Emerging Technologies for Effective Teaching & Learning

Continuing Education Program for Next Education India Pvt Ltd
Conducted by Educational Technology, IIT Bombay
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Introduction to Multimodal Learning Analytics

Ritayan Mitra

Activity : Reflect on the following questions

1) What are the key contributors to student learning?

2) How do you know your students have learned (concept/topic/subject etc.)?

Think for 2 minutes and then share with class.

What goes into learning?

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Learning environment

Curriculu
m
Teach
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Studen
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Test scores

GPA

Other assessments

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Learning environment

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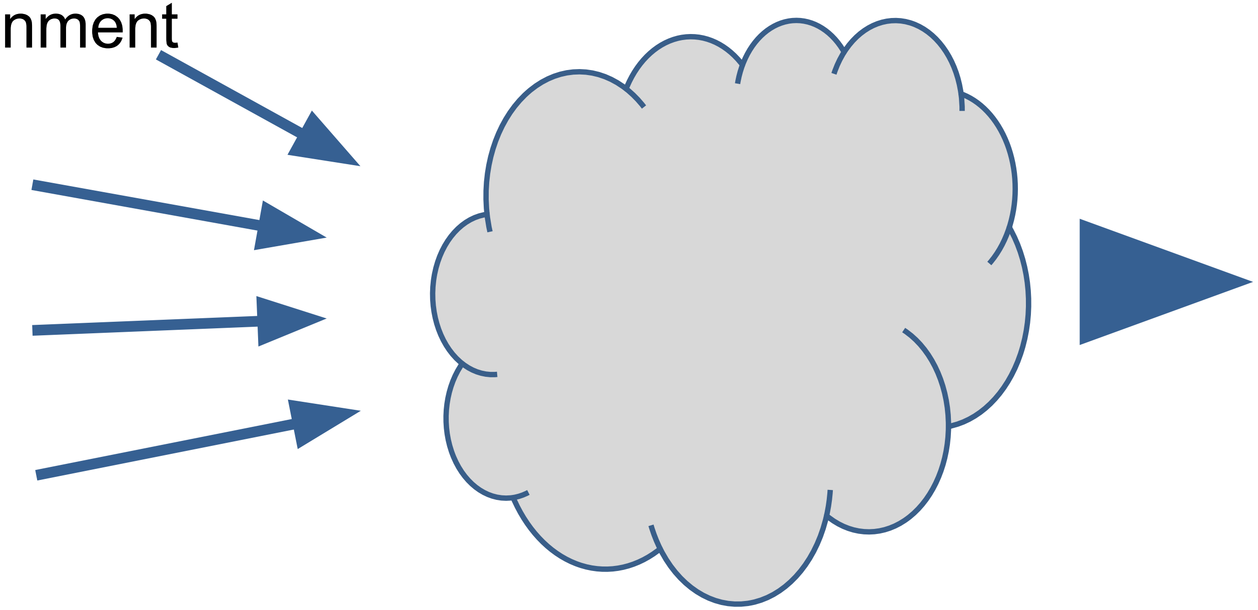

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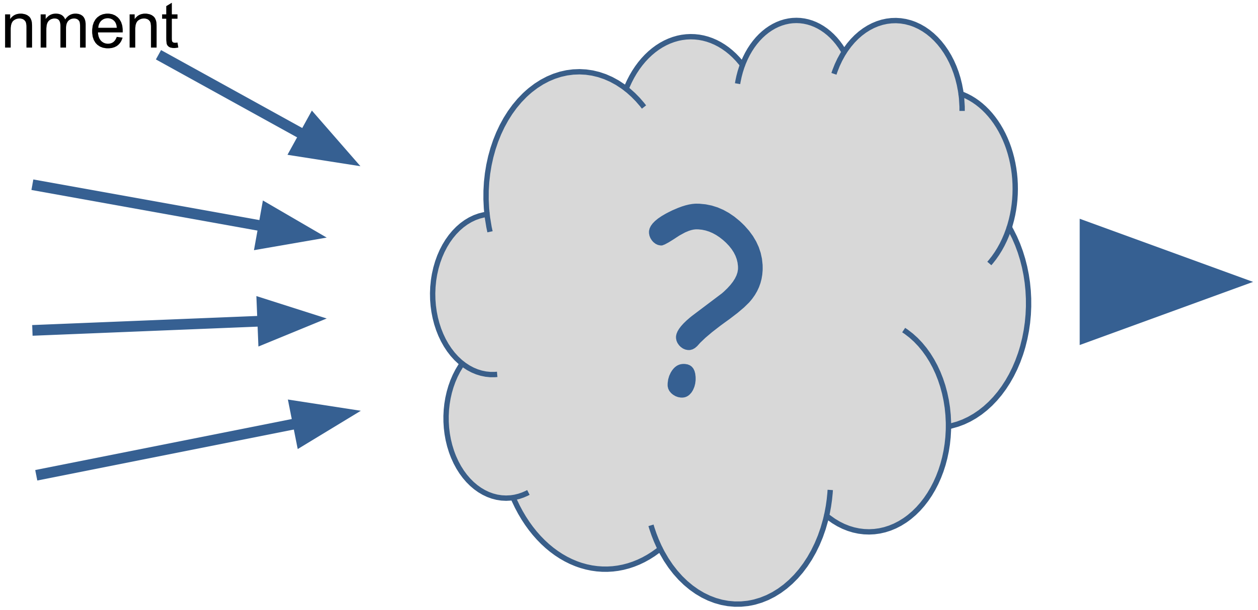

Test scores

GPA

Other assessments

Question: What processes go into learning?

The CAMM processes (COGNITION)

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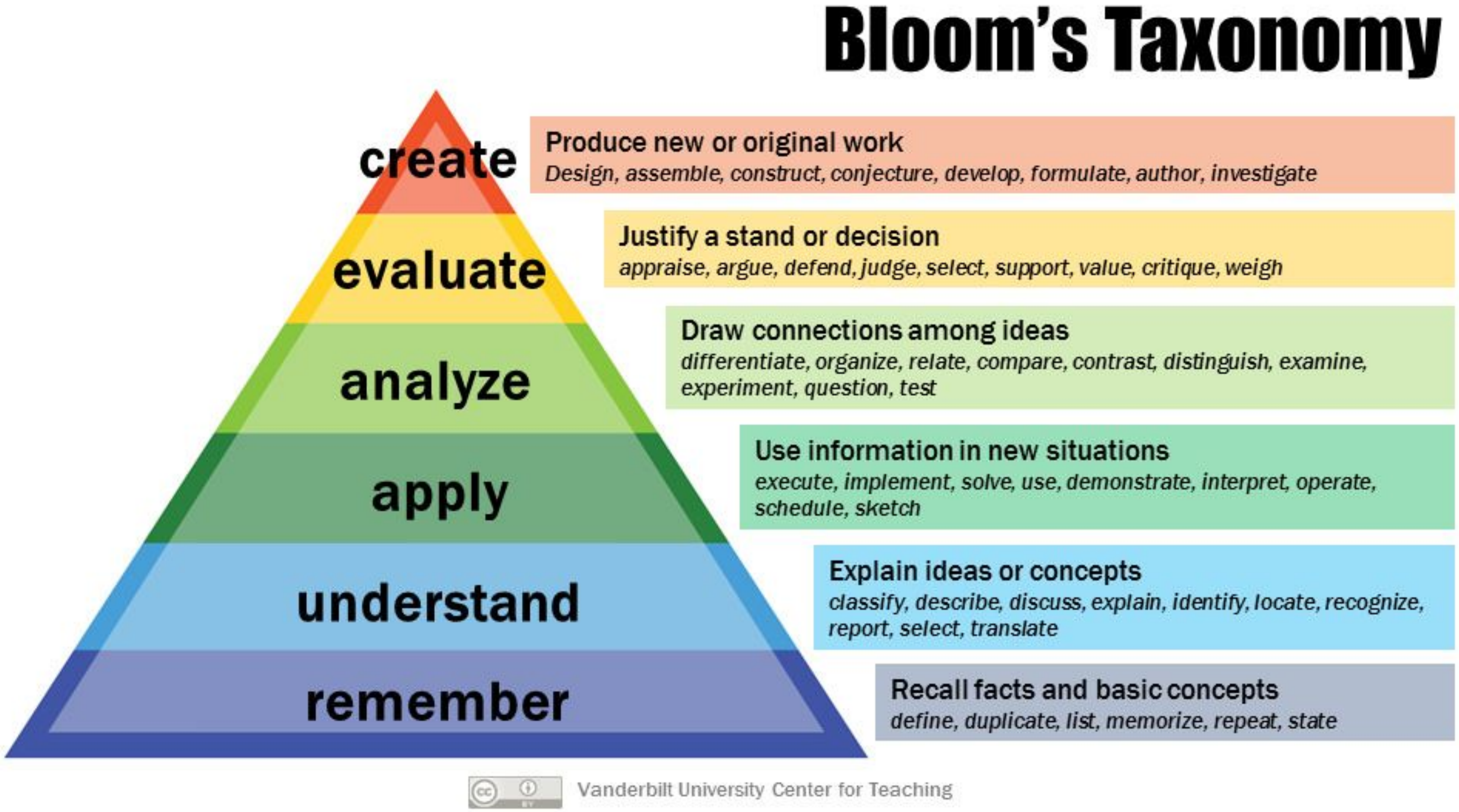

The CAMM processes (AFFECT)

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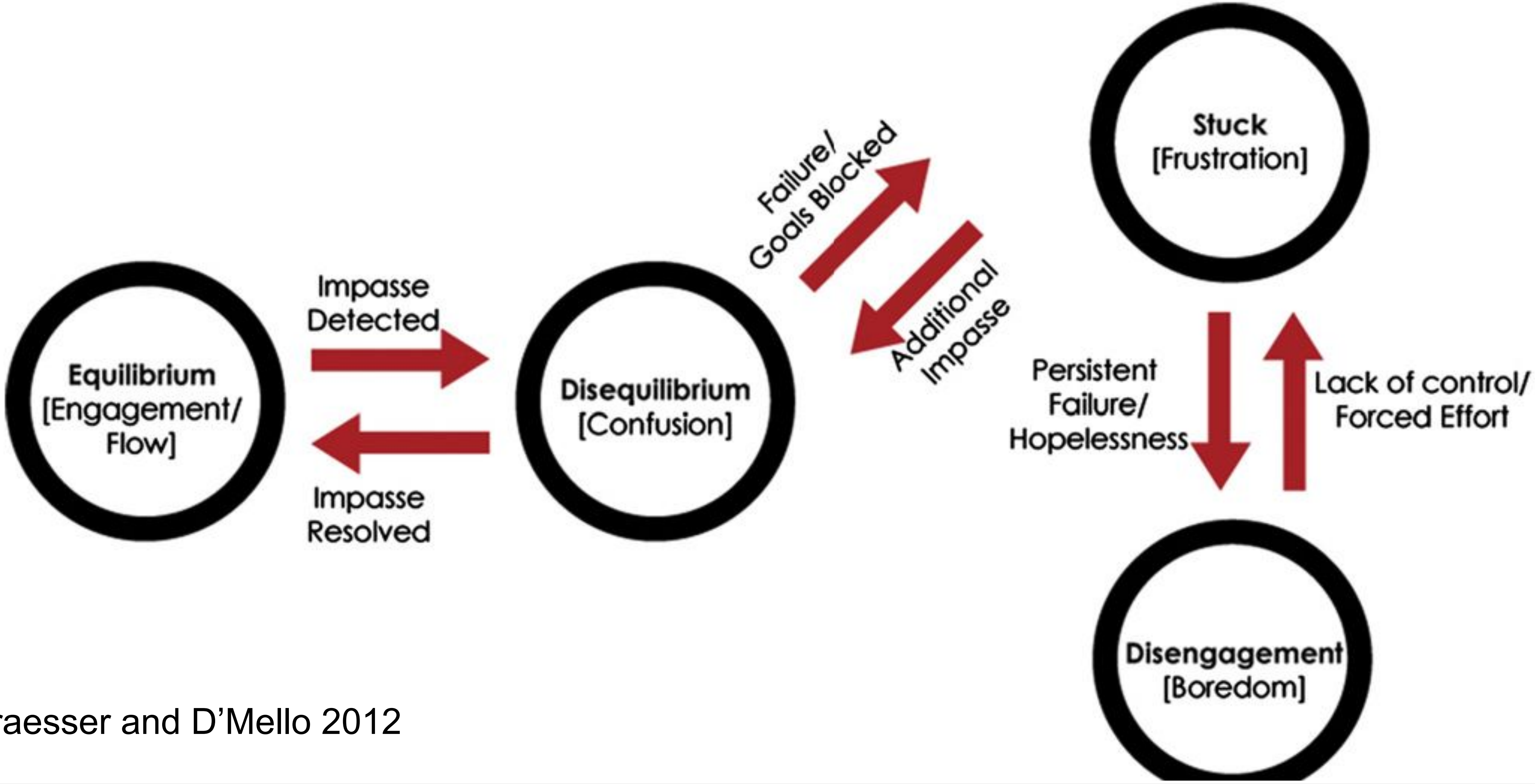

Graesser and D'Mello 2012

The CAMM processes (METACOGNITION)

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Do I understand the concept being taught?

How well do I understand – good, average or poor?

How can I test how much I understood?

What aspect do I not understand?

What should I do in order to learn that aspect?

How does this new knowledge help me understand concept X better?

Now, do I understand concept X better than I did before?

The CAMM processes (MOTIVATION)

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Now let’s look at one of the input variables

Where do we learn?

Where do we learn?

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Where do we learn?

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Where do we learn?

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Where do we learn?

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Where do we learn?

Where do we learn?

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Activity: Raise your hand if you disagree

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The process of learning can be very **complex** and we need special tools to study it

So how do we study this complex process?

Traditional Methods

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- Classroom observation
- Think alouds
- Retrospective self-reflection
- Experience sampling method

But new age technology and computational firepower allow us to do more than just triangulation

Birth of MMLA

LAK Conference 2013

Multimodal Learning Analytics

Paulo Blikstein
Stanford University Graduate School of Education and (by courtesy) Computer Science
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ABSTRACT

New high-frequency data collection technologies and machine learning analysis techniques could offer new insights into learning, especially in tasks in which students have ample space to generate unique, personalized artifacts, such as a computer program, a robot, or a solution to an engineering challenge. To date most of the work on learning analytics and educational data mining has focused on online courses or cognitive tutors, in which the tasks are more structured and the entirety of interaction happens in front of a computer. In this paper, I argue that multimodal learning analytics could offer new insights into students' learning trajectories, and present several examples of this work and its educational application.

would be particularly useful in a time when the need for scalable project-based, interest-driven learning and student-centered pedagogies is growing considerably [e.g., 5]. Both K-12 and engineering education [10, 11], within a transformed societal and economic environment, now demand higher level, complex problem-solving rather than performance in routine cognitive tasks [15]. These approaches have been advocated for decades [9, 12, 16, 18] but failed to become scalable and prevalent, and came under attack during the last decade [e.g., 13, 14]. Automated, fine-grained data collection and analysis could help resolve this tension in two ways. First, they could give researchers tools to examine student-centered learning in unprecedented scale and detail. Second, these techniques could improve the scalability of these pedagogies since they make both assessment and formative feedback, which are more complex and laborious in such

Question: What data can we capture?

Yesterday, in Prof. Ramkumar’s session you heard of **log data**. Today, you have seen how learning can be a **complex process** and learnt CAMM processes that go toward learning.

Based on the above can you think of what other types of data we can capture to shed light on the process of learning?

iMotions multi-modal sensor setup

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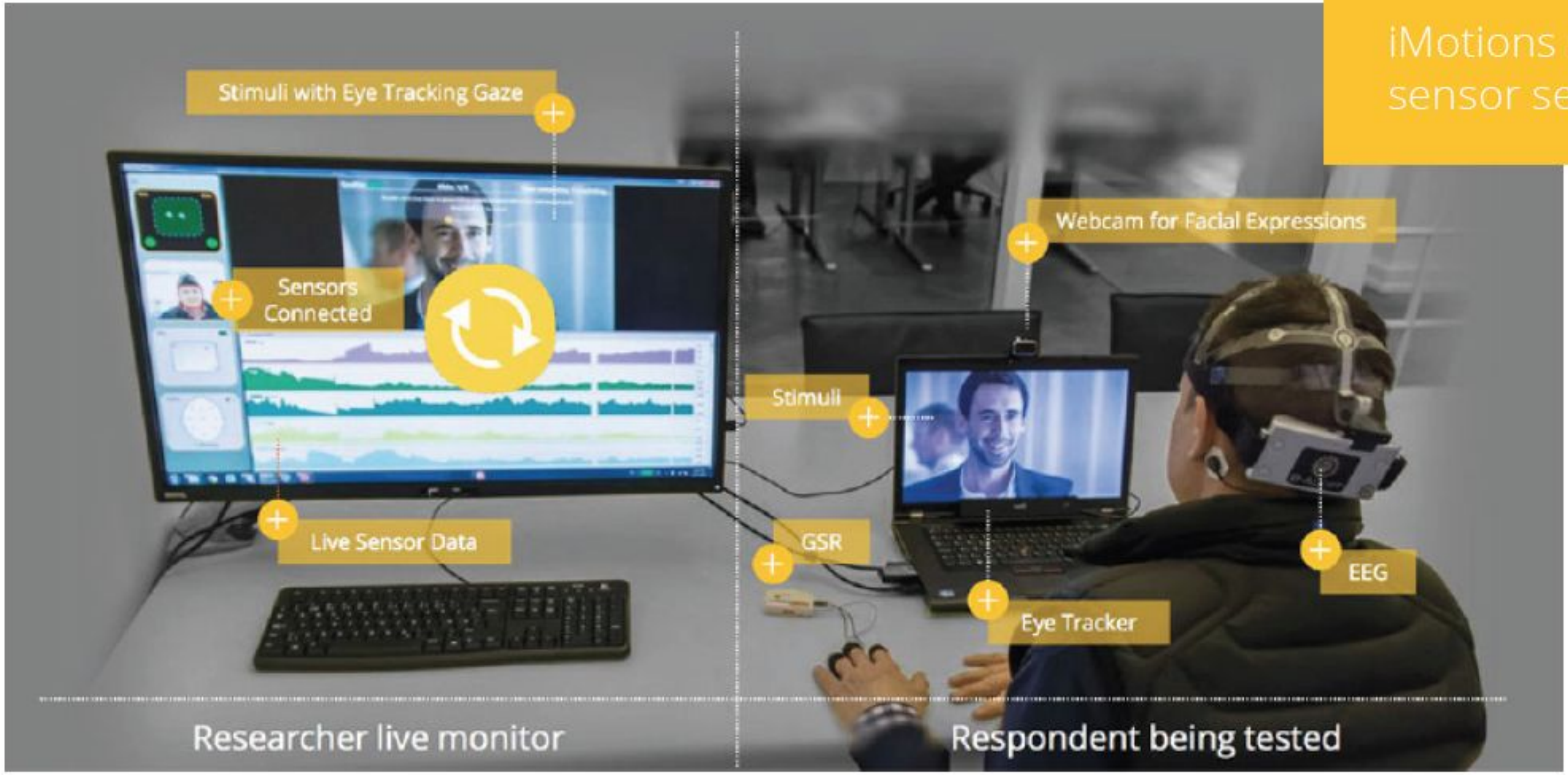

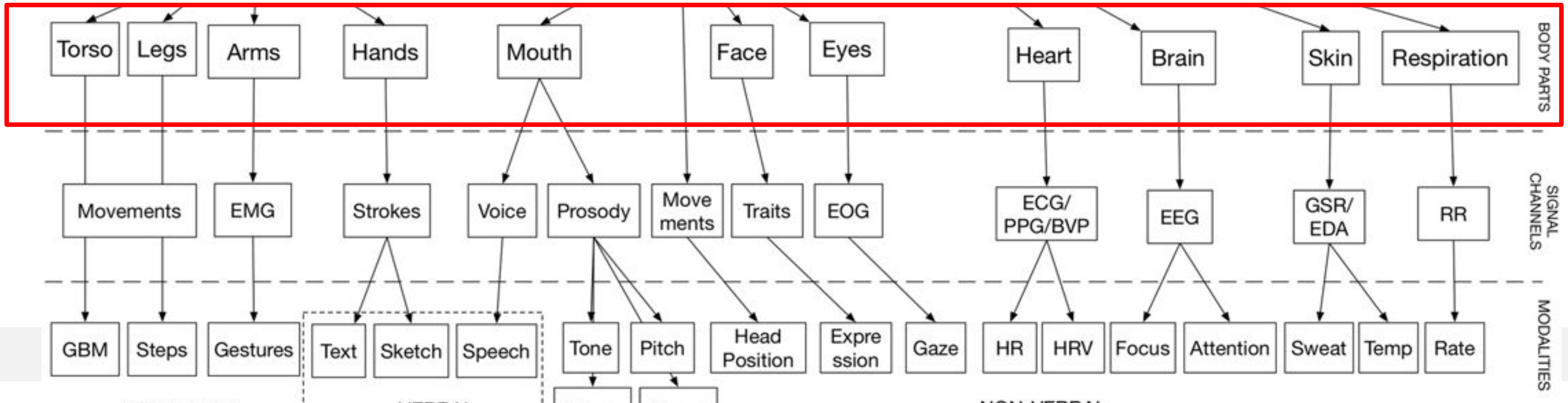

Multimodal data workflow

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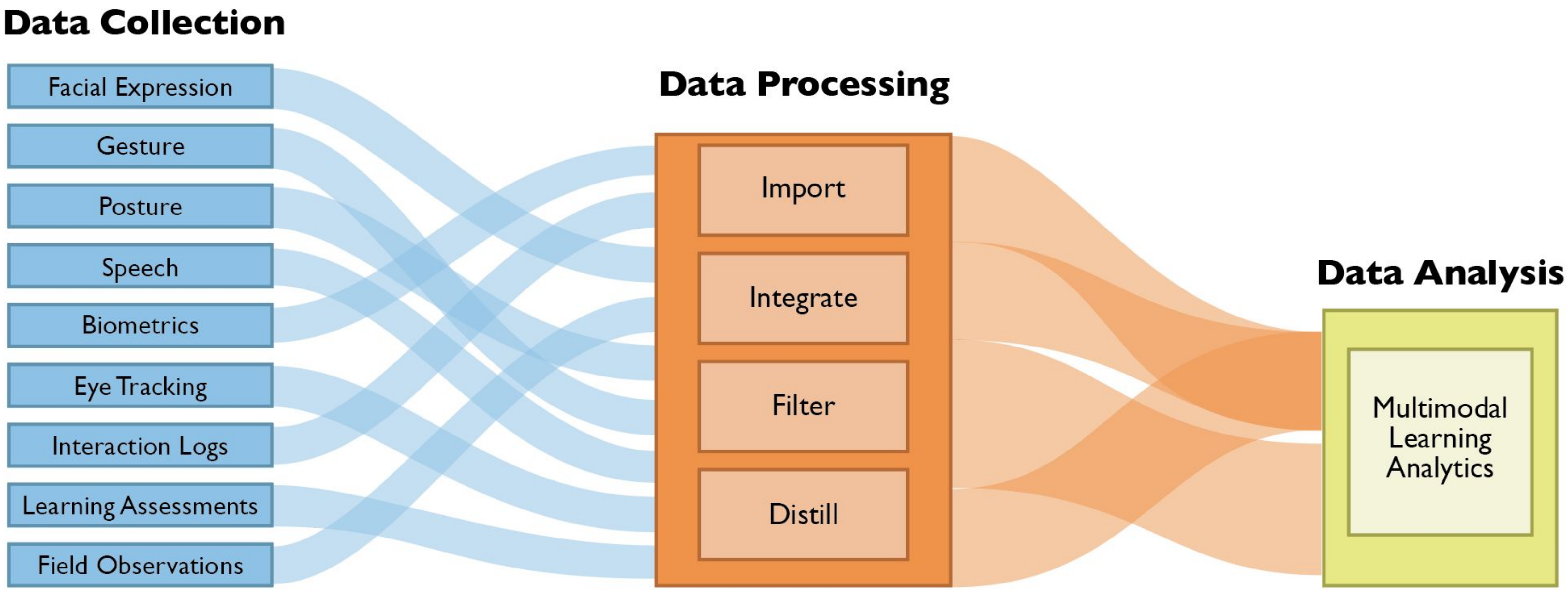

Individual channels of data

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Eye tracking

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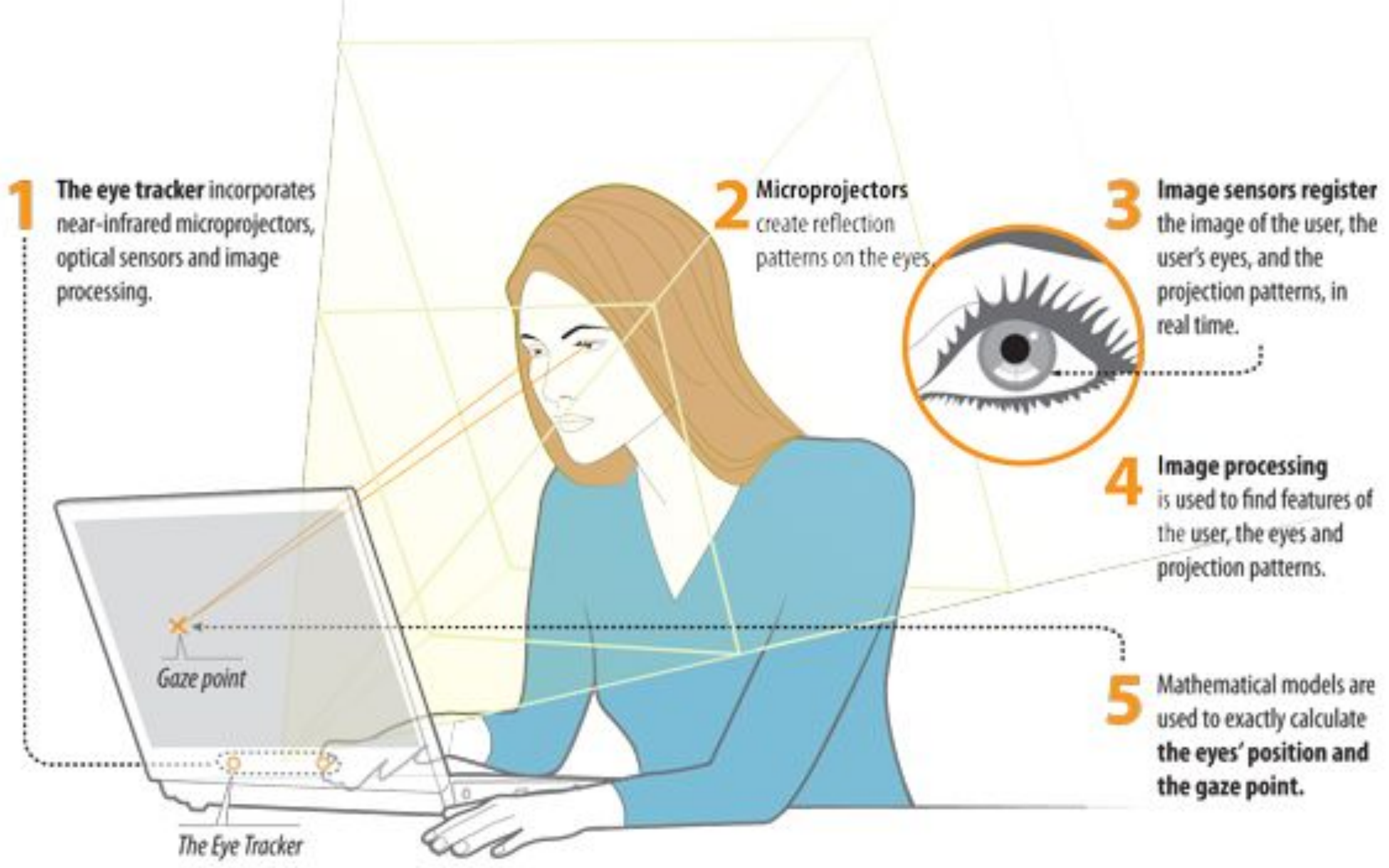


ERP Dashboard Individual metrics
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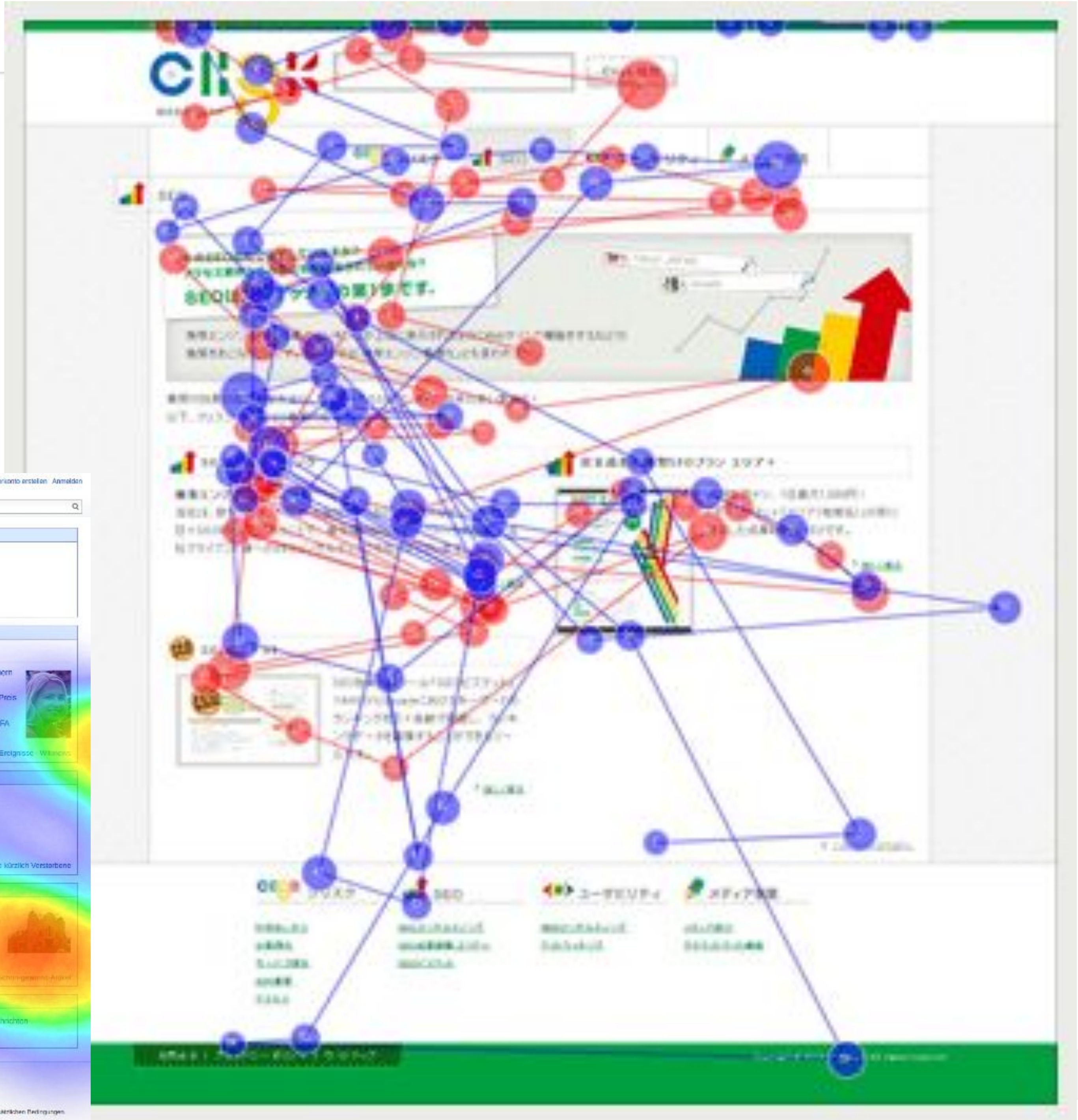
11


Willkommen bei Wikipedia
Artikel des Tages
In den Nachrichten
Kürzlich Verstorbene
Was geschah am 4. Juli?
Schon gewusst?



Galvanic skin response (GSR)

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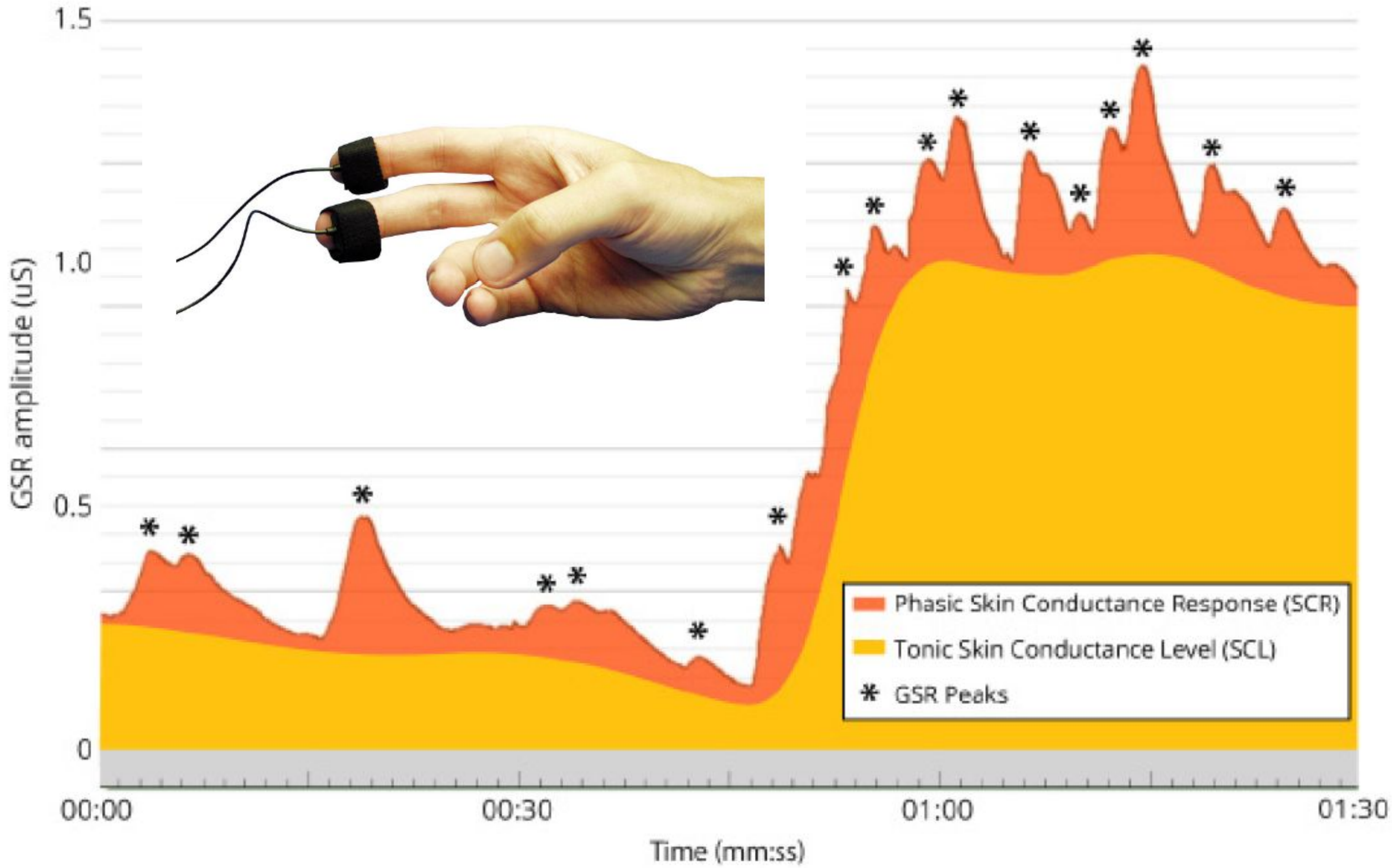

Facial emotion recognition

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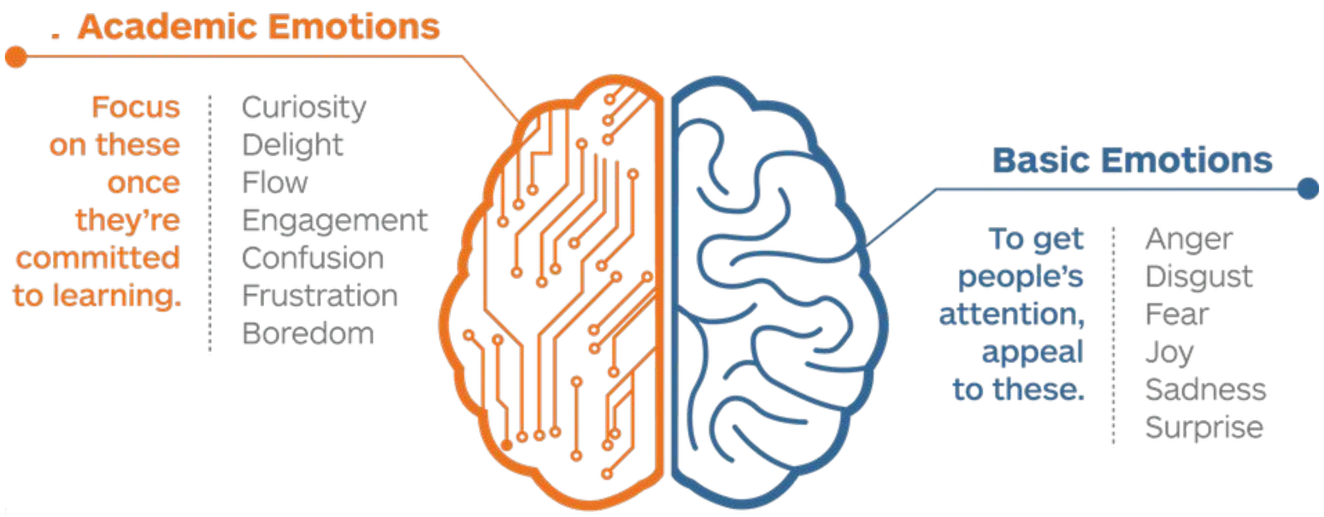
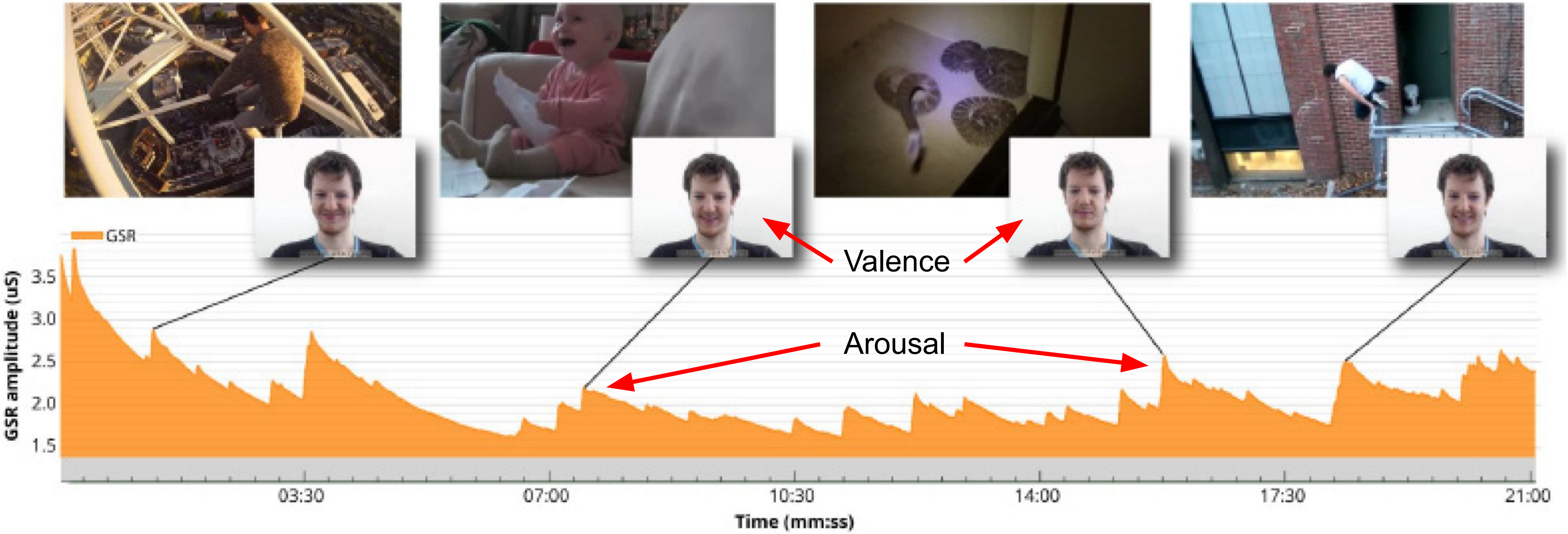


Combining channels



What data should I use?

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Method/Tool	Cognition	Metacognition	Affect	Motivation
Screen Recordings (video and audio)				
Concurrent Think- Alouds				
Eye Tracking				
Log Files				
Facial Expressions of Emotions				
Physiological Sensors (EDA, EMG, EKG, EEG, fNRI)				
Pretest-Posttest-Transfer tests				
Quizzes				
Summaries				
Self Report Questionnaires (AEQ, ERQ, MAI, OMQ, EV, Agent Perception Inventory)				
Metacognitive Judgements				

From Azevedo 2015

Uses of MMLA : Building adaptive interfaces for education

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https://www.youtube.com/watch?v=RyBEUyEtxQo

Uses of MMLA : Machine learning with several sensors

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Using Psycho-Physiological Measures to Assess Task Difficulty in Software Development

Thomas Fritz[†], Andrew Begel[*], Sebastian C. Müller[†], Serap Yigit-Elliott[°], Manuela Züger[†]

[†]University of Zurich
Zurich, Switzerland

[*]Microsoft Research
Redmond, WA USA

[°]Exponent
Bellevue, WA USA

Prediction	Sensors	Precision	Recall	F-Measure
By Participant	**Eye**	**69.16%**	**65.83%**	**65.10%**
	EDA	55.18%	55.77%	51.99%
	EEG	53.05%	56.73%	50.82%
	Eye+EDA	68.37%	64.42%	61.92%
	Eye+EEG	68.58%	63.46%	60.89%
	EDA+EEG	68.02%	64.58%	62.01%
	Eye+EDA+EEG	64.99%	64.58%	62.21%
By Task	Eye	79.17%	66.67%	69.65%
	EDA	75.12%	58.65%	63.80%
	EEG	81.97%	59.62%	63.40%
	Eye+EDA	78.59%	66.35%	70.37%
	Eye+EEG	82.42%	66.35%	69.89%
	EDA+EEG	82.79%	65.63%	69.76%
	Eye+EDA+EEG	**84.38%**	**69.79%**	**73.33%**
By Participant-Task	Eye	66.67%	66.67%	66.67%
	EDA	59.62%	59.62%	59.62%
	EEG	56.73%	56.73%	56.73%
	Eye+EDA	**68.27%**	**68.27%**	**68.27%**
	Eye+EEG	62.50%	62.50%	62.50%
	EDA+EEG	62.50%	62.50%	62.50%
	Eye+EDA+EEG	67.71%	67.71%	67.71%

Fritz et al. 2014

Uses of MMLA : Judicious use of one or two sensors with other data

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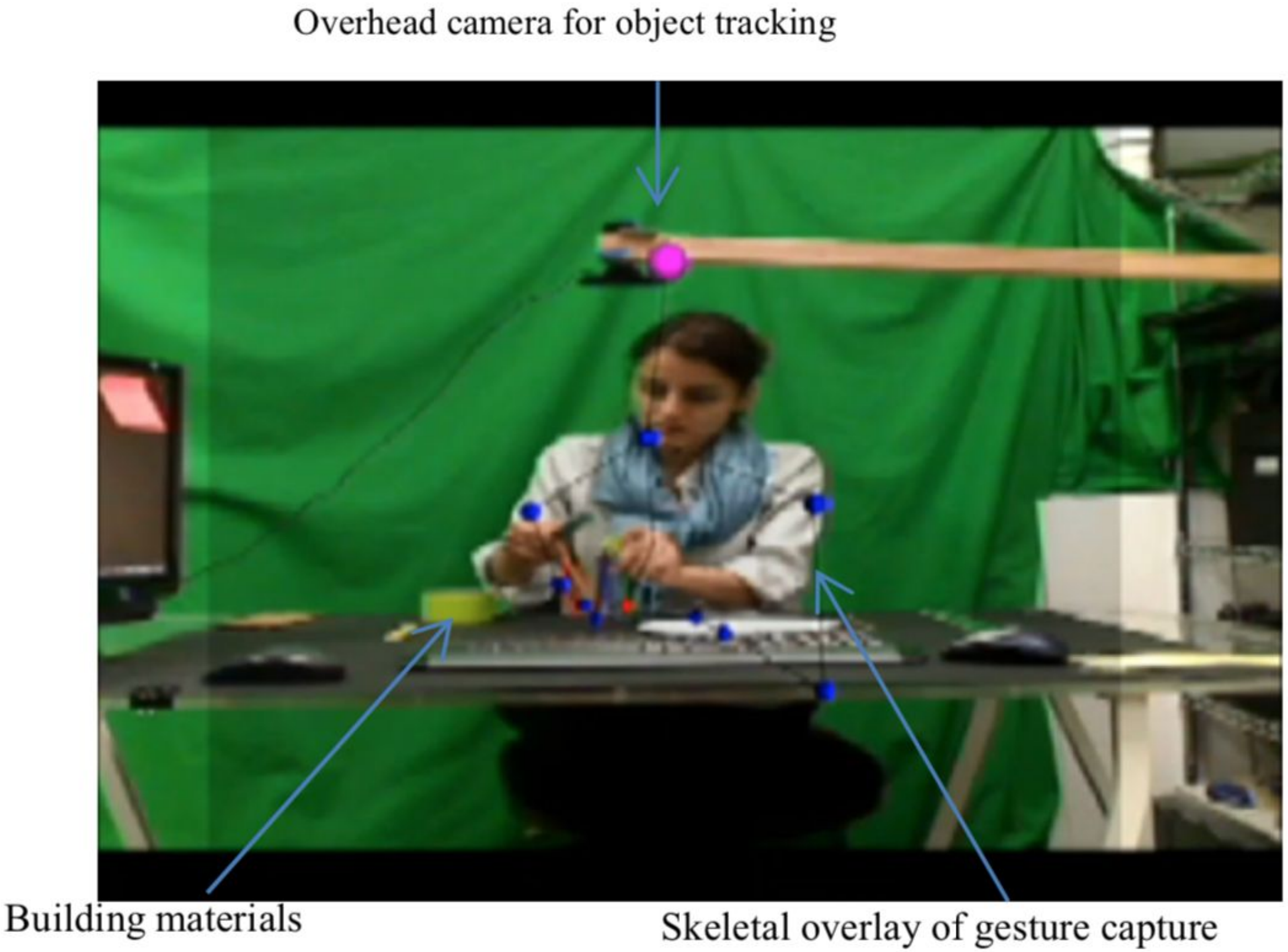

- Used video data to understand how children manipulate objects in a building task
- Gesture data measured with Kinect tracked how they moved their hands
- The two together revealed differences between expert and novice builders

Challenges

- Understanding of confounds in each individual channel of data (currently we handle this with use of multiple channels of data hoping that the strength of one channel will offset the weakness of another)
- How data can be linked back to learning theories
- At what resolution data needs to be aggregated

Thank you

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