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ARIVE Lecture Series

Augmented Experiences: Physiological Sensors/Input and XR

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University of Queensland

Outline

1. Empathic Extended Reality
2. Emotion Detection from Physiological Signals


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Empathic XR

Use of Neurophysiological Signals in Extended Reality

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Empathic XR

Extended Reality Systems that can

Measure | Share | Adapt to | Manipulate

Emotion and *Cognition* in real time

- Physiological (ECG, EDA, EMG, Pupil)
- Neurological (EEG)
- Behavioural (Speech, Posture, Movement)

Measuring Presence with Neurophysiological Signals

(a) HP: hand

(b) HP: pond

(c) HP: high-level view

(d) LP: hand

(e) LP: pond

(f) LP: high-level view

Measuring Presence with Neurophysiological Signals

Data Collected

- EEG (14-Channel Emotive)
- EDA (skin conductance)
- ECG (heart rate)
- Presence Questionnaires

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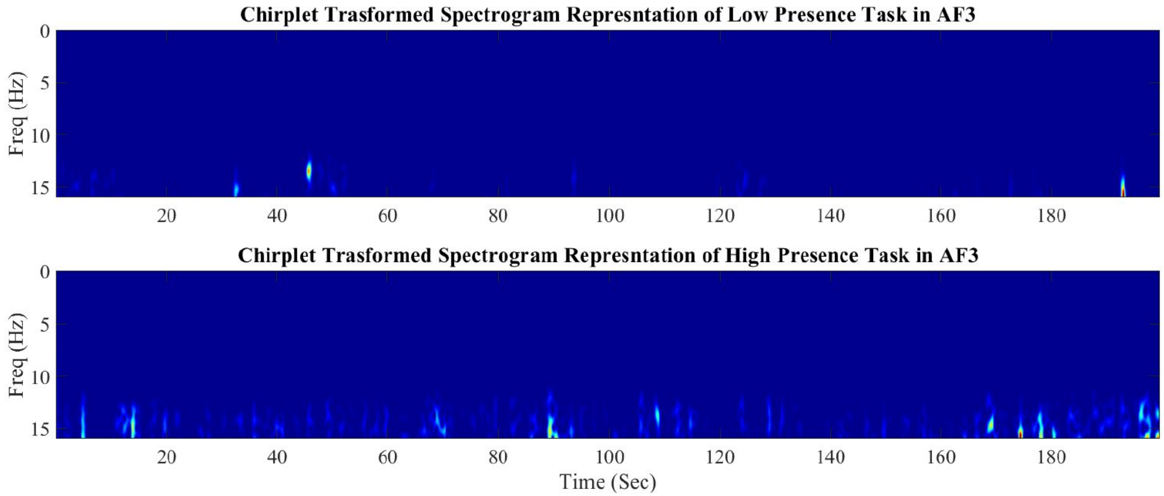
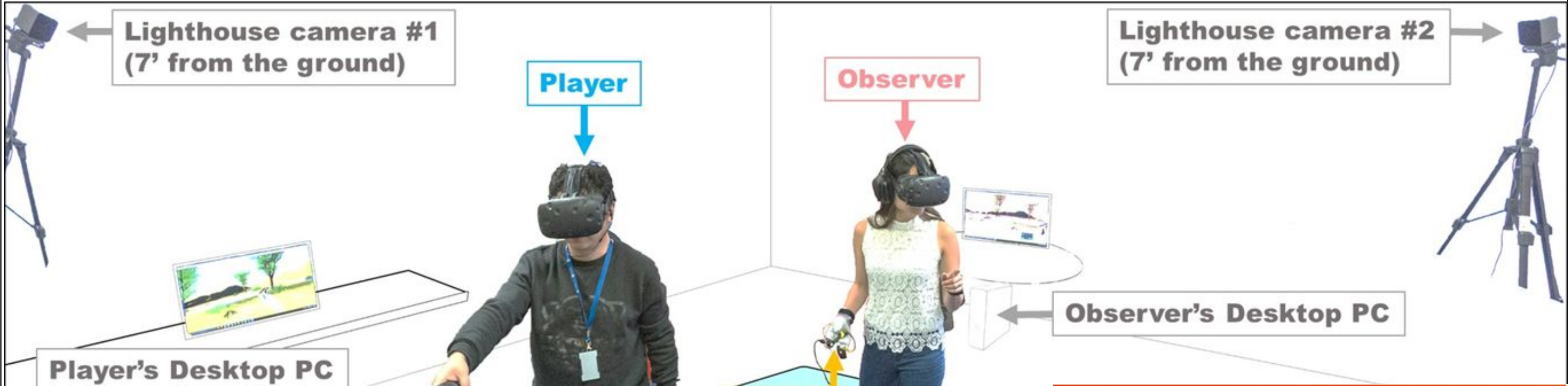
Measuring Presence with Neurophysiological Signals



Results (higher presence causes)

- higher heart rate
- less visual stress
- higher theta and beta activities in the frontal region
- higher alpha activities in the parietal region

Sharing Physiological States in Collaborative VR



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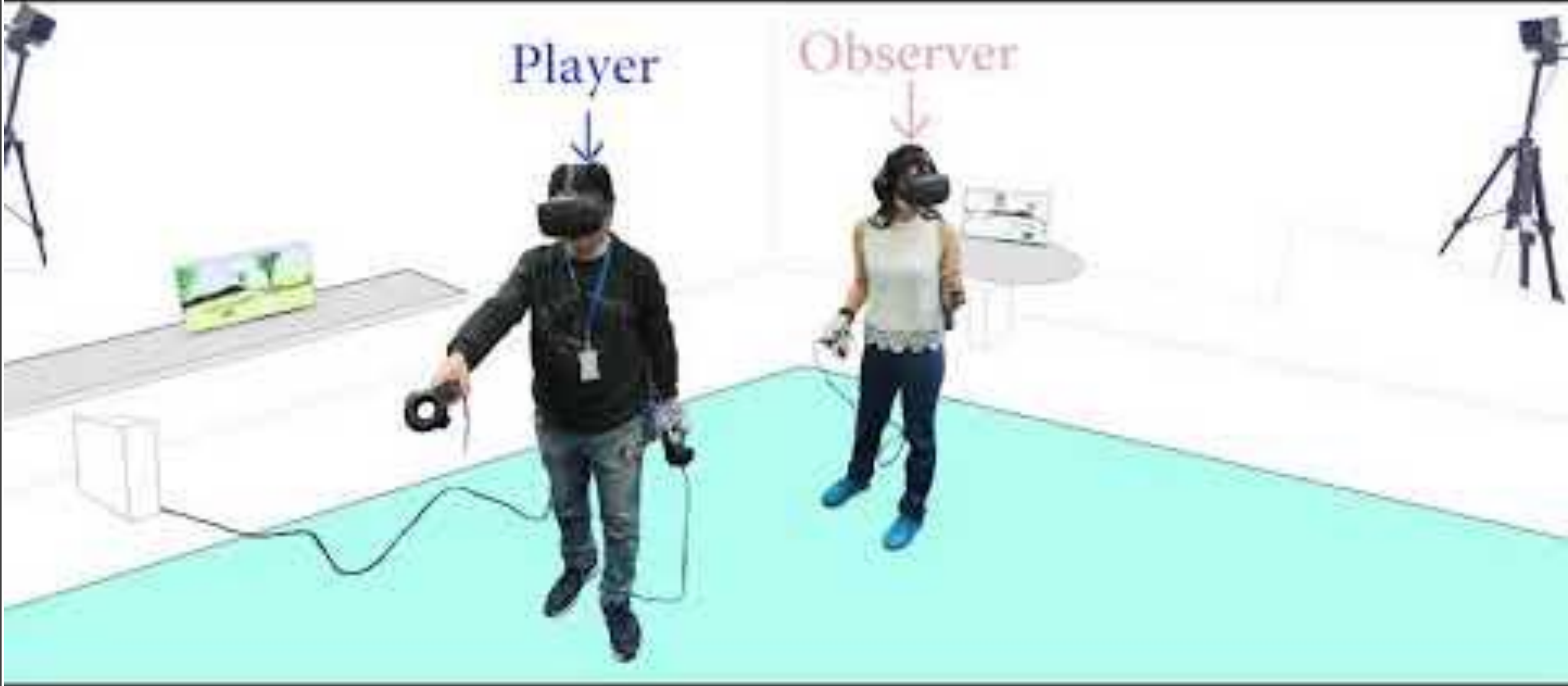

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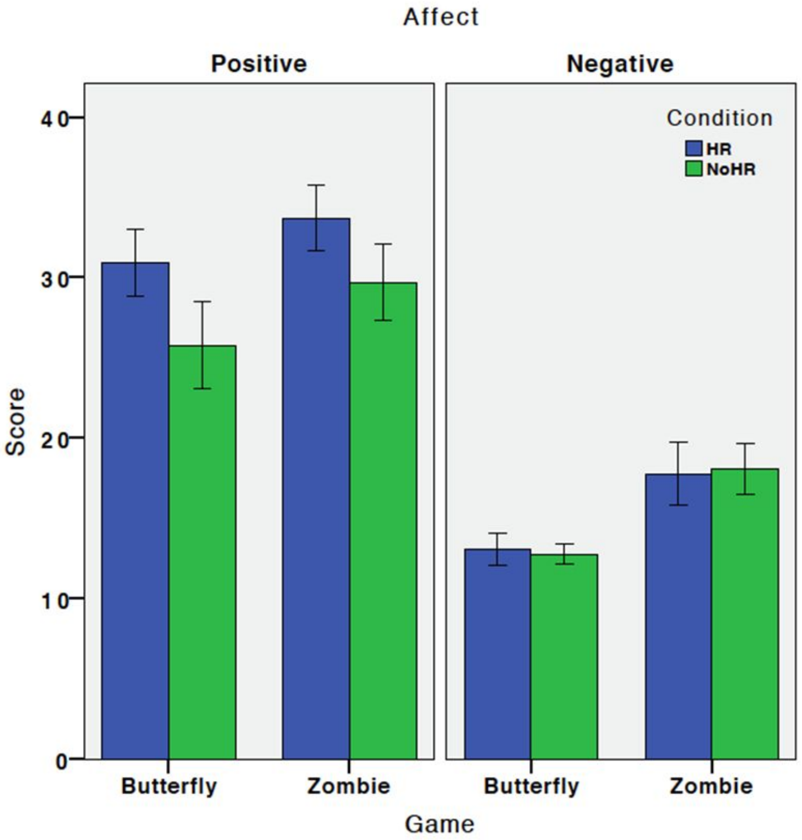
Sharing Physiological States in Collaborative VR



Results

- Higher positive affect (PANAS)
- More communication between collaborators

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Multi-Sensory Heart Rate Feedback

- Audio-Visual
- Audio-Haptic
- Visio-Haptic
- Audio
- None

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Multi-Sensory Heart Rate Feedback

Results

- *Audio-Haptic* ranked best
- More interaction needed for higher presence

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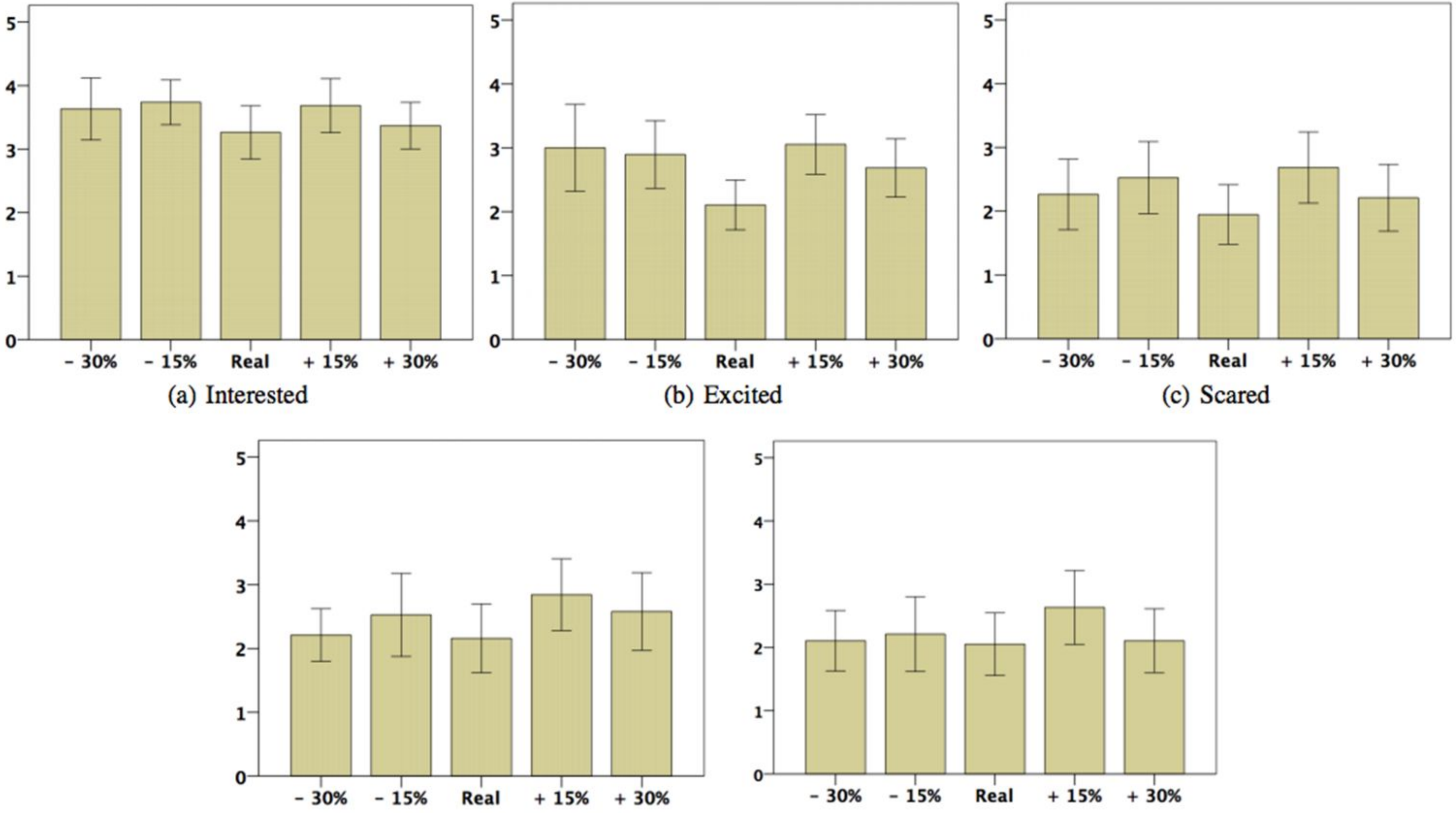
Manipulating Heart Rate Feedback



(a) Interested (b) Excited (c) Scared (d) Nervous (e) Afraid

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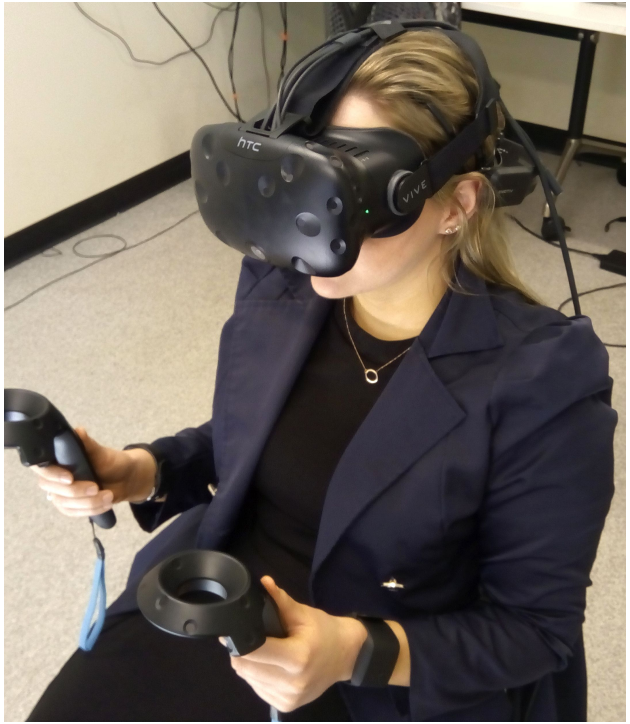
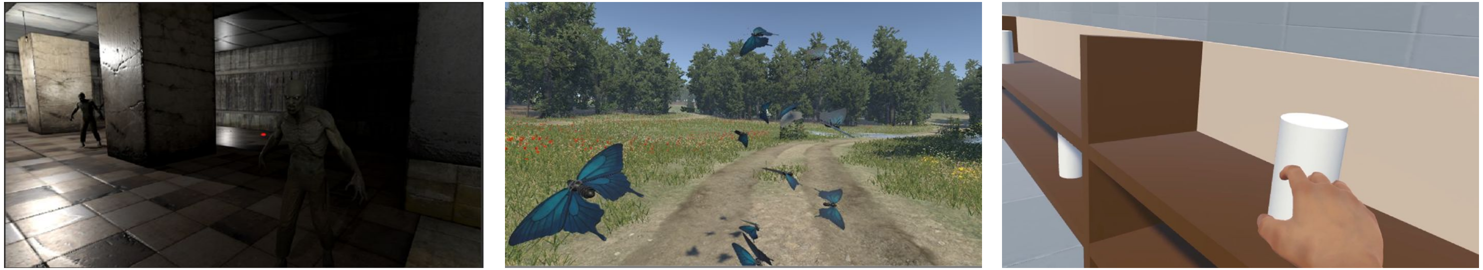
Interacting with Facial Expressions in VR

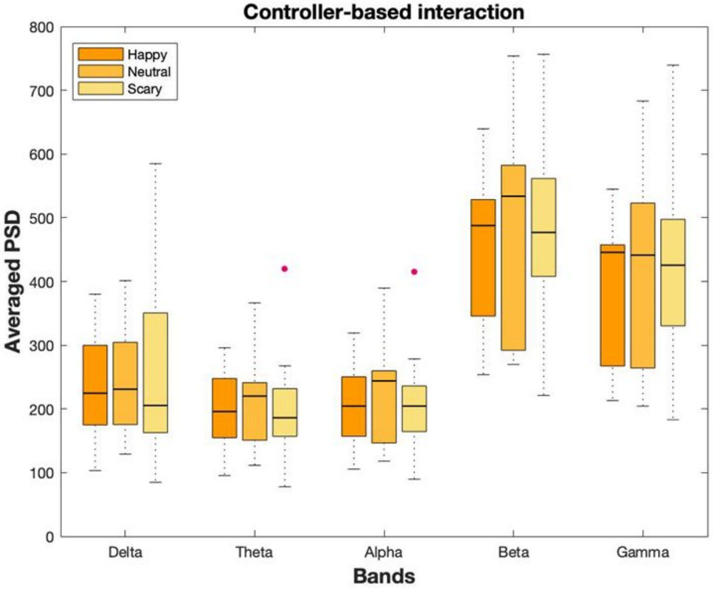
How can people with limited mobility use VR?

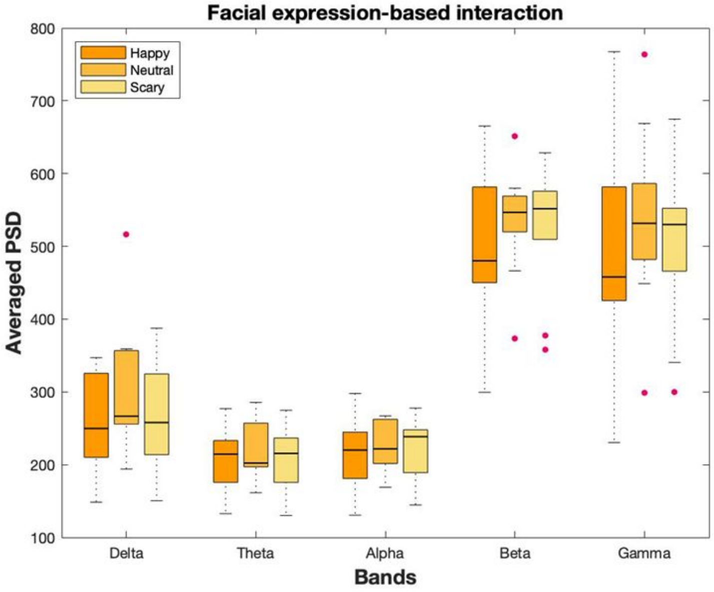


Interacting with Facial Expressions in VR



Interacting with Facial Expressions in VR





Higher gamma activity in facial expression = higher cognitive load

Emotion Detection from Physiological Signals

Mobile sensors are pervasive and unobtrusive…

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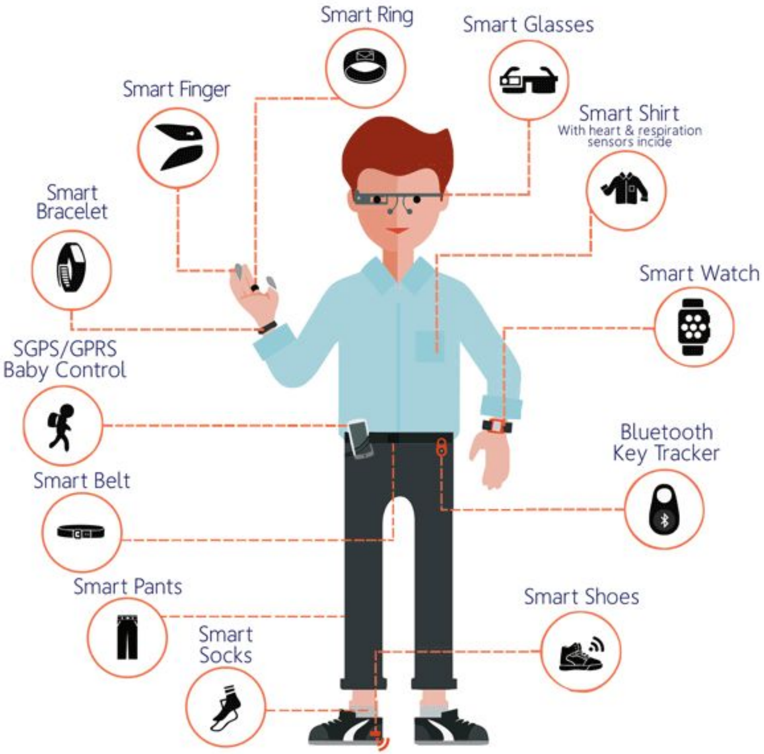

Data from the human body can be logged in everyday life using mobile/wearable devices

24 hours a day

7 days a week

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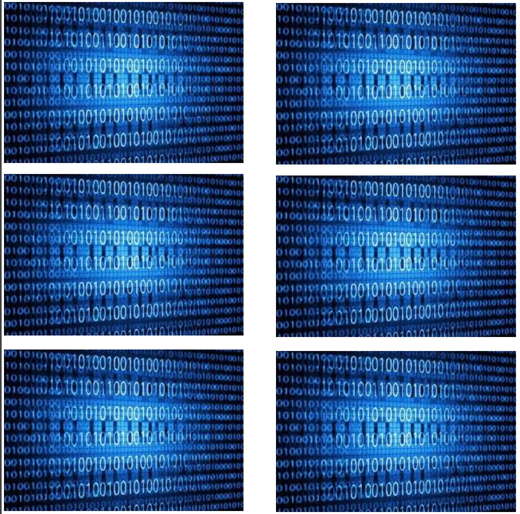
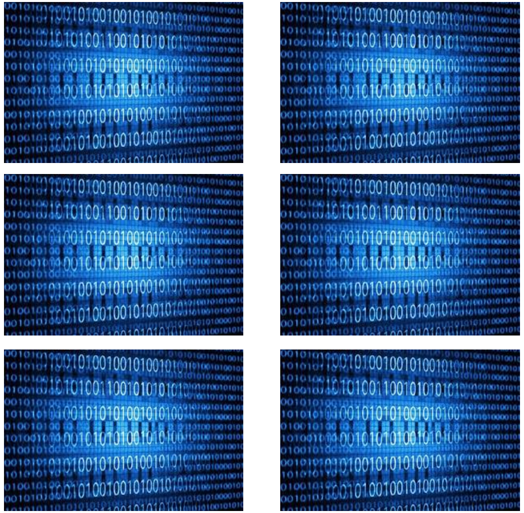
But what do we gain by way of understanding from this mass amount of data?



Data is cheap…

Insight is valuable



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Negative emotions are part of everyday life…
But they are also associated with long-term health problems, such as Coronary Heart Disease

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… so can we use mobile sensors to gain insight into the effects of negative emotion on our cardiovascular health in everyday life?

Take anger/stress for instance…

we all know what it feels like to be angry or stressed

But anger/stress also has a physiological impact…

increased heart rate

increased blood pressure

increased cardiac output

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Physiological signals, including electrocardiogram (ECG), can be measured using wearable sensors…

http://www.shimmersensing.com/products/ecg-development-kit

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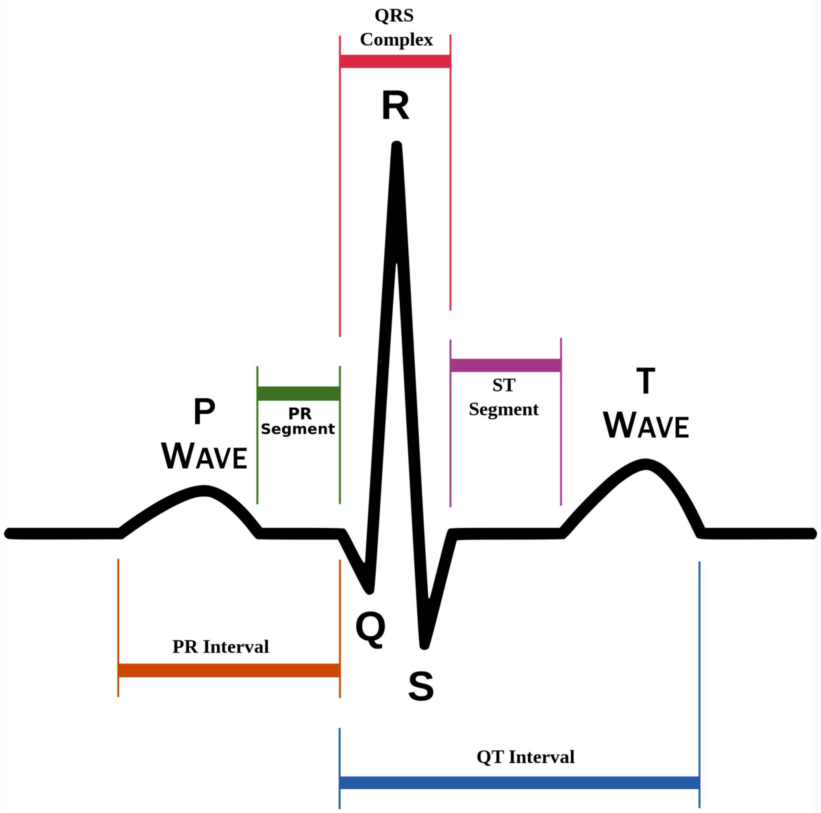
QRS
Complex
R
P
WAVE
PR
Segment
ST
Segment
T
WAVE
Q
S
PR Interval
QT Interval

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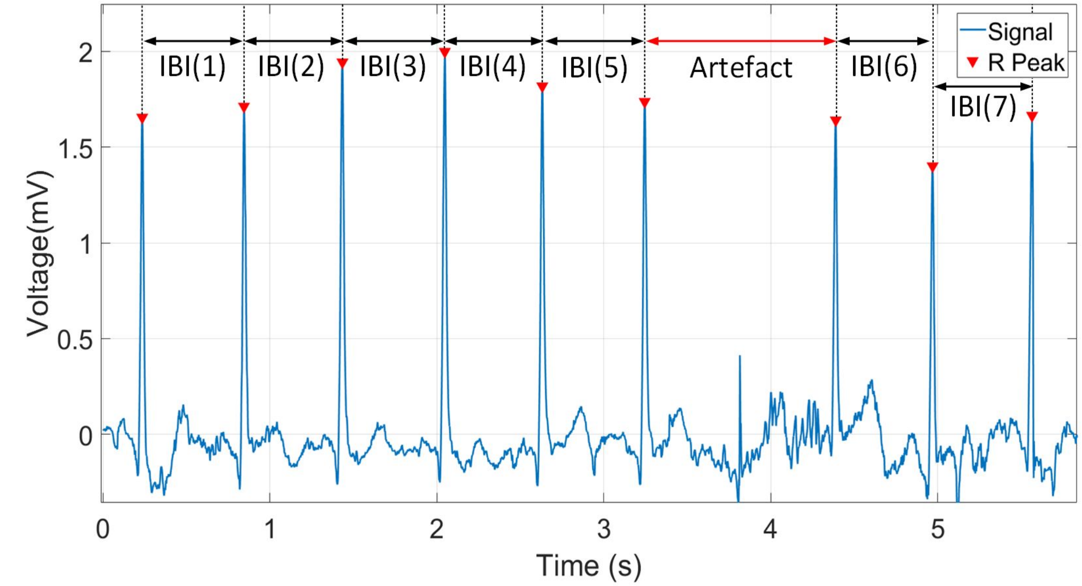
A raw ECG signal needs to undergo extensive pre-processing before feature extraction



Chelsea Dobbins and Stephen Fairclough, "Signal Processing of Multimodal Mobile Lifelogging Data towards Detecting Stress in Real-World Driving," *IEEE Transactions on Mobile Computing*, vol. 18, no. 3, pp. 632–644, May 2018. DOI: 10.1109/TMC.2018.2840153

Time domain features include:

Inter-Beat-Interval (IBI)	• Difference between two R waves (mean/standard deviation)
Heart rate	• Beats per minute (BPM). The number of R waves that occur in one minute
Root Mean Square of the Successive Difference of RR intervals (RMSSD)	• The square root of the mean sum of squared differences of successive R-R beat intervals

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Frequency domain features include:

Total Power (TP)	• Total power of all intervals between 0 and 0.4 Hz
High Frequency (HF)	• Power in the spectrum between 0.15 – 0.4 Hz
Low Frequency (LF)	• Power in the spectrum between 0.04 - 0.15 Hz
Very Low Frequency (VLF)	• Power in the spectrum between 0.0033 and 0.04 Hz
LF/HF	• Ratio between low and high frequency power

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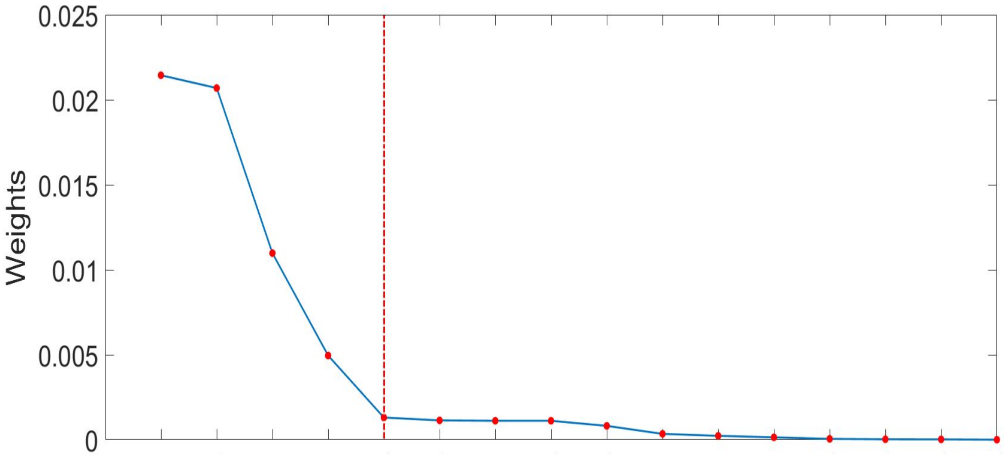
Feature selection can reduce your dataset further



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I. Kononenko, E. Šimec, and M. Robnik-Šikonja, “Overcoming the Myopia of Inductive Learning Algorithms with RELIEFF,” *Applied Intelligence*, vol. 7, no. 1, pp. 39–55, 1997. DOI: 10.1023/A:1008280620621

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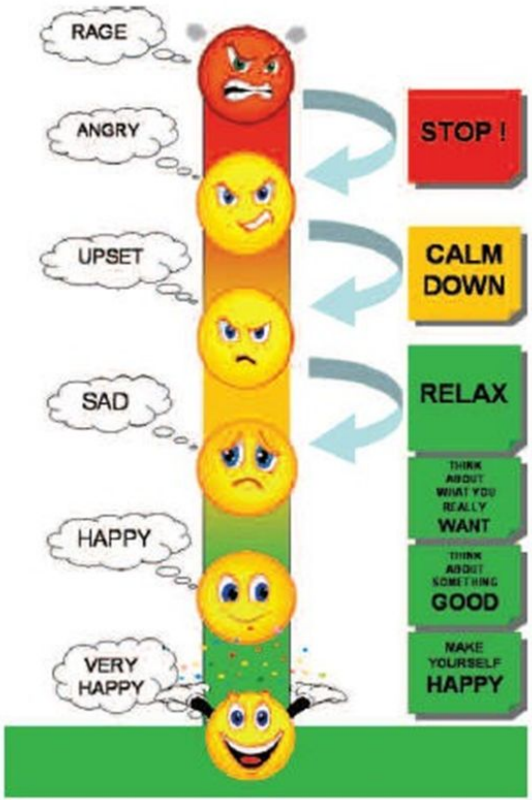
Engagement with health means *understanding* everyday links between cause and effect

Lifelogging systems can deliver this understanding

But only if the data is provided to the person in an *intuitive* and *digestible* form



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