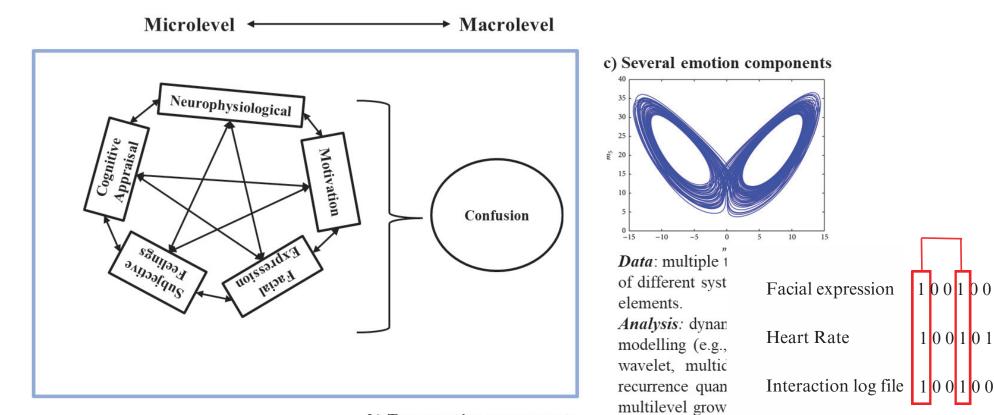


c) Several emotion components

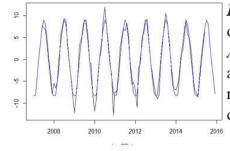


Data: multiple time series of different system elements. Analysis: dynamical modelling (e.g., fractal, wavelet, multidimensional recurrence quantification, multilevel growth model)

Data: Two time series of different system elements. **Analysis**: co-occurrence network analysis; cross-recurrence quantification

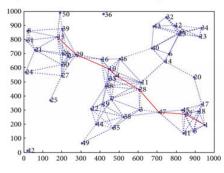


a) Single emotion component



Data: A time series of one system element. *Analysis:* time series analysis, autorecurrence quantification

b) Two emotion components



Data: Two time series of different system elements. *Analysis:* co-occurrence network analysis; cross-recurrence quantification

Thanks for your time!

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Scan here for references!



<u>qr.link/4JwMhz</u>