Universität St.Gallen

Institut für Computer Science
in Vorarlberg

Embedded Sensing: Enabling a Digital Perception of the Real-world

Prof. Dr. Bruno Rodrigues

Embedded Sensing Group (ESG)
ICV-HSG

From insight to impact

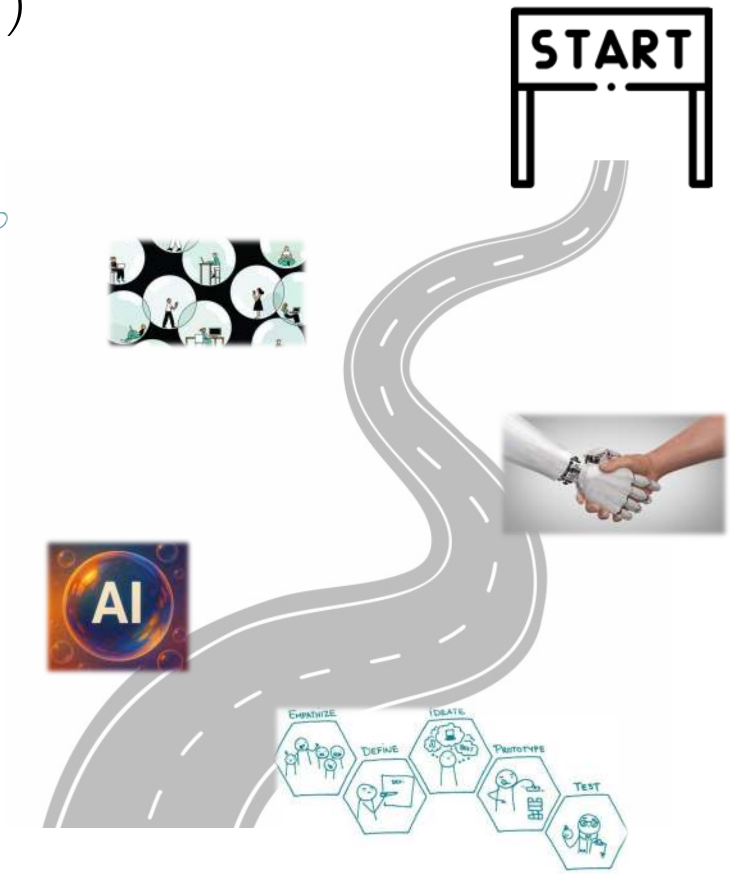
Public Lecture Series – Our Journey (1)

TALK 1
Of filter bubbles and recommendation algorithms: What do we see on social media?
Prof. Dr. Simon Mayer, September 24

TALK 2
Trust in AI: Reality or Utopia?
Prof. Dr. Lukas Gonon, October 1

TALK 3
State-of-AI: Are we in an AI bubble?
Prof. Dr. Damian Borth, October 8

TALK 4
How Software Thinks Today – Rethinking Processes
Prof. Dr. Barbara Weber, November 12



Public Lecture Series – Our Journey (2)

TALK 5

Quantum Computing and Cybersecurity – Secure or Vulnerable?

Prof. Dr. Anna-Lena Horlemann, November 19

TALK 6

Embedded Systems: Enabling a Digital Perception of the Real-world

Prof. Dr. Bruno Rodrigues, November 26

ORGANIZATION

Von Sensoren, KI und Kryptographie: Wie die Informatik unseren Alltag mitgestalte

Dr. Jochen Müller, all days ☺

Who Am I?

ABOUT ME

Assistant Professor for Embedded Sensing Systems and Industrial Networks.

- Institute of Computer Science in Vorarlberg (ICV-HSG). Austria.
- 2024-today

BACKGROUND

- **PhD** (Junior researcher) and **Postdoc** (Senior Researcher) research at the University of Zurich
  - Network security and wireless sensing
  - 2016-2023
- **MSc** (Junior researcher) at the University of São Paulo
  - Energy-efficiency in networks
  - 2013-2016

"Research focus lies in bridging theory and practice in IoT, wireless sensor networks, and network security"

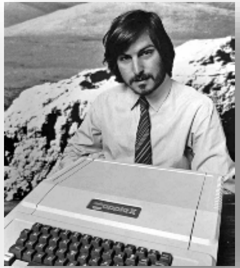
Agenda

1. **Embedded Systems are Everywhere**
2. Sensing Foundations
3. From Sensing to Action
4. Sensing in the Real-world
5. Outlook

The Invisible Computers Around Us: Embedded Systems

- Until 1980s information processing was mainly associated with mainframe computers
- In the 1990s miniaturization allowing information processing in personal computers (PC)
- In 1991, Mark Weiser coined the term "**Ubiquitous computing**", where computing could process information anytime, anywhere

An IBM 360/91 mainframe (1964)



Steve Jobs and his Apple II (1977)

The Computer for the 21st Century

Specialized elements of hardware and software, connected by wires, radio waves and infrared, will be so ubiquitous that no one will notice their presence

by Mark Weiser

The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.

Consider writing, perhaps the first information technology. The ability to represent spoken language symbolically for long-term storage freed informa-

is approachable only through complex jargon that has nothing to do with the tasks for which people use computers. The state of the art is perhaps analogous to the period when scribes had to know as much about making ink or baking clay as they did about writing.

The arcane aura that surrounds personal computers is not just a "user in-

The idea of integrating computers seamlessly into the world at large runs counter to a number of present-day trends. "Ubiquitous computing" in this context does not mean just computers that can be carried to the beach, jungle or airport. Even the most powerful notebook computer, with access to a worldwide information network, still

Ubiquitous Computing by Mark Weiser (1991)

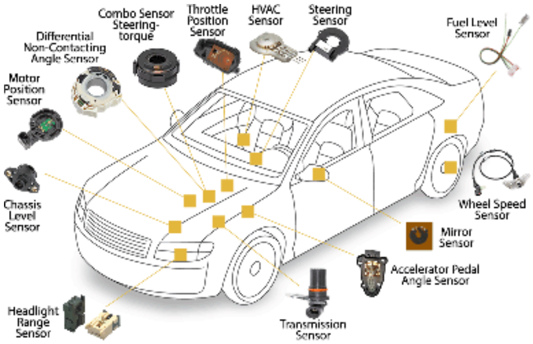
"The most profound technologies are those that disappear" Mark Weiser, 1991.

Defining Embedded Systems: Two Perspectives

A SYSTEMS PERSPECTIVE

"Embedded systems are information processing systems embedded into enclosing products"

Prof. Peter Marwedel



Smarter products: "… an average modern car has between 60 to 100 sensors…"

https://www.eedesignit.com/the-evolution-of-sensors-in-automotive-applications/

A TECHNICAL PERSPECTIVE

"An embedded system is some combination of computer hardware and software, either fixed in capability or programmable, that is designed for a specific function or for specific functions within a larger system."

Prof. Em. Lothar Thiele

Smarter manufacturing: even non-digital products are affected by embedded sensing systems

https://www.sathguru.com/news/2020/04/23/technology-trends-that-will-shape-indias-food-processing-industry-in-the-post-covid-world/

From **Perceiving** the Real-world…

TRANSLATING THE REAL-WORLD

Measure physical quantities and converts into digital signals, that can be read by an observer or instrument

APPLICATION RANGE

Diverse applications ranging from personal fitness tracking to life-critical industrial applications

SENSOR TYPES

Active/passive, contact/non-contact, absolute/relative

TRENDS

Ongoing trend to produce **smaller sensors**, which are more **resource-efficient, accurate**, and **reliable**

… To **Reacting** to The Real-world

ACCURACY AND PRECISION

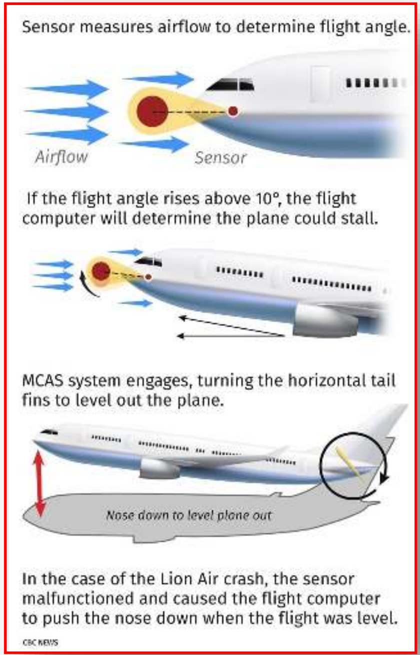
- Key enablers of any **Cyber-physical System**
- Accuracy is how close a measured value is from the real value and precision refers to the reproducibility of measurements

PERFORMANCE AND RELIABILITY

- Accurate information in a timely manner
- Certain decision-making systems requires extremely reliable information (e.g., healthcare, aviation)

SAFETY, **SE**CURITY, AND **PR**IVACY

- Preventing accidental failures harmful to humans
- Preventing malicious users
- Preventing misuse of information



https://www.seattletimes.com/business/boeing-aerospace/preliminary-report-due-today-on-737-max-crash-in-ethiopia/


FAA cautions airlines on maintenance of sensors that were key to 737 MAX crashes

Boeing relied on single sensor for 737 Max that had been flagged 216 times to FAA

How Boeing 737 MAX's flawed flight control system led to 2 crashes that killed 346

Angle-of-Attack (AOA) sensors

How many sensors do you think you carry with you right now?

Sensors Around You: **Within your Smartphone**

- Smartphones are portable multi-sensor platforms representing the "main" interface with the real-world
- 92% of the Swiss population own a smartphone […] of which 97% use it daily
  - "… an average smartphone has between 15 to 20 sensors… "
- Typical sensors:
  - Inertial/motion, positioning and navigation (GPS, accelerometer)
  - Environmental (light, proximity)
  - Imaging and audio (cameras)

https://www2.deloitte.com/ch/en/pages/press-releases/articles/deloitte-in-switzerland-smartphones-become-control-centre.html
https://www.honor.com/sa-en/blog/how-many-sensors-are-there-in-a-smartphone/
https://ieeexplore.ieee.org/abstract/document/6362778/

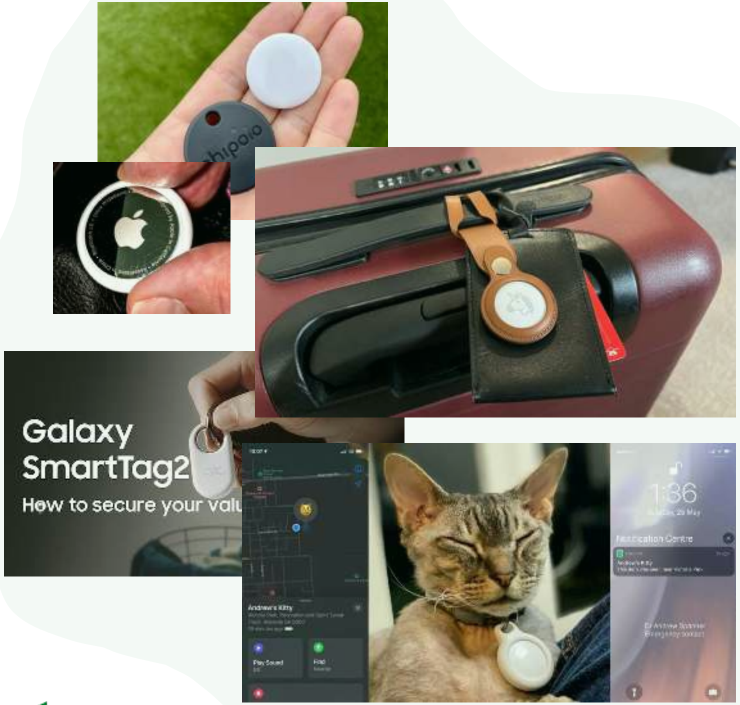
Sensors Around You: **Within Fitness Trackers**

- Comes in many shapes, sizes, and sensors
- Typical sensors:
    - Inertial/motion to detect your movement, steps, orientation, velocity
    - Physiological such as heart rate, blood monitoring, body temperature
    - Environmental/location to detect the surround lights, GPS, and microphones

https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-023-02350-w
https://istarmax.com/blog/sensors-in-smart-watches-and-fitness-trackers-how-do-they-work/
https://en.wikipedia.org/wiki/Samsung_Galaxy_Watch_series?utm_source=chatgpt.com

Sensors Around You: **Within Many Accessories**

SMART TAGS



EARBUDS/HEADPHONES

https://www.youtube.com/watch?v=PB_8dGKh9Jl&t=154s

https://www.sensecapmx.com/product/

https://www.rabbit.tech/rabbit-r1

PERSONAL AI GADGETS

How many sensors do you think that surrounds you? Your house, company, this room

Our "Surroundings" are becoming increasingly digital…

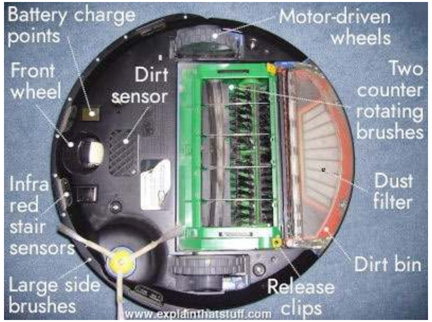
You probably walked by one of this today

Presence sensors

You probably have seen or own one of these

IP Cameras

You probably have seen or own one of these



Vacuum cleaners

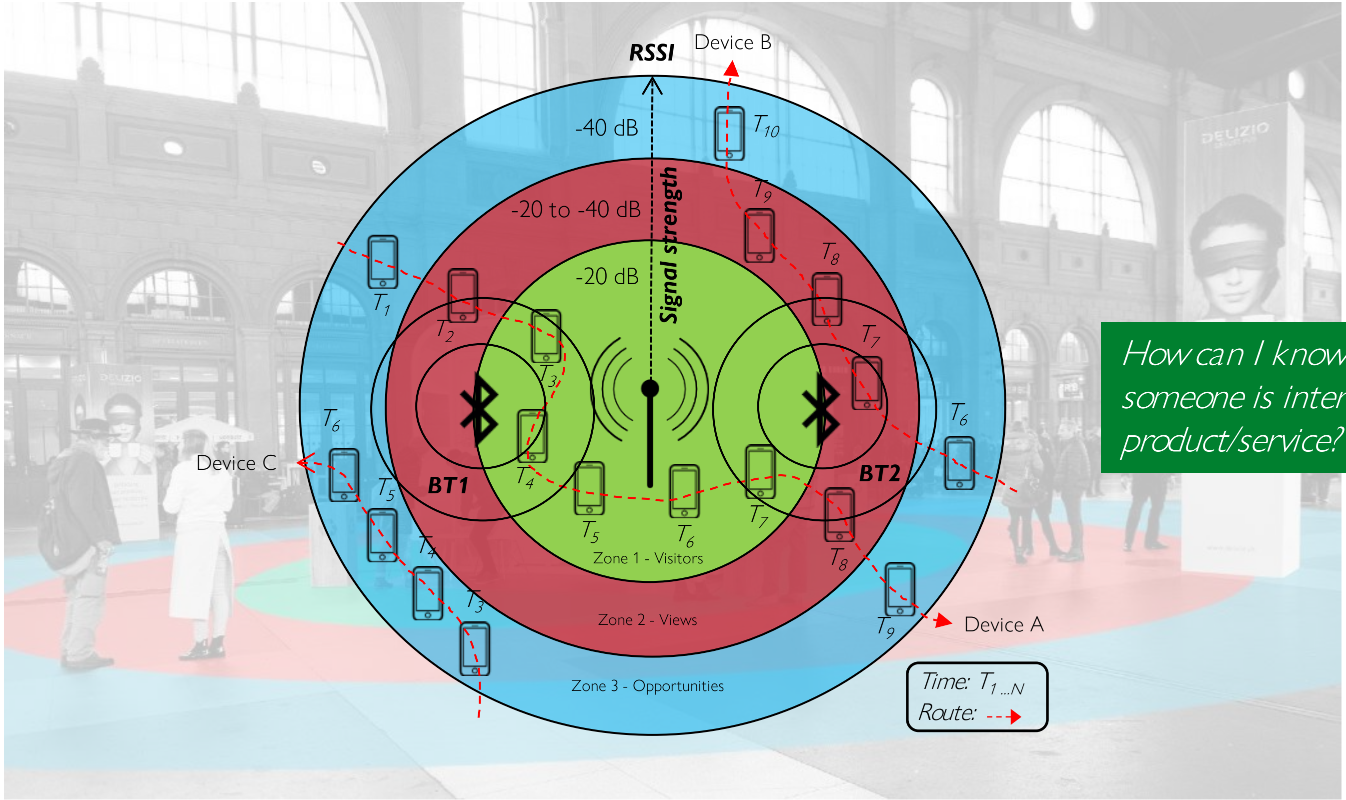
Smart lock

Smart thermostat

… and highly-connected

Sensing people walking by using wireless signals emitted by mobile phones

Wireless signals provide meaningful information



How can I know whether someone is interested in a product/service?

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Agenda

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How do we actually sense something in the real-world?

The "Measurement Devices"

Measurement devices perform a complete measuring function, from initial detection to final indication. The important aspects of measurement system are:

SENSOR

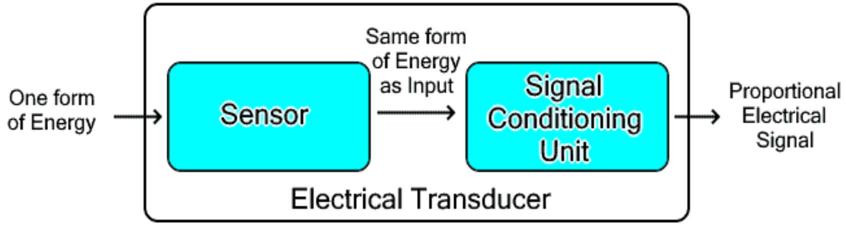
- Primary sensing element
- Makes physical contact with the variable being measured and detects changes and provides a corresponding output signal that can be measured.

TRANSDUCER

- Converts one form of energy to another form of energy.
- Example: a transducer measures pressure, load, force, or other states, and converts the reading into an electrical or electronic signal.

TRANSMITTER

- Contains the transducer and produces an amplified, standardized energy signal



https://www.electricaltechnology.org/2021/11/transducer.html

Example 1: The Human Body

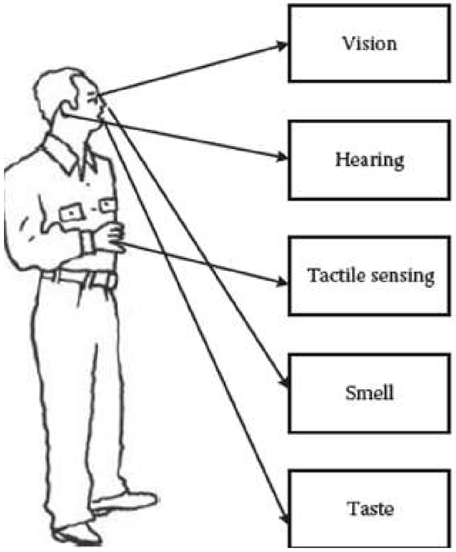
BIOLOGICAL SENSING PROCESS

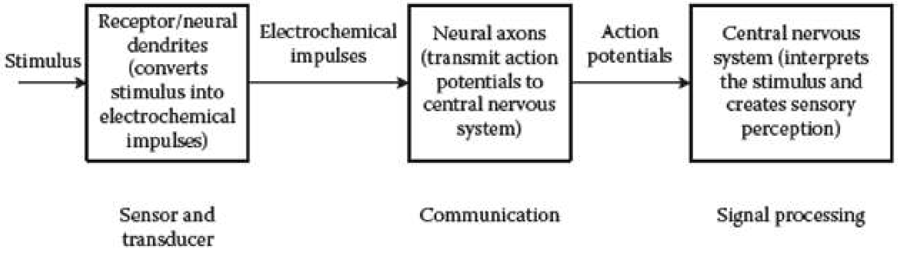
- A stimulus is received and neurons convert the energy into electromechanical impulses
- The brain interprets and produces the corresponding sensory perception

SENSORS

TRANSDUCER

TRANSMITTER





Example 2: Brake-by-Wire

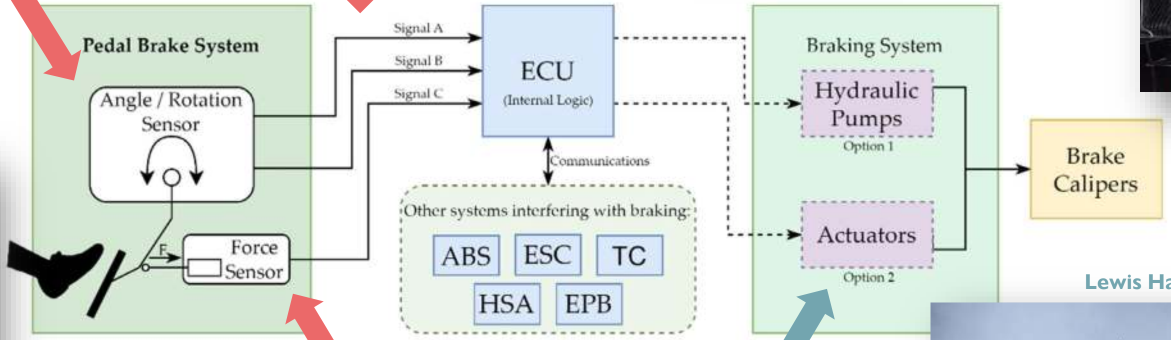
Hydraulic system

Brake caliper

TRANSMITTER

SENSOR

Pedals – McLaren F1



TRANSDUCER

ACTUATORS

Lewis Hamilton, SF-25

Note that the schematics is not from an actual F1 car ☹

https://maxf1.net/en/braking-system/

“Sensing is the process of converting ***physical*** *energy to* ***electrical*** *energy”*

The Conversion Process

EXAMPLE

Sensors generate signals by converting an external stimulus into an electrical, mechanical, or optical signal.

*The **DHT-11** contains a humidity sensing capacitor and a thermistor:*

- *The sensor processes the captured data and generates a digital signal using a one-wire protocol.*
- *It sends a 40-bit data packet (humidity, temperature, and checksum) to a microcontroller.*

PHYSICAL TO ELECTRICAL

- Humidity: uses a capacitive sensors acting both as a sensor and transducer
- Temperature: uses a thermistors also acting as a sensor and transducer

ELECTRICAL TO DIGITAL

- Samples the capacitance and resistance changes acting as a transducer
- Converts to humidity and temperature values

DATA TRANSMISSION

- Encodes the readings into a 40-bit signal and transmits the data using a **1-wire protocol** via GPIO

How the DHT11 Works.
https://www.youtube.com/watch?v=p_aKKp_nRUM&t=38s

How accurate are the readings?

In other words, how well the physical world is represented digitally?

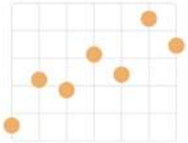
Signals Basics

'Signals are a physical representation of data in function of time and location"

CLASSIFICATION

- Continuous time/discrete time
- Continuous values/discrete values
- **Analog** signal = continuous time and continuous values
- **Digital** signal = discrete time and discrete values

Continuous (analog) data



Discrete (digital) data

PARAMETERS OF PERIODIC SIGNALS

- Period T, frequency $\frac{1}{t}$, amplitude A, phase shift ϕ
- Represented as a **sine wave**: $s(T) = A \times \sin 2\pi ft + \phi$

Real-world vs Digital World

What the real-world looks like

Continuous (analog) data

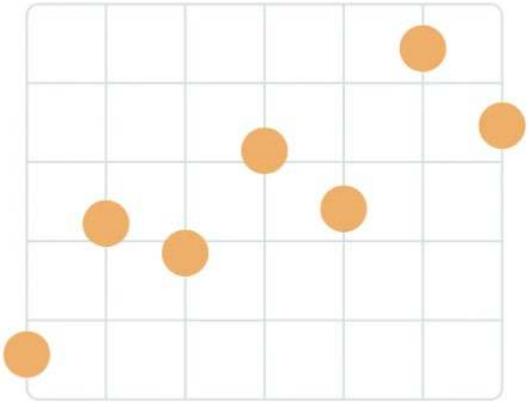
Temperature sensor (DHT11)

Sample

Write

Discretize

What the digital-world looks like



Discrete (digital) data

Discretization Through Sampling

The DHT11 **sample the environment at regular intervals**. Instead of an infinite set of values for all possible times t, we obtain values at **specific discrete time** points where T_n are discrete points T_1, T_2,:

$$S(T_n) = \big(H(T_n), T(T_n)\big)$$

If the sampling rate is F_s Hz, then the sampling interval (time between consecutive readings) is:

$$\text{ů}\, t = \frac{1}{F_s}$$

	DHT11	DHT22
Operating Voltage	3 to 5V	3 to 5V
Max Operating Current	2.5mA max	2.5mA max
Temperature Range	0-50°C / ± 2°C	-40 to 80°C / ± 0.5°C
Humidity Range	20-80% / 5%	0-100% / 2-5%
Sampling Rate	1 Hz (reading every second)	0.5 Hz (reading every 2 seconds)
Advantage	low cost	More Accurate

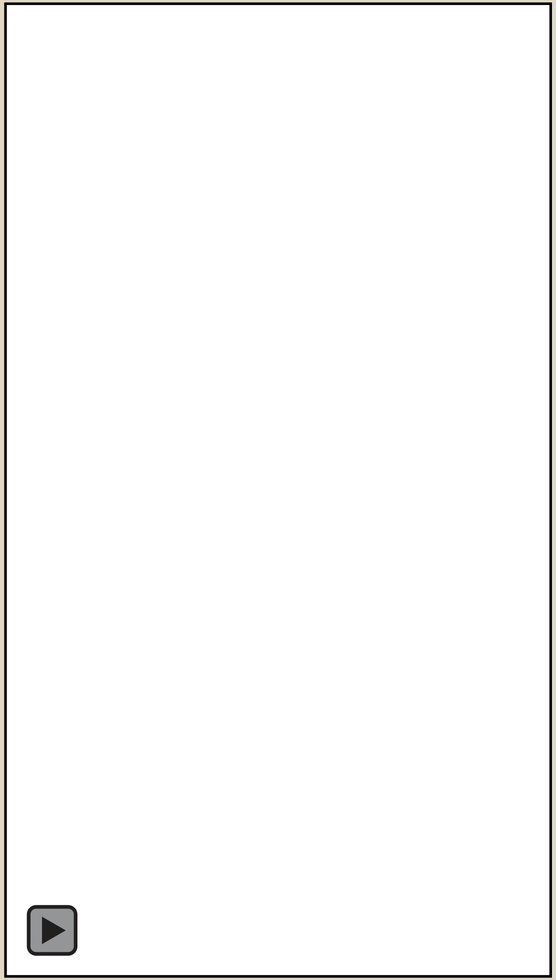
For example:

- If F_s = 1 Hz → The sensor takes one reading **every second** (Δt = 1s).
- If F_s = 0.5 Hz → The sensor takes one reading **every 2 seconds** (Δt = 2s).

Example

Fly-by-wire System

Sampling rate: How much is too much?



https://www.youtube.com/shorts/cJZn0Frme2o

How Would You Define?

Suppose we have these “ranges” of values for sampling frequencies

- MINIMUM
- BALANCED
- MAXIMUM

Application	What is measured	Sampling rate
DHT-11 Temperature Sensor	Air Temperature & Humidity	
Smartphone Sensors	Position, Velocity, & Trajectory	☺
Fly-by-wire Sensors	Angle of Attack (AOA) & Air Pressure	

Sampling Rate

PROBLEM

The choice of sampling rate directly impacts the accuracy of the digital representation of $S(t)$:

How frequently do we need to sample a continuous signal to perfectly represent it in the digital domain?

- If the **sampling rate is too low** (e.g., one sample every 10 seconds), rapid changes in temperature or humidity may be missed.
- If the **sampling rate is too high**, it may consume unnecessary power without significantly improving accuracy.

Agenda

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History of the Nyquist-Shannon Sampling Theorem

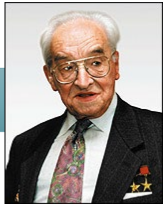
The Nyquist-Shannon Sampling Theorem is the result of a series of mathematical and engineering discoveries, evolving over time from the early 20th century.

1807 – 1822: Joseph Fourier: invented the "Fourier Analysis", representing signals as sinusoids.

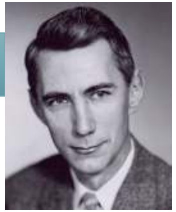
1915: E.T. Whittaker: Introduced mathematical interpolation functions (precursor to sampling theory)

Edmund Taylor

1928: Harry Nyquist: Defined the minimum sampling rate needed for telegraph signals.



1933: Vladimir Kotelnikov: Independently derived the sampling theorem in Russia



1948: Claude Shannon: Generalized and mathematically proved the theorem for all signals

Finding The Sampling Rate – Nyquist-Shannon Theorem

Nyquist-Shannon sampling theorem:

A band-limited continuous-time signal can be completely represented by its samples if it is sampled at a rate at least ***twice the highest frequency component*** *in the signal.*

- To avoid missing important variations, the sampling rate f_s should be at least twice the maximum frequency:

$$f_s \geq 2f_{max}$$

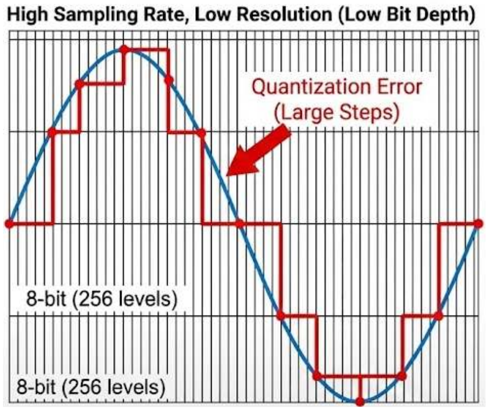
Where:

- f_s *is the sampling frequency (how many times per second the signal is sampled).*
- f_{max} *is the highest frequency present in the original signal.*
- $2f_{max}$ *is called the Nyquist rate, and* f_{max} *is the Nyquist frequency.*

Sampling Rate Alone is Not Sufficient …. Resolution Also Matters!

Even if we sample fast enough (above Nyquist rate), low resolution can still cause errors in signal reconstruction.

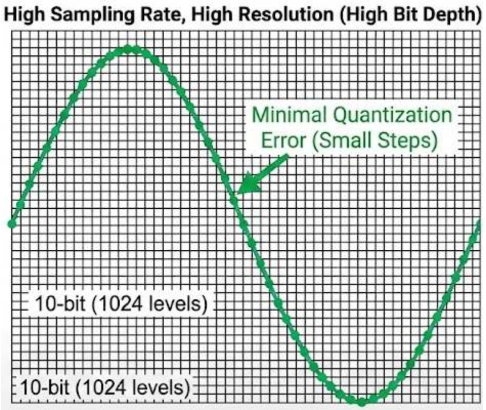
- **Sampling rate** (Nyquist-Shannon): captures frequency samples at the time-domain.
- **Resolution** (Bit depth): how accurately we represent amplitude at each sample.



DEFINITION

Resolution is the smallest detectable change in a signal that can be distinguished by the system.

- Higher the bit depth, higher resolution → more precise measurements
- Example: A **10-bit ADC** can represent 2^{10}= **1024** discrete levels, while an **8-bit ADC** has **256** levels.



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Sampling Rate and Resolution

SCENARIO

- A temperature sensor is placed inside an industrial furnace, where the temperature fluctuates due to periodic heating cycles. The sensor must capture these variations accurately to regulate the furnace.

- The true temperature inside the furnace follows a periodic oscillation:

$$\mathrm{T}(t) = \ 500 + 50\sin(2\Pi f t) \ \ \textit{where}\ \boldsymbol{f} = \mathbf{2}\ \boldsymbol{Hz}$$

Case	Sampling Rate	Resolution	Result
Ideal	5 Hz (above Nyquist)	12-bit ADC	Accurate temperature
Low sampling-rate (aliasing)	3 Hz (below Nyquist)	12-bit ADC	Misses fast temperature variations
Low resolution	5 Hz (above Nyquist)	8-bit ADC	Detects changes but with large steps (low accuracy)

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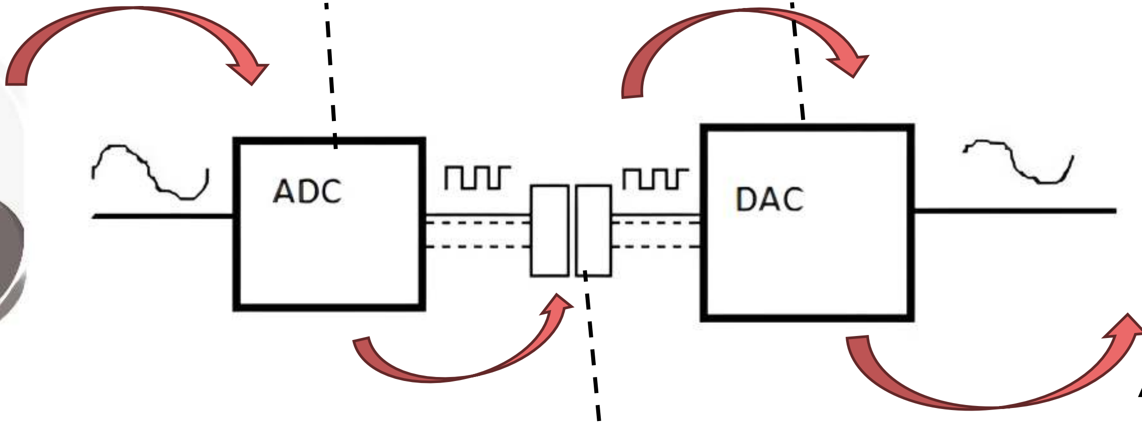
From **Perceiving** (Sensing) to **Reacting** (Actuating)

ADC converts the sensor data into a digital form.

DAC converts the processed signal back to analog.



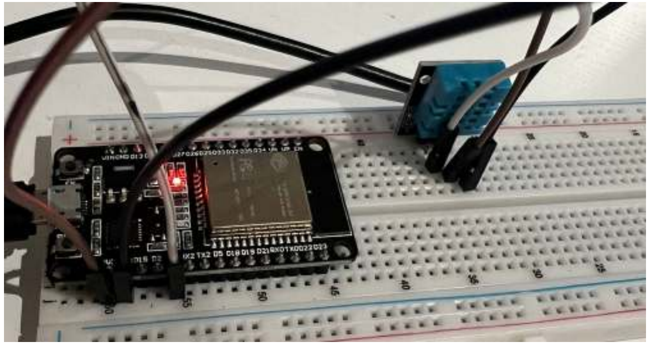
Sensors measure physical phenomena (analog).

Information Processing analyzes and modifies the signal.

Actuators respond to the analog signal (e.g., sound).

Information Processing

Is the computational task performed after the analog signal has been converted into digital

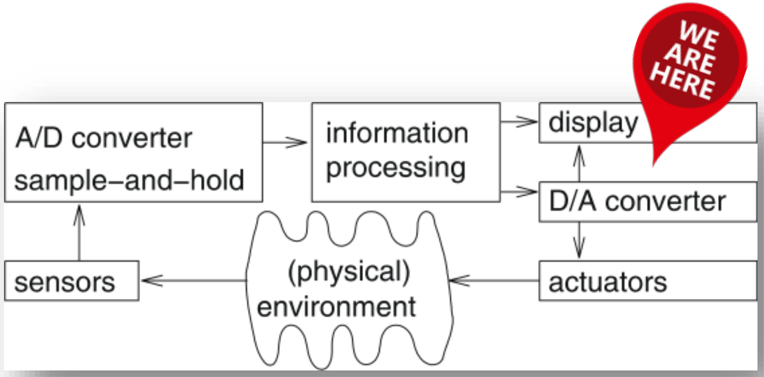


- Here's our hero **DHT11** in action

```
// Define GPIO pin and sensor type
#define DHTPIN 4            // GPIO pin where the DHT11 signal pin is connected
#define DHTTYPE DHT11        // Specify the sensor type (DHT11)

// Initialize DHT sensor
DHT dht(DHTPIN, DHTTYPE);

void setup() {
  Serial.begin(9600);
  Serial.println("Initializing DHT11 sensor...");
  dht.begin();
}

void loop() {
  // Wait 2 seconds between readings (DHT11 requires ~2s)
  delay(2000);

  // Read temperature and humidity
  float humidity = dht.readHumidity();
  float temperature = dht.readTemperature(); // Celsius by default

  // Check if readings are valid
  if (isnan(humidity) || isnan(temperature)) {
    Serial.println("Failed to read from DHT sensor!");
    return;
  }

  // Print the results
  Serial.print("Humidity: ");
  Serial.print(humidity);
  Serial.print(" %\t");
  Serial.print("Temperature: ");
  Serial.print(temperature);
  Serial.println(" °C");
}
```

Relevant, but not our focus today

The Other-way Around: **Digital-to-Analog Converter (DAC)**



DAC does the opposite process of an ADC

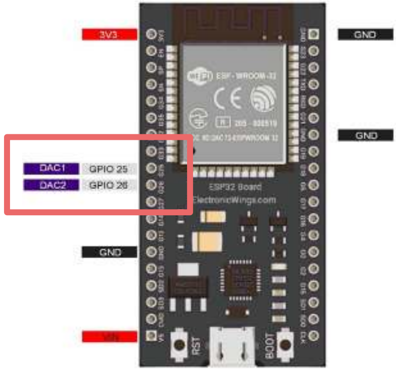
DEFINITION

A DAC transforms a digital value (discrete levels) into a continuous analog signal.

- Converts a binary representation of a number to an actual analogue voltage on an external pin.

- Resolution: how many voltage levels.
  - Example: 12-bit DAC represent $2^{16} = 4096$ voltage levels.

- Sampling rate: how often a DAC updates output values



ESP32 has an 8-bit DAC

DAC Examples

AUDIO SYSTEMS

- You **<u>certainly</u>** know it from audio systems as sound is inherently analog
- High(er) resolution and sample rates provide way, way better audio quality

OTHER APPLICATIONS

- Driving **actuators** (motors, speakers, analog control circuits).
- Controlling **voltage-based devices** (e.g., LED dimming, servo motors).

Analog Engineer's Circuit

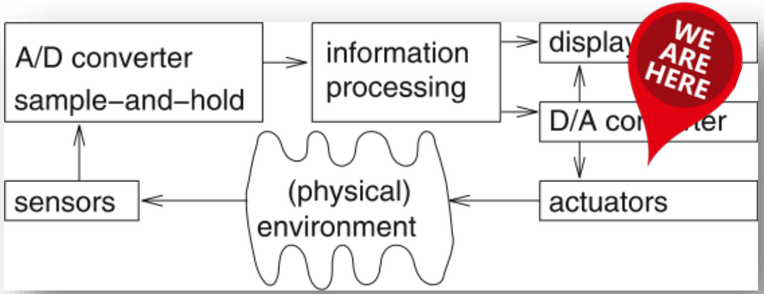
Smart DAC LED Biasing Circuit with Low-Power Sleep Mode

Texas Instruments

Lastly: **Actuators**

Actuators converts a digital or analog control signal into physical motion or change (e.g., movement, heat, light, force).

- Range from large ones that are able to move tons of weight to tiny ones with dimensions in the µm area
- **Not only analog ☺**



Type	Example	Control Type
Motor	DC motor, servo	PWM/DAC
Heating	Peltier element	DAC/GPIO
Movement	Solenoid	GPIO
Light	Bulb, LED	PWM/DAC
Sound	Buzzer, speaker	DAC/PWM
Mechanical	Valve, pump	DAC/GPIO

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Mental Health Awareness

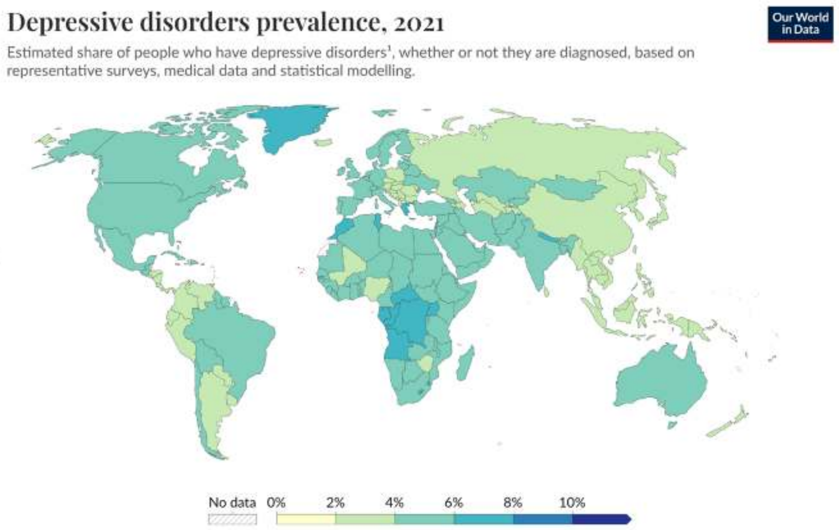
FACTS

- Mental health is a growing crisis worldwide, yet diagnosis is extremely difficult.

- **280 million** people affected in 2023 (reported-only)[1]
  – Depression accounts for **4.3%**[2] of the global disease burden

Many people can't get or do not look for help:

- **Limited diagnosis** methods: subjectivity and unreliable
- **Bad accessibility** for certain groups
- **Harmful connotation** of depression



IHME, 2024: Global Burden of Disease

> *"Depression and anxiety are among the leading causes of illness and disability among adolescents. Half of all mental health disorders in adulthood start by age 18."*

World Health Organization (WHO)[1]

[1] WHO: https://www.who.int/news-room/fact-sheets/detail/depression.
[2] Scientific Reports: https://www.nature.com/articles/s41598-024-62381-9.
[3] IHME, 2024: Global Burden of Disease.

The House as a Perception Layer

PASSIVE MONITORING

- No need for wearables, charging, or manual mood journaling
- Reduced "anxiety" once people are already in their living environment

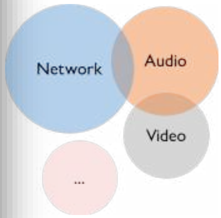
LONGITUDINAL BASELINE

- Possible to analyze behavioral baseline over months of data
- Compare and detect subtle behavioral drifts
- Multi-modality

PRIVACY BY DESIGN

- No data is up-streamed to a cloud server or leave the premises

  (well, at least in the system proposed here)



IHearYou: Linking Acoustic Features to DSM-5 Depressive Behavior Indicators

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CareNet: Linking Home-router Network Traffic to DSM-5 Depressive Behavior Indicators

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Case 1:

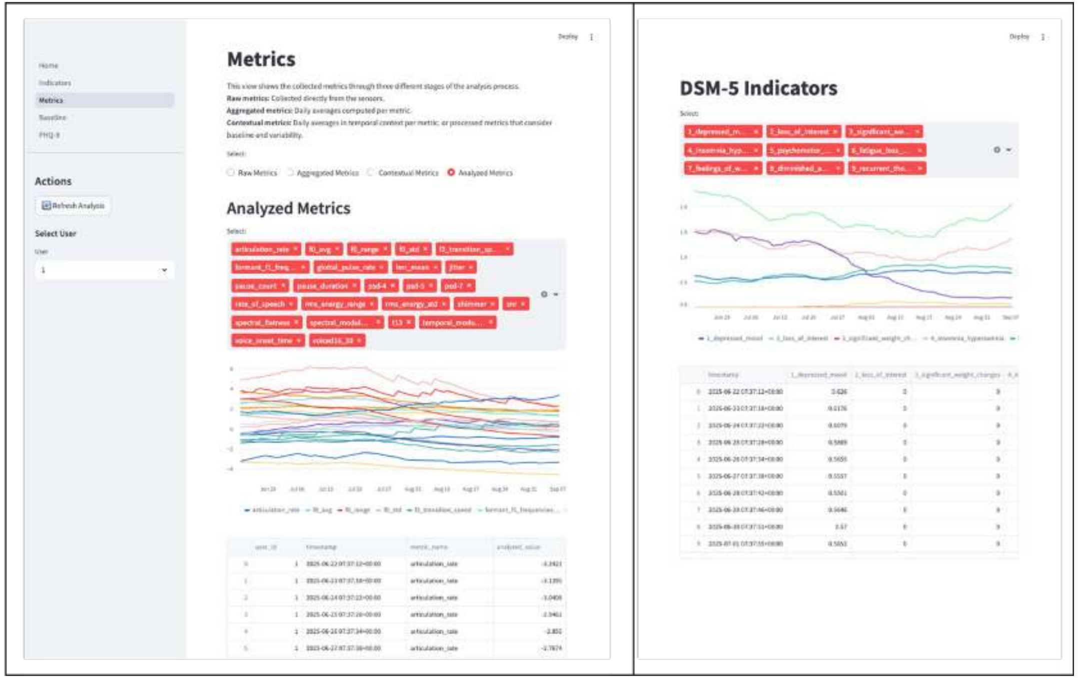
IHearYou – Linking Speech Features to Depression Symptoms

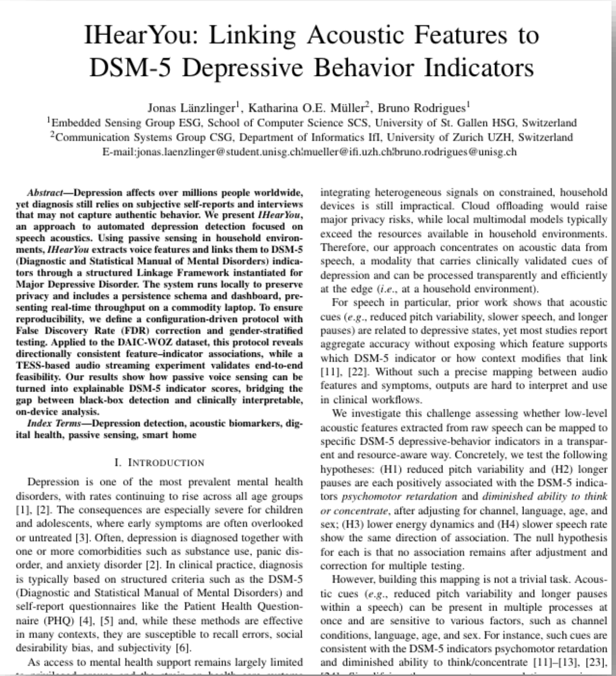
APPROACH

- Explainable translation rules between **voice** features and depression symptoms
- Important to measure against own personal baseline (longitudinal)
- All data is computed at the household

Video trimmed ~ 2:30 mins

Demonstration





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***Abstract*—Depression affects over millions people worldwide, yet diagnosis still relies on subjective self-reports and interviews that may not capture authentic behavior. We present *IHearYou*, an approach to automated depression detection focused on speech acoustics. Using passive sensing in household environments, *IHearYou* extracts voice features and links them to DSM-5 (Diagnostic and Statistical Manual of Mental Disorders) indicators through a structured Linkage Framework instantiated for Major Depressive Disorder. The system runs locally to preserve privacy and includes a persistence schema and dashboard, presenting real-time throughput on a commodity laptop. To ensure reproducibility, we define a configuration-driven protocol with False Discovery Rate (FDR) correction and gender-stratified testing. Applied to the DAIC-WOZ dataset, this protocol reveals directionally consistent feature–indicator associations, while a TESS-based audio streaming experiment validates end-to-end feasibility. Our results show how passive voice sensing can be turned into explainable DSM-5 indicator scores, bridging the gap between black-box detection and clinically interpretable, on-device analysis.**

***Index Terms*—Depression detection, acoustic biomarkers, digital health, passive sensing, smart home**

I. Introduction

Depression is one of the most prevalent mental health disorders, with rates continuing to rise across all age groups [1], [2]. The consequences are especially severe for children and adolescents, where early symptoms are often overlooked or untreated [3]. Often, depression is diagnosed together with one or more comorbidities such as substance use, panic disorder, and anxiety disorder [2]. In clinical practice, diagnosis is typically based on structured criteria such as the DSM-5 (Diagnostic and Statistical Manual of Mental Disorders) and self-report questionnaires like the Patient Health Questionnaire (PHQ) [4], [5] and, while these methods are effective in many contexts, they are susceptible to recall errors, social desirability bias, and subjectivity [6].

As access to mental health support remains largely limited

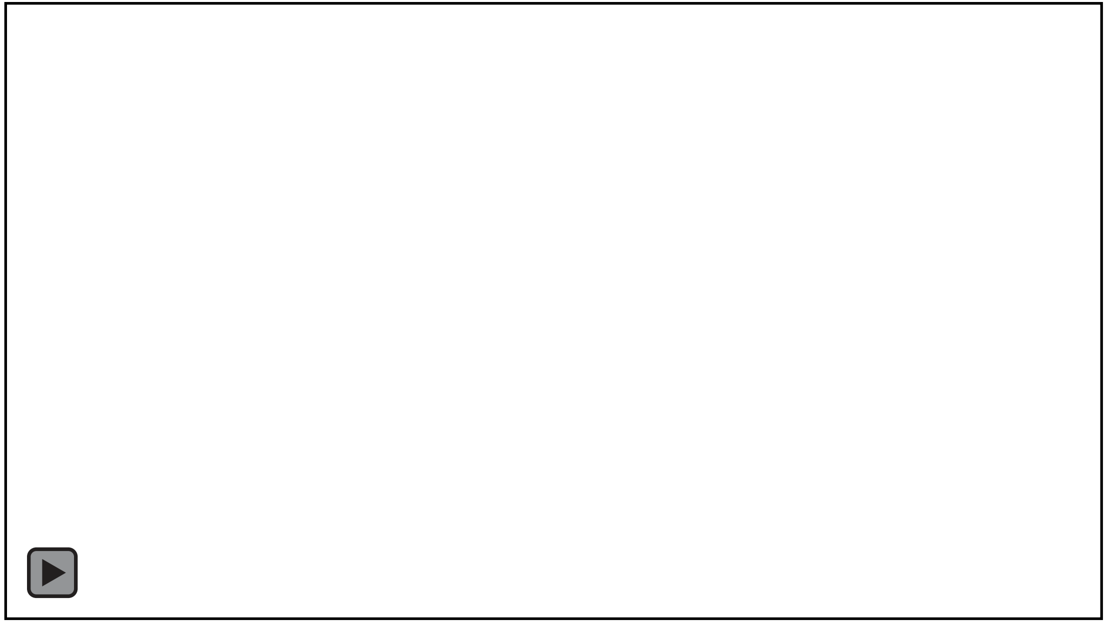
integrating heterogeneous signals on constrained, household devices is still impractical. Cloud offloading would raise major privacy risks, while local multimodal models typically exceed the resources available in household environments. Therefore, our approach concentrates on acoustic data from speech, a modality that carries clinically validated cues of depression and can be processed transparently and efficiently at the edge (*i.e.*, at a household environment).

For speech in particular, prior work shows that acoustic cues (*e.g.*, reduced pitch variability, slower speech, and longer pauses) are related to depressive states, yet most studies report aggregate accuracy without exposing which feature supports which DSM-5 indicator or how context modifies that link [11], [22]. Without such a precise mapping between audio features and symptoms, outputs are hard to interpret and use in clinical workflows.

We investigate this challenge assessing whether low-level acoustic features extracted from raw speech can be mapped to specific DSM-5 depressive-behavior indicators in a transparent and resource-aware way. Concretely, we test the following hypotheses: (H1) reduced pitch variability and (H2) longer pauses are each positively associated with the DSM-5 indicators *psychomotor retardation* and *diminished ability to think or concentrate*, after adjusting for channel, language, age, and sex; (H3) lower energy dynamics and (H4) slower speech rate show the same direction of association. The null hypothesis for each is that no association remains after adjustment and correction for multiple testing.

However, building this mapping is not a trivial task. Acoustic cues (*e.g.*, reduced pitch variability and longer pauses within a speech) can be present in multiple processes at once and are sensitive to various factors, such as channel conditions, language, age, and sex. For instance, such cues are consistent with the DSM-5 indicators psychomotor retardation and diminished ability to think/concentrate [11]–[13], [23],

CareNet – *Linking Network Features to Depression Symptoms*



Video trimmed ~ 3mins

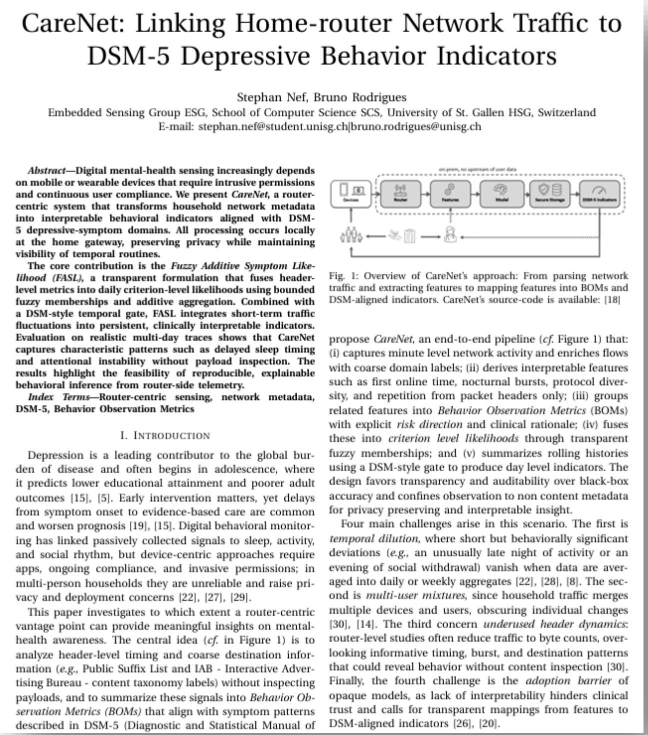
APPROACH

- Explainable translation rules between **network** features and depression symptoms
  - Here, we call it Behavioral Observation Metrics (BOMs)

- Important to measure against own personal baseline (longitudinal)

- All data is computed at the household

Demonstration



CareNet: Linking Home-router Network Traffic to DSM-5 Depressive Behavior Indicators

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***Abstract*—Digital mental-health sensing increasingly depends on mobile or wearable devices that require intrusive permissions and continuous user compliance. We present *CareNet*, a router-centric system that transforms household network metadata into interpretable behavioral indicators aligned with DSM-5 depressive-symptom domains. All processing occurs locally at the home gateway, preserving privacy while maintaining visibility of temporal routines.**

The core contribution is the *Fuzzy Additive Symptom Likelihood (FASL)*, a transparent formulation that fuses header-level metrics into daily criterion-level likelihoods using bounded fuzzy memberships and additive aggregation. Combined with a DSM-style temporal gate, FASL integrates short-term traffic fluctuations into persistent, clinically interpretable indicators. Evaluation on realistic multi-day traces shows that CareNet captures characteristic patterns such as delayed sleep timing and attentional instability without payload inspection. The results highlight the feasibility of reproducible, explainable behavioral inference from router-side telemetry.

***Index Terms*—Router-centric sensing, network metadata, DSM-5, Behavior Observation Metrics**

I. Introduction

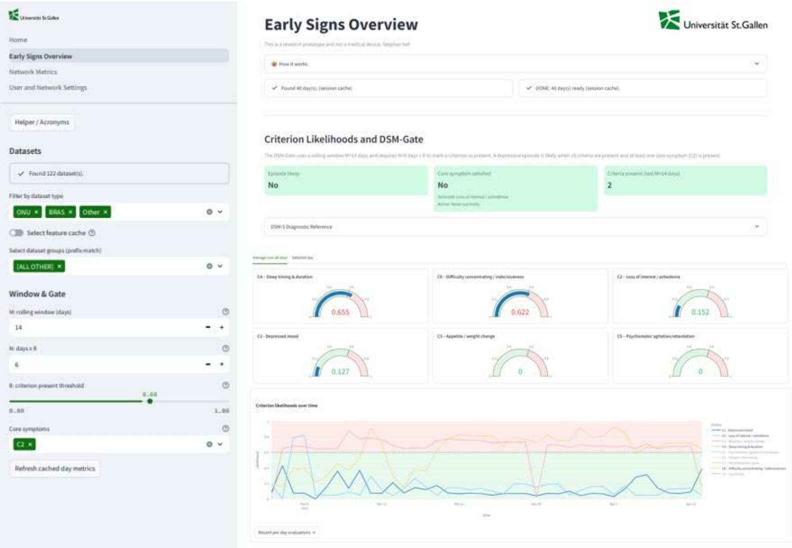
Depression is a leading contributor to the global burden of disease and often begins in adolescence, where it predicts lower educational attainment and poorer adult outcomes [15], [5]. Early intervention matters, yet delays from symptom onset to evidence-based care are common and worsen prognosis [19], [15]. Digital behavioral monitoring has linked passively collected signals to sleep, activity, and social rhythm, but device-centric approaches require apps, ongoing compliance, and invasive permissions; in multi-person households they are unreliable and raise privacy and deployment concerns [22], [27], [29].

This paper investigates to which extent a router-centric vantage point can provide meaningful insights on mental-health awareness. The central idea (*cf.* in Figure 1) is to analyze header-level timing and coarse destination information (*e.g.*, Public Suffix List and IAB - Interactive Advertising Bureau - content taxonomy labels) without inspecting payloads, and to summarize these signals into *Behavior Observation Metrics (BOMs)* that align with symptom patterns described in DSM-5 (Diagnostic and Statistical Manual of

Fig. 1: Overview of CareNet's approach: From parsing network traffic and extracting features to mapping features into BOMs and DSM-aligned indicators. CareNet's source-code is available: [18]

propose *CareNet*, an end-to-end pipeline (*cf.* Figure 1) that: (i) captures minute level network activity and enriches flows with coarse domain labels; (ii) derives interpretable features such as first online time, nocturnal bursts, protocol diversity, and repetition from packet headers only; (iii) groups related features into *Behavior Observation Metrics* (BOMs) with explicit *risk direction* and clinical rationale; (iv) fuses these into *criterion level likelihoods* through transparent fuzzy memberships; and (v) summarizes rolling histories using a DSM-style gate to produce day level indicators. The design favors transparency and auditability over black-box accuracy and confines observation to non content metadata for privacy preserving and interpretable insight.

Four main challenges arise in this scenario. The first is *temporal dilution*, where short but behaviorally significant deviations (*e.g.*, an unusually late night of activity or an evening of social withdrawal) vanish when data are averaged into daily or weekly aggregates [22], [28], [8]. The second is *multi-user mixtures*, since household traffic merges multiple devices and users, obscuring individual changes [30], [14]. The third concern *underused header dynamics*: router-level studies often reduce traffic to byte counts, overlooking informative timing, burst, and destination patterns that could reveal behavior without content inspection [30]. Finally, the fourth challenge is the *adoption barrier* of opaque models, as lack of interpretability hinders clinical trust and calls for transparent mappings from features to DSM-aligned indicators [26], [20].



Agenda

Universität St.Gallen

Embedded Systems: A Tale of Two Sides

PERVASIVE

- In many wearable applications, cars, airplanes, phone, radios, chemical plants, industrial plants and countless other applications.
- The world has never been so connected (and in **filter bubbles**)

AUTOMATION

- Industrial applications being used for process control, monitoring, and safety, and in medicine being used for diagnostics, There monitoring, critical care, and public health.

They make our life easier!

What about Privacy?

- Automation and convenience is excellent, but at what cost?
  - Data generated by embedded systems (wearable sensors, smart homes/buildings, cars), is **highly valuable**.
- **Training LLM models** with “high-quality” data
  - Real-world data from cyber physical systems.
- **Marketing advertisement**: how many times have you seen an advertisement that was “coincidence”?
  - (it is not a coincidence)

Why data quality is non-negotiable for LLM training

A small amount of bad data can ‘poison’ even the largest AI models, researchers warn

BY WILL KNIGHT BUSINESS OCT 22, 2025 2:00 PM

AI Models Get Brain Rot, Too

A new study shows that feeding large language models low-quality, high-engagement content from social media lowers their cognitive abilities.

Article | Open access | Published: 24 July 2024

AI models collapse when trained on recursively generated data

How smartphones build a dossier on you

kaspersky daily

How Google makes money with ads

Google's main source of revenue is advertising – mostly from ads on our own sites and apps. We created this guide to help you understand the basics of how we make money with advertising.

If you own Ray-Ban Meta glasses, you should double-check your privacy settings

TechCrunch

Considerations

- Overview of embedded systems, sensors, and how sensing actually works.
  – A how to adequately fine-tune concepts like **sampling** and **resolution** to achieve a great view of the real-world

- Cyber-physical Systems provide several societal **benefits**:
  – Integration, automation, and a convenience layer in many applications.
- …But it comes at a cost: **at which extent privacy is non-negotiable?**

Thank you and Merry Christmas!

University of St.Gallen

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ASSOCIATION OF MBAS ACCREDITED

“From insight to impact”