And How Does that Make You Feel?

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Affective Computing (Partially from Wikipedia)

Affective computing is the study and development of systems and devices that can recognize, interpret, process, and simulate [or respond to] human affect.

It is an interdisciplinary field spanning computer science, psychology, and cognitive science.

The modern branch of this area of computer science originated with Rosalind Picard’s 1990’s book called Affective Computing.
Affective Computing

A motivation for the research is the ability to simulate empathy

The machine can interpret the emotional state of humans and adapt its behavior to them, giving an appropriate response for those emotions

But, we can also give feedback to humans as to their emotional state for awareness
Current Research

Non-invasive methods for picking up additional signals that users naturally give off while using a computer system.

Translate these signals into meaningful input leading to systems that respond appropriately to changes in the user's state.

(Could also lead to systems that are annoying, so must be done carefully.)
Current Trends: Self Monitoring, QS

The market for wearable monitoring exploded in 2011

Advances in sensor technologies (e.g., accelerometers)
Smart phones,
Faster wireless networks
Longer battery life
Sensors will be worn inside and outside of our bodies!
Three Use Cases

Mary Czerwinski: How can we help people detect and relieve their stress and anxiety?

Erin Solovey: Can we help people drive better and avoid accidents even when they are distracted?

Andrew Begel: Can we design interventions to stop software developers from causing bugs when they are confused or frustrated with their code?
Mary Czerwinski
Outline

• Current Trends
• AffectAura
• Entendre
• Textile Mirror
• Butterfly Affect
• UnDoStress
• Conclusions and Future Work
Emotional health plays a fundamental role in our quality of life (World Health Organization, 2005)

Understanding our emotional habits is key to a better, healthier lifestyle (e.g., reduced stress, obesity, etc.)

Some families really need this help (e.g., ADHD, Autism, etc.)

Beyond Fitness... is Emotional Fitness

Product Interest....detecting joy, frustration of users
First Focus – STRESS and ANXIETY

**Obesity**
51% of obese people eat too much due to stress (Kivmaki et al., 2002)

**Cardiovascular health**
3x increase in hypertension and 2.2x increase in cardiovascular mortality in high stress jobs (Pickering, 2001)

**Stress management**
69% report importance but only 32% handle it well (APA, Stress in America, 2010)
First Application: AffectAura (CHI 2012)

AffectAura is the first emotional prosthetic that automatically logs a user’s emotional states and allows them to reflect on this information over long periods of time.
AFFECTAURA

Daniel McDuff, Ashish Kapoor, Amy Karlson, Asta Roseway, Mary Czerwinski
Next Application – Entendre: Feedback on Clinical Empathy (Pervasive Health 2013)

Clinician empathy is associated with patient outcomes
- Satisfaction
- Adherence to treatment
- Less anxiety
- Fewer complications

Empathy is not taught in medical school
Empathy is hard to measure
Doctors’ time is extremely valuable – need to design and study a different way
Empathy Measurement and Feedback

Self-report of physicians
Self-report of patients
Observational coding
Can we describe the empathic nonverbal communication of a whole clinic encounter?
How feasible is it to provide real-time feedback to clinicians about their empathy?

Need to build a wizard-of-oz system to explore possibilities before building full system
Can We Map Theories? Lab Study Needed

Honest Signals (Pentland, 2009) (proven system)
Activity
Consistency
Influence
Mimicry

Interpersonal Circumplex (Wiggins, 2003)
Affiliation, Control
Warm, Cold
Dominant, Submissive
Wizard-of-Oz Lab Study

Brought in 16 healthcare professionals ranging from EMT, nurses, doctors to Clinicians

They went through a scenario with a trained medical “performer” using the tool

WOZ rated empathy in real time

Performer rated their empathy afterwards

Entendre feedback

Mentor Participant
Health professional

Mentee Participant
Standardized performer
Feedback on First Design (N=16)

Avg. Response (1=low, 5=high):

- Helpful: 3
- Informative: 4
- Interesting: 3
- Confusing: 2
- Distracting: 3
Could Art Work? Textile Mirror (TEI 2013)

An interactive prototype designed to actuate a user’s current emotional state through the movement of fabric

Felecia Davis, PhD Candidate
MIT School of Architecture (internship)
Results: Quantitative

• There was a significant effect in terms of positive emotion before v. after observing the fabric, $F(3, 64) = 3.3, p < .03$.

• Of course, the passage of time could also have been a factor; though when asked, participants discounted this.

• There was a sentiment that this could be really useful in the home, or school, especially with ADHD or autistic family members—even grandparents.
Soooo, ….Butterfly Affect: Actuated External Awareness (PETRA 2012)

Actuating mood in real time via wearables

Diana MacLean, PhD Candidate
Stanford University
(internship)
User with MoodWings in Driving Simulator
Users Drove Somewhat More Safely with MoodWings

No significant differences in #crashes, #centerline crossings, #speed infractions

Avg. % Distance Speeding:
10% (Butterfly Condition)
17% (Control Condition)
p = 0.04
User Qualitative Findings

Users reported feeling significantly more aware of their stress levels in the Actuated condition (mean=5.4, scale=1-7) than in the Stationary condition (mean=3.4) (Mann-Whitney U=156.5, n1=n2=11, p=0.046).

Users were stressed in 14/33 scenarios in the Actuated condition, compared to 5/33 scenarios in the Stationary condition (signif).

Users noticed butterfly actuations in 29/33 (88%) Actuated condition scenarios, and stated that they saw no actuations in 27/33 (82%) Stationary condition scenarios.
“I would feel comfortable wearing the butterfly around other people.”
(1 = disagree; 7 = agree.)
Last Application: UnDoStress
(Submitted to CHI 2014)

Stress Relief + Coping without Actuation

Pablo E. Paredes
Advisor: Mary Czerwinski
Mentors: Asta Roseway, Ran Gilad-Bachrach
In collaboration with Kael Rowan
Our Contribution: New Age Stress Management ... Using Pop Culture

Intervention Mashup

H1? Can we generate a micro intervention suite inspired by pop culture?
... stress management for every occasion!

H2: Can we use ML to determine a successful policy to match the best intervention with your current state (personal characteristics + context)

H3: Can we generate long term behavioral change by gently moving people’s coping strategies from destructive to constructive?
Video
What Have We Learned?

We can stress users out...
By showing them their stress levels

Users aren’t used to thinking about their emotional state
A few are highly skeptical of ML

Some users dislike external, actuated awareness
Others really like it; we continue to iterate on designs here

We can use technology to do real-time, or just-in-time interventions
And users can develop better coping skills through intelligent advice

We find this especially encouraging for doctors, patients, parents, etc.
Next generation HCl

Goal: expand bandwidth between human & computer

Approach: identify signals people naturally give off and adapt systems appropriately

Potential domains: medicine, education, driving, aviation, UAVs, video games, mobile
Brain & Body Sensing

Continuous, real time measures
Electrocardiogram (EKG)
Skin Conductance
Functional near-infrared spectroscopy brain sensing

Practical for real-world settings
Quick set up time
Comfortable, safe, portable
Permits regular computer usage
Real-time brain & body input

Passive, implicit input channel
Capture subtle cognitive state changes
Augment traditional input devices
Adaptive, context-aware systems

Examples
Adapting autonomy levels
Modifying quantity of information
Transform modality of info presentation
Task allocation, manage task load, difficulty
Classifying Driver Workload Using Physiological & Driving Performance Data
Driver Workload
Motivation

# people injured or killed on U.S. roadways in motor vehicle crashes involving distracted driving:

[US NHTSA, 2011]

3,331 killed

~387,000 injured
Motivation

Advanced in-vehicle tech (e.g. GPS)
Drivers bring tech into car
Advanced automation
Approach

Passive, automatic cognitive workload detection during natural driving using body sensing and driving metrics
Two Field Studies

Experiment 1: Within Individuals
On-road driving
2-back task
40 minutes of physiological and vehicle data
20 subjects

Experiment 2: Across Individuals
On-road driving
n-back tasks
4 minutes of physiological and vehicle data
99 subjects
Vehicle Equipment & Sensors

Electrocardiogram (EKG)
Skin conductance
Driving speed
Steering wheel position
Acceleration data
Secondary Task Procedure

Delayed digit recall task, Similar to n-back
Correct response: number presented 2 periods earlier

<table>
<thead>
<tr>
<th>Stimulus</th>
<th>8 7 4 5 2 3 1 9 6 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response</td>
<td>. . 8 7 4 5 2 3 1 9</td>
</tr>
</tbody>
</table>
Experiment 1: Build Individual Models

<table>
<thead>
<tr>
<th>30 sec 2-back</th>
<th>90 sec Recovery and baseline</th>
<th>30 sec 2-back</th>
<th>90 sec Recovery and baseline</th>
<th>30 sec 2-back</th>
<th>90 sec Recovery and baseline</th>
</tr>
</thead>
</table>

Each subject completed a total of 24 epochs of the 2-back task.

20 participants: (9 female), mean age 23.9, (SD 23)

24 30-second examples of elevated and normal workload

Entire 2-minute period (n-back & rest) would be in training or test
Feature extraction

Raw input data

Feature extraction

Average, std, ... of each stream in the window becomes a feature
Experiment 1 Classification Results

- 69-75% cross-validation accuracy: all features, depending on algorithm
- 71-74% cross-validation accuracy: heart Rate features only
- Reasonable accuracy, using simple features and classification methods, HR alone even has promise
- 24 trials = ~48 minutes of data per person, training on 43 minutes
  - Okay for proof-of-concept, not ideal for real-world
  - Future: improved methods to shorten this
  - Classification across individuals may reduce/eliminate this training time (Experiment 2)
**Experiment 2: Build Generalized Models**

<table>
<thead>
<tr>
<th>Age group (years)</th>
<th>Mean (SD)</th>
<th>Females</th>
<th>Males</th>
</tr>
</thead>
<tbody>
<tr>
<td>20-29</td>
<td>24.75 (2.81)</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td>40-49</td>
<td>44.74 (3.01)</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>60-69</td>
<td>63.97 (3.02)</td>
<td>16</td>
<td>16</td>
</tr>
</tbody>
</table>

Presentation order of task level (0, 1, or 2-back) counterbalanced across subjects.

Block 1:
- 30 sec 0-back
- 30 sec 0-back
- 30 sec 0-back
- 30 sec 0-back

150 seconds task recovery

Block 2:
- 30 sec 1-back
- 30 sec 1-back
- 30 sec 1-back
- 30 sec 1-back

150 seconds task recovery

Block 3:
- 30 sec 2-back
- 30 sec 2-back
- 30 sec 2-back
- 30 sec 2-back
Experiment 2 results

Heart rate change during experiment drive

Skin conductance level change during experiment drive
Experiment 2 Classification Results

Highest accuracy was in the low-90s
Tradeoff between window size and accuracy
Overlap had little effect
Feature combos had clear effects on classification results.
Conclusion

1. Study real-world task in large field studies

2. Record body sensor & task data

3. Classify cognitive workload level
Future

Additional driving measures, brain & body sensors, classification algorithms
More granular recognition of workload levels
More realistic tasks, Cross-task classification
Ready-to-go workload detection when user enters vehicle
Integrate measure into future cars (e.g. steering wheel, seat back)
Andrew Begel
Which Code is More Difficult to Understand?

```csharp
using Graphics;

namespace Study {  
    public class Drawing {  
        public static void Main(string[] args) {  
            Circle c = new Circle();  
            Triangle t1 = new Triangle();  
            Square s = new Square();  
            Triangle t2 = new Triangle();  

            Graphics.draw(t2);  
            Graphics.draw(t1);  
            Graphics.draw(c);  
            Graphics.draw(s);  
        }  
    }  
}
```

```csharp
using Graphics;

namespace Study {  
    public class Drawing {  
        public static void Main(string[] args) {  
            Object objectA = new Circle();  
            Object objectK = new Circle();  
            Object objectX = new Square();  
            Object objectB = new Triangle();  

            Graphics.draw(objectX);  
            Graphics.draw(objectA);  
            Graphics.draw(objectB);  
            Graphics.draw(objectK);  
        }  
    }  
}
```
Why Are Some Codes Harder than Others?

Several research areas tackle this question:
  - CS Education
  - Psychology of Programming
  - Program Comprehension

And its implications:
  - Testing and Automatic Verification
  - Code Reviews
  - Mining Software Repositories
Our Vision

Research Questions
1. Can we correlate developers’ cognitive and emotional states with their perception of task difficulty?
2. How well do these states predict long-term effects on software (e.g. bugs, productivity)?

Interventions

When we detect that a developer is in the zone, we could signal his teammates to delay non-critical interruptions.

We could refactor the cognitively difficult parts of the codebase where developers lose the most productivity.

Armed with a task difficulty classifier, we could help stop developers from making mistakes!
15 professional software developers
C# programmers from Seattle area. 14 male, 1 female. 27 – 60 years old.

8 tasks with various levels of difficulty
Type 1: Do these rectangles overlap?
Type 2: What are the last three shapes drawn by `main()`?

3 psycho-physiological sensors
EEG, EDA, Eye tracking

8 task ratings and 1 ranking over all tasks
Study Tasks

8 Tasks:
(2 types)

Variations:
Variable names (mnemonic vs. obfuscated)
Loops with various complexity
Nested ?: operator
Randomly-ordered field assignments

Cognitive Abilities:
Working memory
Spatial relations
Math and Logic
using Graphics;

namespace Study {

class Drawing {

    public static void Main(string[] args) {
        Rectangle t = new Rectangle();
        t.leftBottom = new Point(2, 2);
        t.leftTop = new Point(2, 6);
        t.rightTop = new Point(6, 6);
        t.rightBottom = new Point(6, 2);
        Graphics.draw(t);

        Rectangle s = new Rectangle();
        s.leftTop = new Point(11, 5);
        s.leftBottom = new Point(5, 5);
        s.rightBottom = new Point(5, 9);
        s.rightTop = new Point(11, 9);
        Graphics.draw(s);
    }

}}

Do these rectangles overlap?
Do these rectangles overlap?
Study Setup
Psycho-Physiological Sensors

**EEG** (Electroencephalogram)
- $\alpha$, $\beta$, $\gamma$, $\delta$, $\theta$ waves
- eye blinks
- attention, meditation
- visual attention, mental workload, etc.
- attention™, meditation™

**EDA** (Electrodermal activity)
- tonic signal (low freq)
- phasic signal (high freq)
- general state of arousal
- surprise

**Eye tracking**
- gaze location
- fixations and saccades
- pupil size
- code location
- reading vs. scanning
- cognitive load
Task Difficulty Metrics

Recorded participants’ task completion times.

After each task, participant filled out NASA Task Load Index (TLX) survey.

At end of study, participant ranked tasks by relative difficulty (1 – 8).
Watch a Developer at Work!
Our Analysis Approach

Data recording
Data cleaning
Sliding time windows (optional)
Feature extraction
Naïve Bayes classifier
Developers’ perceived difficulty
Task Difficulty Ratings

The metrics were highly correlated.

NASA TLX vs. task difficulty ranking
  Spearman: $r_{116} = 0.587$, $p < 0.01$

Task difficulty ranking vs. task completion time
  Spearman: $r_{116} = 0.724$, $p < 0.01$

Simplified metrics by nominalizing NASA TLX and task difficulty ranking into Boolean easy/difficult.

Correlation: Boolean NASA TLX score vs. Boolean task difficulty
  $\chi^2(1, 116) = 57.954$, $p < 0.01$ (accuracy 85%)

Triangulation between metrics validates our results.
Machine Learning Predictors: By Participant
Results: By Participant
Machine Learning Predictors: By Task
Results: By Task

![Graph showing results by task]
Machine Learning Predictors: By Participant-Task

- P01
  - T1: P01
  - T2
  - T3
  - ... (omitted)
  - T8: P01

- P15
  - T1: P15
  - T2
  - T3
  - ... (omitted)
  - T8: P15

Test data

Training data
Results: By Participant-Task
Discussion
Research Reflections

What were the challenges in making these technologies and techniques work?
What are the practical applications for this research?
This is a really different interaction technique. How will this affect application design in the future?
Get more information

Swipe your name badge in the back of the room

Save the planet and return your name badge before you leave (on Tuesday)
Backup Slides for Mary Czerwinski
Methodology

N = 80
Longitudinal → 4 weeks

Tests:

**Daily:** Mood Self Rating + Sensors
**Weekly:** Qualitative, Depression, Coping, Affect
**Pre / Post Survey:** Depression, Coping, Affect, Life Events, Personality, Happiness, Tech usage

2 x 2 Experiment (ML v. Random; Selection from Menu or Not) between subjects design.
## User Model Input and Sensor Types

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Parameters</th>
</tr>
</thead>
</table>
| User Trait Data    | - Personality - BIG5 (agreeableness, conscientiousness, extraversion, neuroticism, openness)  
|                    | - Positive and Negative Affect - PANAS                                        
|                    | - Depression - PHQ-9                                                          
|                    | - Coping Strategies - CSQ                                                      
|                    | - Demographics: gender, age, marital status, income, education, employment, professional level 
|                    | - Social Network: Facebook usage, size of online social network and number of good friends 
| Self Report Data   | - Last reported energy and mood                                               
|                    | - Time since last self report                                                 
|                    | - Energy and Mood (average and variance)                                     
|                    | - Number of self reports                                                      |

<table>
<thead>
<tr>
<th>Sensor / API</th>
<th>Feature</th>
</tr>
</thead>
</table>
| Calendar           | - Number of (free, not free) calendar records (before, during and after an intervention) 
|                    | - Time until the next meeting                                              |
| GPS                | - Number of records (at home, at work, null)                              
|                    | - Time since GPR record at work                                            
|                    | - Signal quality (average, last record)                                   
|                    | - Location (distance to home, distance to work)                           
|                    | - Distance traveled                                                       |
| Time               | - Time and day                                                             
|                    | - Lunch or Night time                                                      |
| Accelerometer      | - X,Y,Z average, variance (jerk) – 30,120 min                              
|                    | Number of accelerometer records (30, 120 min)                              |
| Screen Lock        | - Number of events                                                         
|                    | - Time since last lock event                                                |
Application usage

Began with Experience Sampling Method (ESM)

Around every 90 minutes (+/- 30), request to self-report came as a phone notification

User could choose to ignore, but they would get reminded when they looked at their phone again
<table>
<thead>
<tr>
<th>Therapy Group</th>
<th>Techniques and Therapies</th>
<th>Intervention Name</th>
<th>Intervention Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive Psychology</td>
<td>- Three good things</td>
<td>Food for the Soul</td>
<td>Prompt (individual): “Everyone has something they do really well... find an example on your Facebook timeline that showcases one of your strengths.”</td>
</tr>
<tr>
<td></td>
<td>- Best future self</td>
<td></td>
<td>url: <a href="http://www.facebook.com/me/">http://www.facebook.com/me/</a></td>
</tr>
<tr>
<td></td>
<td>- Thank you letter</td>
<td>Social Souls</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Act of kindness</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Strengths</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Affirm values</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive Behavioral</td>
<td>- Cognitive reframing</td>
<td>Master Mind</td>
<td>Prompt (social): “Write a friend asking for ideas on how to accomplish something you want.”</td>
</tr>
<tr>
<td></td>
<td>- Problem solving therapy</td>
<td></td>
<td>command: email: {subject: “Asking my friends for ideas}</td>
</tr>
<tr>
<td></td>
<td>- Cognitive Behavioral</td>
<td>Mind Meld</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Therapy</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Interpersonal Skills</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Visualization</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Meta-cognitive</td>
<td>- Dialectic Behavioral</td>
<td>Wise Heart</td>
<td>Prompt (individual): “Affirmations always make me feel better, here, check these out.”</td>
</tr>
<tr>
<td></td>
<td>Therapy</td>
<td></td>
<td>url: <a href="http://m.pinterest.com/search/pins/?q=affirmation">http://m.pinterest.com/search/pins/?q=affirmation</a></td>
</tr>
<tr>
<td></td>
<td>- Acceptance and Commitment Therapy</td>
<td>Better Together (Social)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Mindfulness</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Emotional Regulation:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Somatic</td>
<td>- Relaxation</td>
<td>Body health</td>
<td>Prompt: &quot;Cats are hilarious except when they want to eat me. Check out a few of these and show it to your friends.”</td>
</tr>
<tr>
<td></td>
<td>- Sleep</td>
<td></td>
<td>url: <a href="http://m.pinterest.com/search/pins/?q=funny">http://m.pinterest.com/search/pins/?q=funny</a> cats</td>
</tr>
<tr>
<td></td>
<td>- Exercise</td>
<td>Social Time</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Breathing</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Laughter</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Technical Approaches/ Challenges

ML Algorithm:
Contextual bandit problem [Wang, Kulkarni & Poor]

Model: Random Forest [Breiman and Cutler]
L2 Stress | Context + Intervention
UCB algorithm [Auer, Cesa-Bianchi & Fischer] → add uncertainty to score

Retraining model on a daily basis
Daily incremental changes by changing the scores on the leaves of the trees without changing the structure of the trees
ESM - In order to indicate stress levels users entered it with a slider before and after the intervention (this delta was fed to the ML model).
Once selected, Bubo gives you the instructions for your activity. Here is an example from Food for the Soul.

“Good deeds create positive outcomes, let’s try one”

“Time goes by so fast…find a moment or memory you like in your Facebook timeline.”

Click PLAY to launch your activity. Click CHECK after you complete it.
Here is another example
CHALLENGE: Stimulate users to use the app... pay per use, but limit it to avoid system being gamed

Use at least 10 times per week, enter stress levels at least 10 times per week and fill out end of week survey to get a lottery ticket.
<table>
<thead>
<tr>
<th></th>
<th>Random recommendation</th>
<th>Machine learning recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cannot select from menu</strong></td>
<td>22 users 1307 interventions</td>
<td>21 users 1176 interventions</td>
</tr>
<tr>
<td><strong>Can select from menu</strong></td>
<td>26 users 1444 interventions</td>
<td>26 users 1550 interventions</td>
</tr>
<tr>
<td>Answers to “What have you learned from this study?” (multiple choice)</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>---------------------------------------------------------------</td>
<td>----</td>
<td></td>
</tr>
<tr>
<td>To be more aware of my stress levels</td>
<td>70.3%</td>
<td></td>
</tr>
<tr>
<td>That being more aware of my stress level is stressful</td>
<td>34.4%</td>
<td></td>
</tr>
<tr>
<td>Simple ways to control my stress</td>
<td>65.6%</td>
<td></td>
</tr>
<tr>
<td>Nothing</td>
<td>7.8%</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>4.7%</td>
<td></td>
</tr>
</tbody>
</table>
The PHQ-9 response data was analyzed for the 20 participants who used the app all 4 weeks. A significant effect of week, $F(4,76)=2.9$, $p=.026$, was found, and ML was borderline significant, but no effect was observed for the Selection variable. This means that, regardless of conditions, these participants rated being statistically significantly less depressed while they used our tool over 4 weeks.
Using the same 20 participants...
We identified a significant week x ML/Random interaction, $F(4,56)=4.18$, $p=.005$; ML conditions resulted in significantly higher ratio of constructive to destructive coping behaviors.
Save the planet and return your name badge before you leave (on Tuesday)
Backup Slides for Erin Solovey
Applications: Humans & Autonomy
We use biometrics to measure and respond to your thoughts, feelings and emotions.

Neurosky Mindband  Q Affectiva 2.0  Tobii Eye Tracker  Heart Rate Monitor

Pressure-Sensitive Keyboard  Shimmer3 GSR+  Microsoft Touch Mouse