With great POWER

comes great RESPONSIBILITY

22. April 2026 | Dr. Katharina Schüller
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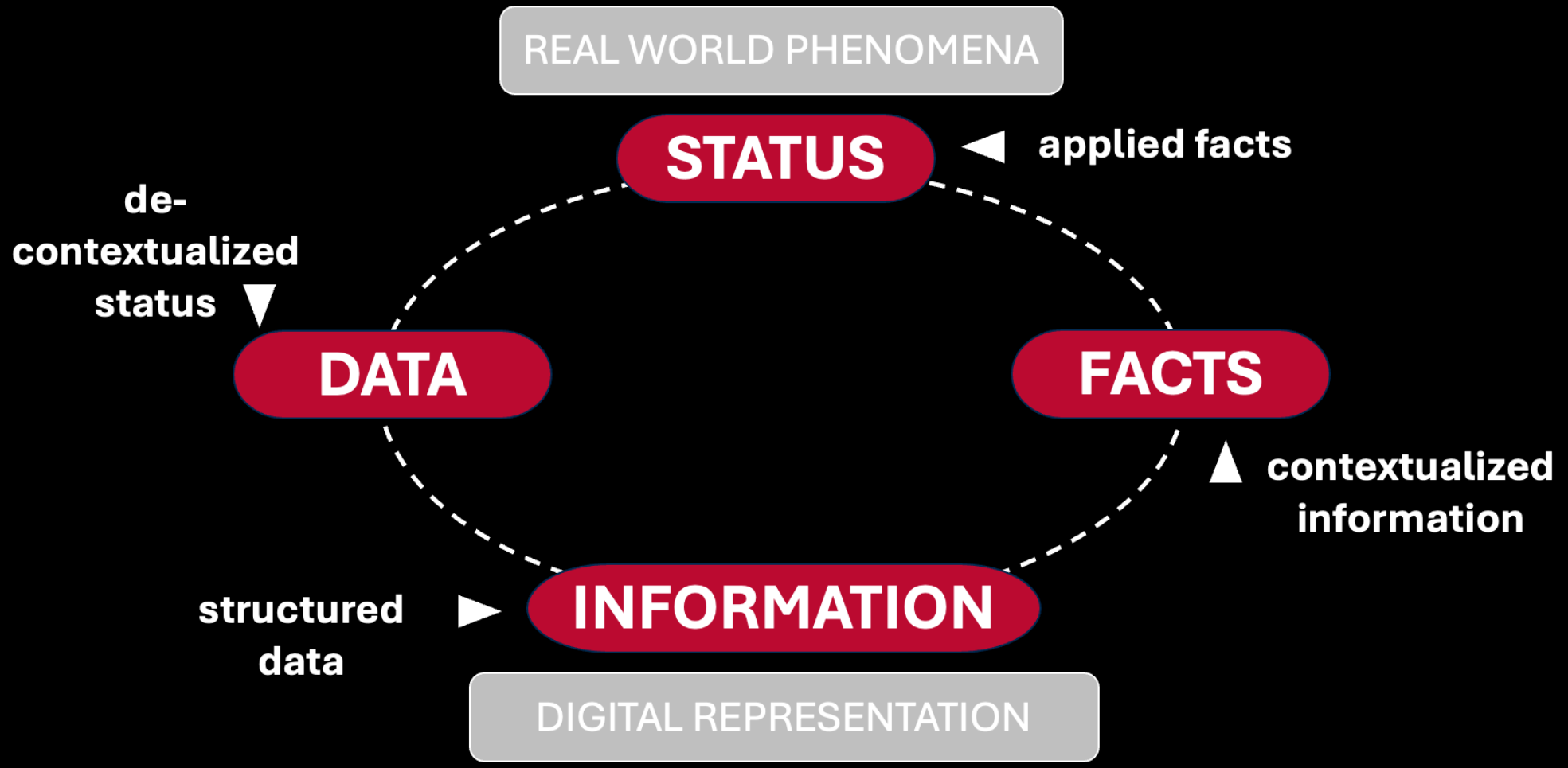
TRUST

01

STATISTICAL THINKING IN A NUTSHELL – P7015 STANDARD FOR DATA & AI LITERACY



Source: According to IEEE P7015/D1 (2025)

DATA

02

TOTAL SURVEY ERROR FRAMEWORK

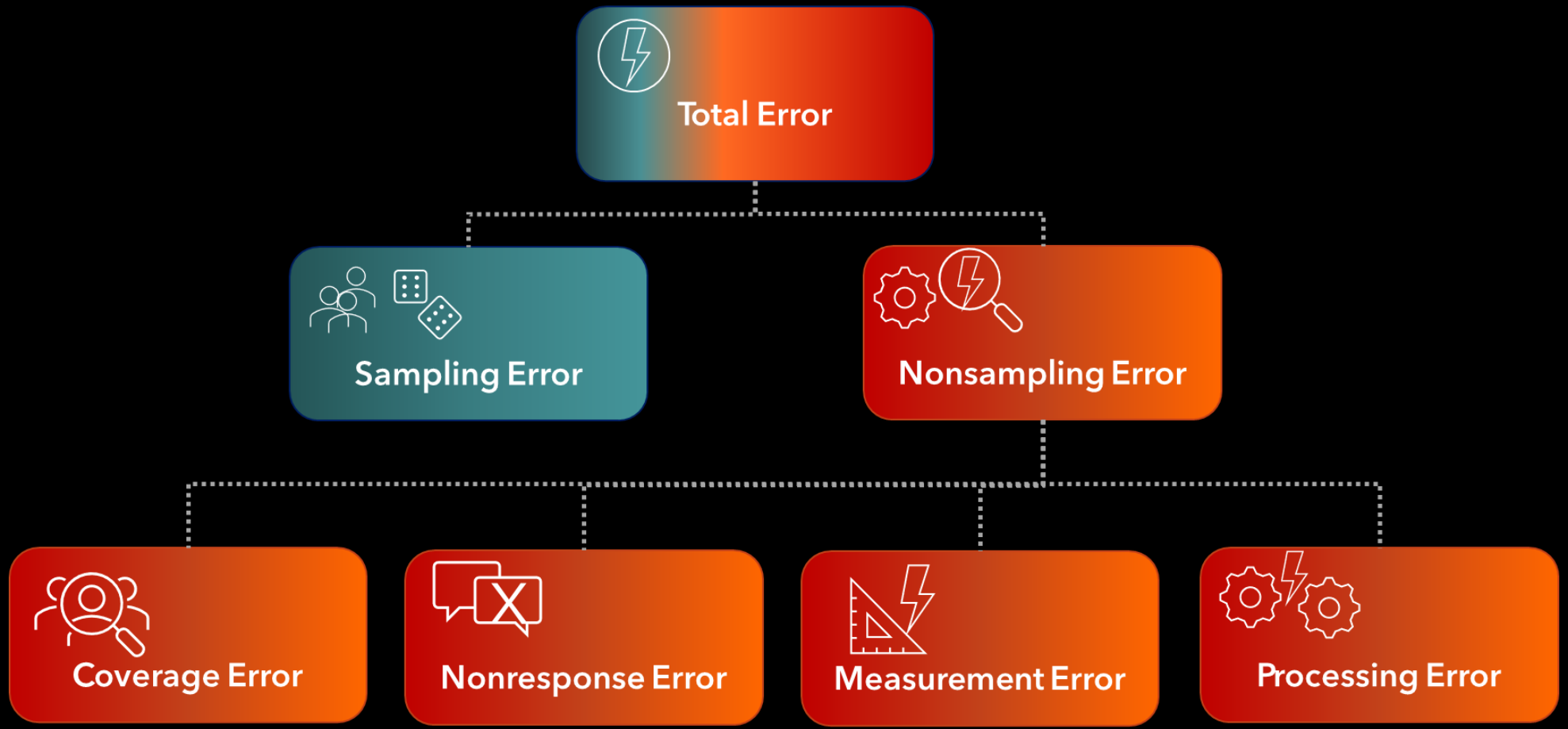


Image source: Own representation, based on Lohr, S. (2021): Sampling: Design and Analysis.

WHAT IF THE DARK SIDE IS NOT LIKE THE BRIGHT SIDE?

Photo: Marty McGuire | Unsplash

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%

99%

IMAGE RECOGNITION ALGORITHMS DISCRIMINATE AGAINST WOMEN AND POC

65%

Buolamwini & Gebru (2019): Intersectional Accuracy Disparities in Commercial Gender Classification

20x

SCORING ALGORITHMS GIVE MEN HIGHER CREDIT CARD LIMITS

Antwort an @dhh

I'm surprised that they even let her apply for a card without the signed approval of her spouse? I mean, can you really trust women with a credit card these days??!

David Heinemeier Hansson auf Twitter
(Developer Ruby on Rails, Founder & CTO Basecamp, NYT Bestselling Author)

WHAT YOU MEASURE IS WHAT YOU MANAGE (AND VICE VERSA): RACIAL BIAS IN HEALTH

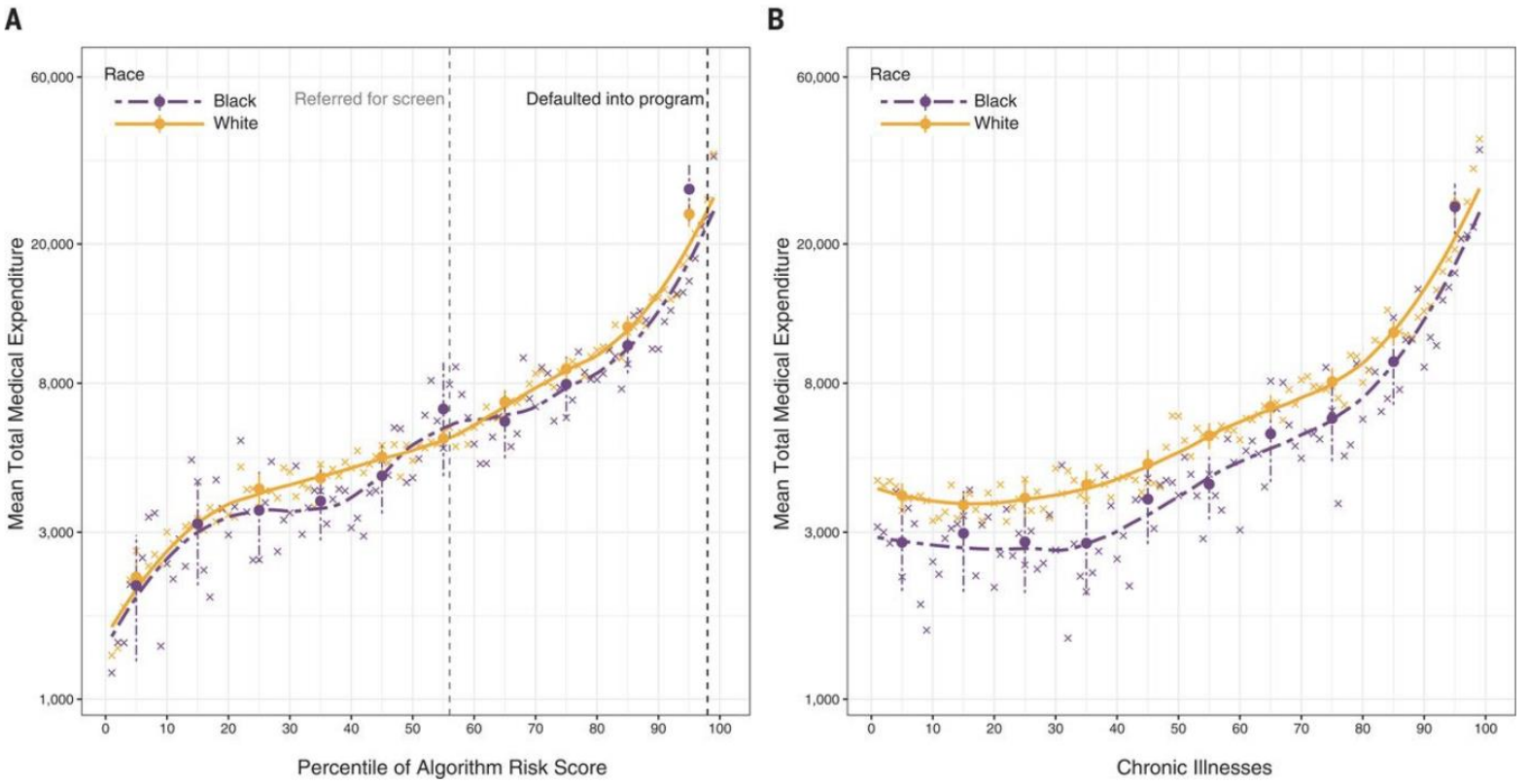


Fig. 3 **Costs versus algorithm-predicted risk, and costs versus health, by race.**

„Less money is spent on Black patients who have the same level of need, and the algorithm thus falsely concludes that Black patients are healthier than equally sick White patients.“

Source: Obermeier at al. (2019): Dissecting racial bias in an algorithm used to manage the health of populations

6

110.000	54,60
125.000	60,00
140.000	65,40
155.000	70,80
170.000	76,20

8

110.000	54,80
125.000	60,00
140.000	85,40
155.000	70,80
170.000	76,20

LIES, DAMNED LIES, AND SCANS: THE XEROX SCANDAL

Sources: Xerox Workcenter 7535 | Xerox
David Kriesel (2013): Xerox Workcentres are Switching Written Numbers when Scanning

ENCODING ERRORS (GARBAGE IN): OVERTRUST IN THE DATA

Selection Bias The data used to train the system are **not representative of the real population**, so some groups or situations are under- or overrepresented.

Historical Bias The data accurately reflect reality **as it was in the past**, but they also reproduce **existing social inequalities or discriminatory patterns**.

Measurement Bias The system measures the **wrong construct or an imperfect proxy**, so the data systematically misrepresent the phenomenon of interest.

Processing Bias Errors in **data processing, feature selection, model training, or optimization** may distort information even when the original data were correct.

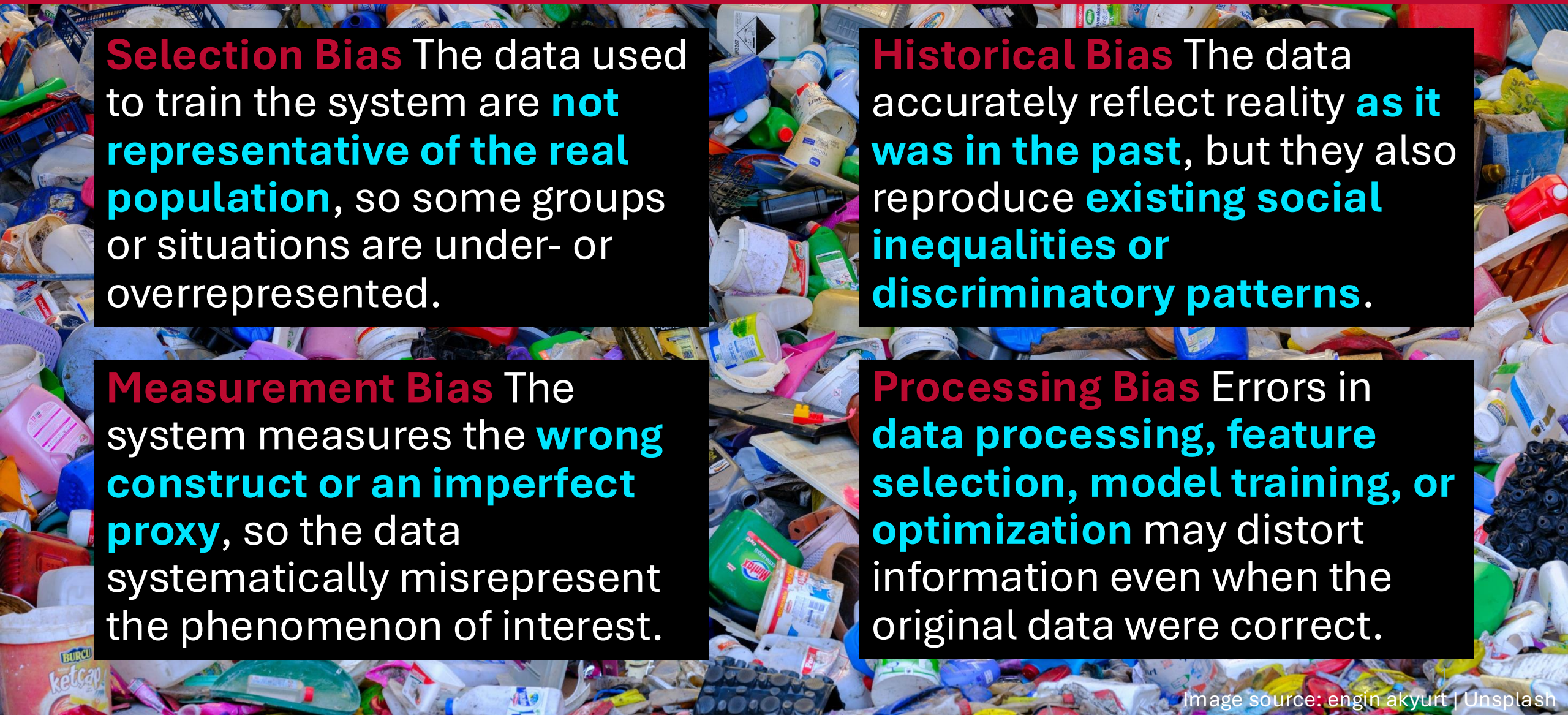


Image source: engin akyurt | Unsplash

Nobody wants
"DATA".
What they
want are the
ANSWERS.

David Hand

Why can‘t we simply use GOOD DATA to build FAIR ALGORITHMS?

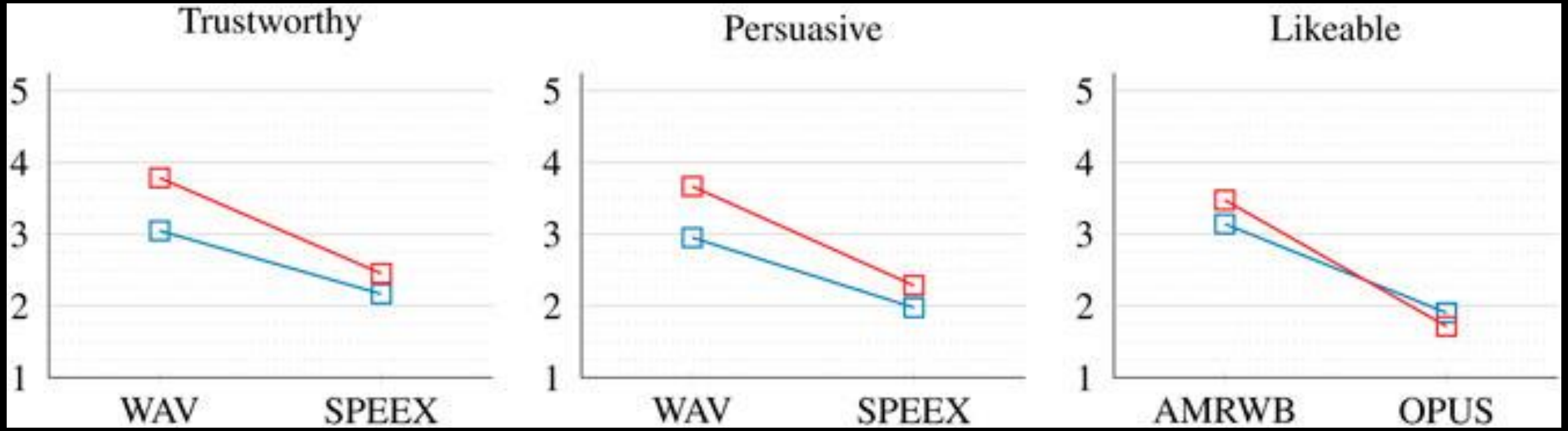
MEANING

03

“THIS AI CAN MAKE AN EERILY ACCURATE PORTRAIT USING ONLY YOUR VOICE“

Oh et al. (2019): Speech2Face: Learning the Face Behind a Voice

https://petapixel.com/2022/04/04/this-ai-can-make-an-eerily-accurate-portrait-using-only-your-voice/



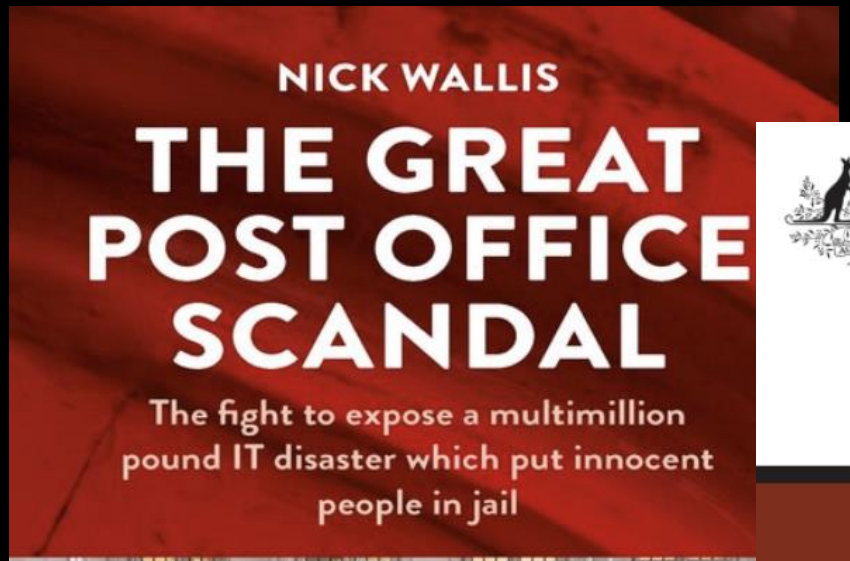
“WOMEN'S VOICES SEEM LESS COMPETENT IN VIDEO CONFERENCES“

-38

-29

FIGURE 1. Changes of selected perceived charisma related attributes for men (—⊟—) and women (—⊟—).

Siegert & Niebuhr (2021): Case Report: Women, Be Aware that Your Vocal Charisma can Dwindle in Remote Meetings



ALGOCRACY: HOW GOVERNMENT BY ALGORITHMS FAILED

Images: Bath Publishing Limited; Royal Commission; mystic_mabel | Wikipedia

DECODING ERRORS (GARBAGE OUT): OVERTRUST IN THE ANSWERS

Association Bias The system learns **statistical associations in the data and treats them as meaningful relationships**, often reproducing stereotypes or socially constructed correlations.

Confirmation Bias Models and users tend to **favor patterns that confirm existing assumptions**, while contradictory signals or outliers are ignored or underweighted.

Automation Bias People tend to **trust and follow automated system outputs**, even when they are incorrect, and are less likely to question or override algorithmic decisions.

Image source: Pawel Czerwinski | Unsplash

THINKING FAST:
PATTERNS, SIGNALS, CAUSALITY

Photo: Private

WHEN STATISTICAL ILLITERACY MEETS GENERATIVE AI

BILD

Hey_ BILD-KI | BILD+ INFOS ZU BILDPLUS | DEBATTE | WETTER | BILDPLAY | MARKTPLATZ | ZEITU

STARTSEITE NEWS POLITIK REGIO UNTERHALTUNG KAUFBERATER SPORT FUSSBALL RATGEBER GESUNDHEIT

BILD › Leben & Wissen › Auto › Mobilität und mehr › Verkehrsunfälle: DAS sind die gefährlichsten Straßen Deutschlands

Unfall-Hotspots in den Städten

DAS sind die gefährlichsten Straßen Deutschlands

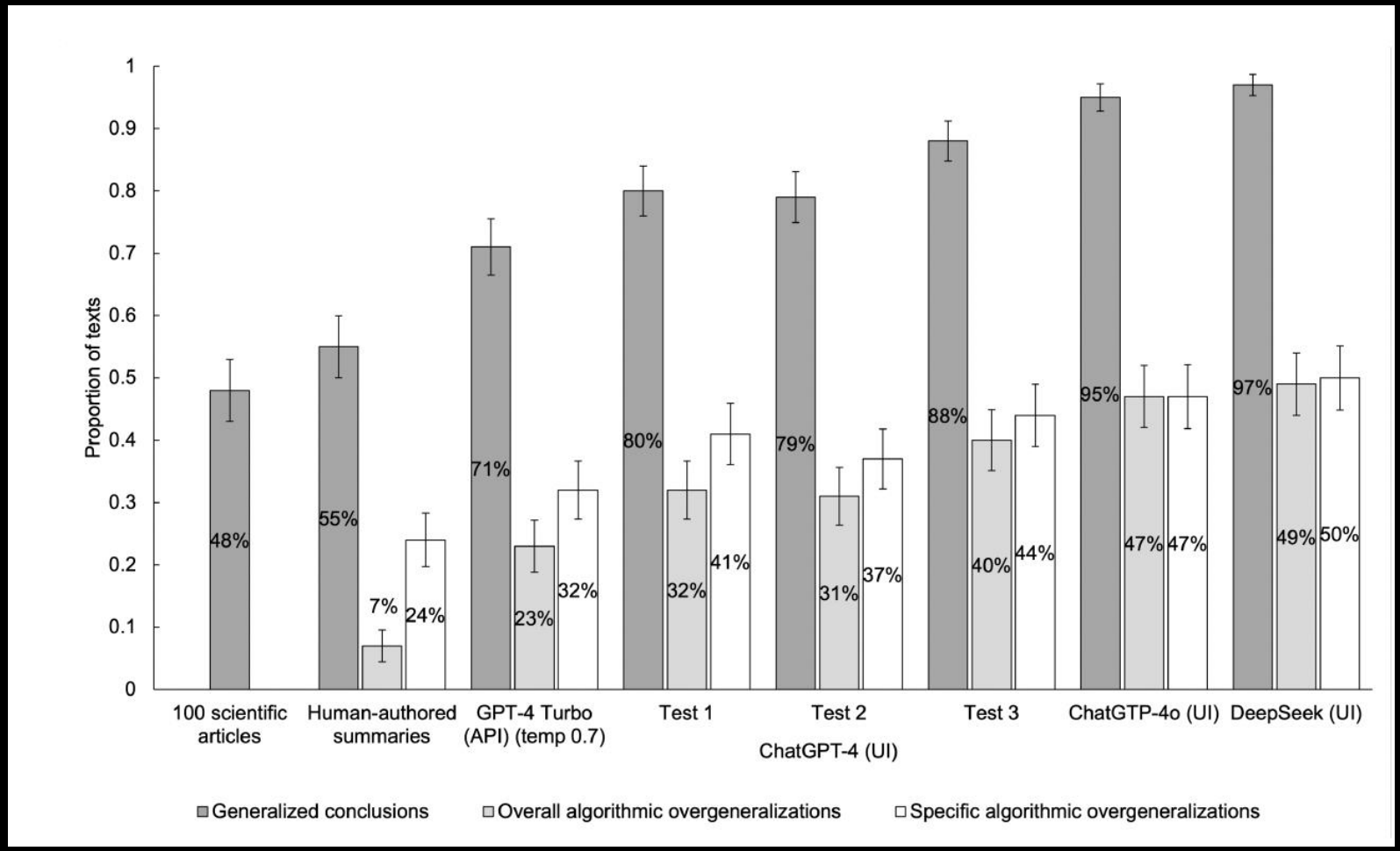
3 in Hannover, 2 in Hamburg, 2 in Berlin

Eine der bekanntesten Straßen in Frankfurt verzeichnet laut einer Auswertung der Allianz Direct deutschlandweit die meisten Unfälle – auch mit Schwerverletzten.

„None of these results are supported by the data.“

Source: BILD; Frankfurter Rundschau, Unstatistik des Monats (November 2025)

„GRÜNE FAHREN SUV UND JOGGEN MACHT UNSTERBLICH“: GENERALIZATION BIAS



„Our results indicate a strong bias in many widely used LLMs towards overgeneralizing scientific conclusions, posing a significant risk of large-scale misinterpretations of research findings.“

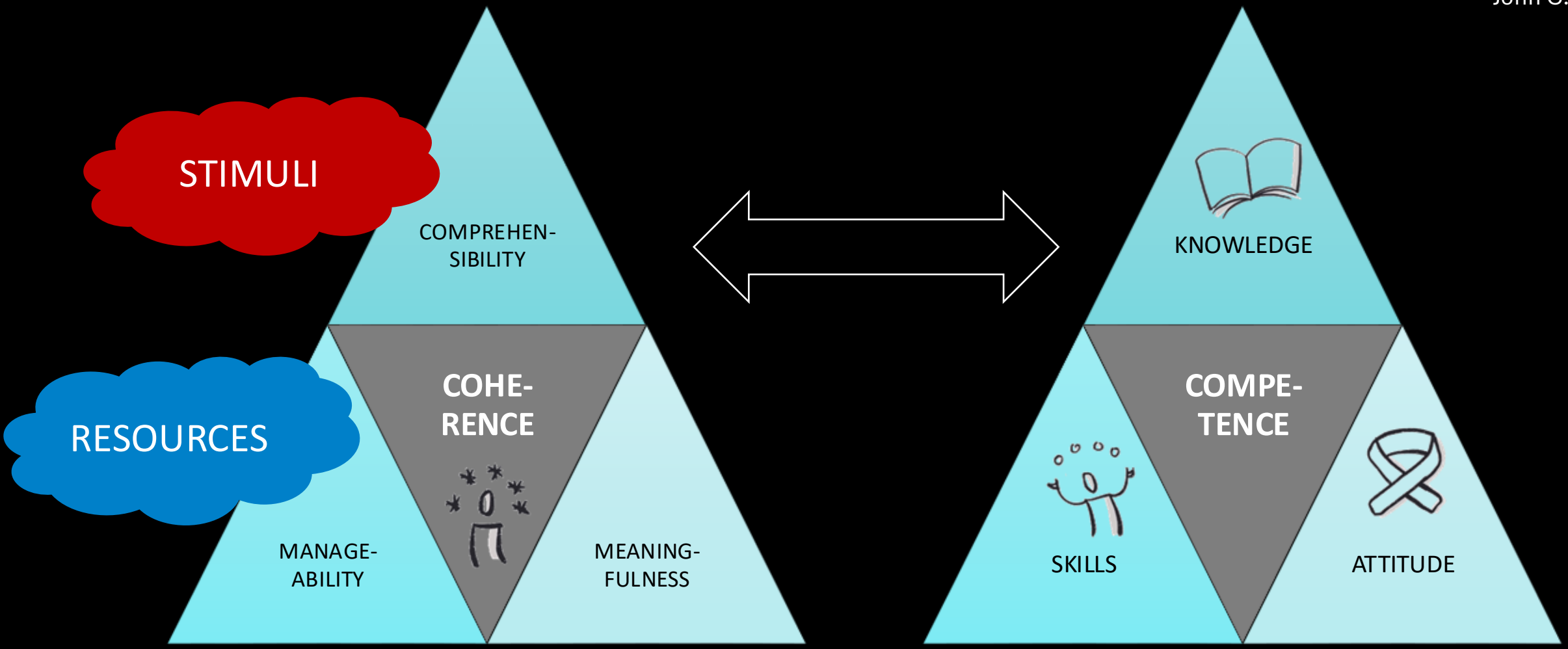
Source: Peters and Chin-Yee (2026): Generalization bias in large language model summarization of scientific research

WHEN THE RECIPIENT IS NO LONGER HUMAN: SCIENCE COMMUNICATION FOR AI

Photo: Tamara Malaniy | Unsplash

HOW TO SURVIVE IN A WORLD “DESIGNED TO FAVOR MACHINES OVER HUMANS AT WORK”

John C. Havens



Antonovsky (1987): Unraveling the mystery of health. How people manage stress and stay well.

Schüller et al. (2021): The Data Literacy Charter

LITERACY

05

DIGITAL INTELLIGENCE (DQ): IEEE 3527.1

- Technical, cognitive, meta-cognitive, and socio-emotional competencies
- Grounded in universal moral values
- Enable individuals to face the challenges and harness the opportunities of digital life

DATA & AI LITERACY:

- Ability to generate, process, analyze, present meaningful information from data
- Develop, use, and apply artificial intelligence (AI) and related algorithmic tools and strategies
- Guide informed, optimized, and contextually relevant decision-making processes

CODING

|A| Establish a Data Culture

|B| Provide Data

|C| Exploit Data

Remove Context

DECODING

|F| Derive Actions

|E| Interpret Data

|D| Interpret Results

Add Context

SYSTEM

A.1 Identify Data Use Cases

A.2 Specify Data Use Cases

A.3 Coordinate Data Use Cases

F.3 Evaluate Impact

F.2 Act Data-Driven

F.1 Identify Potential Actions

OBJECTS

B.1 Plan

B.1.1 Model Data Use Cases

B.1.2 Meet Data Protection/Security

E.3 Reconstruct Data Concept

B.2 Obtain

B.2.1 Identify Data Sources

B.2.2 Integrate Data

E.2 Trace Back Data Sources

B.3 Prepare

B.3.1 Verify Data

B.3.2 Preprocess Data

E.1 Decode Transformations

DATA

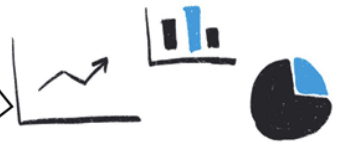
C.1 Analyse Data

D.3 Interpret Data Analyses

C.2 Visualise Data

D.2 Interpret Data Visualisations

C.3 Verbalise Data



D.1 Interpret Data Verbalisations

DATA PRODUCTS

HFD DATA LITERACY FRAMEWORK (EXAMPLES)

C1: Analyze Data	Knowledge	Knows estimation methods and algorithms; knows possible causes of artifacts
	Skills	Can represent measurable relationships in models; can anticipate future uses of analysis results
	Attitudes	Shows ”Analytical fairness" as a basic attitude, i.e. willingness not to perform analyses if the risk of misuse is high
D3: Interpret Analyses	Knowledge	Understands statistical terms; knows about statistical fallacies (e.g., correlation vs. causation)
	Skills	Can identify the characteristics of the data from a key figure; can question the extent to which the interpretation of a result depends on contextual knowledge
	Attitudes	Shows openness to new insights, even if they contradict previous beliefs

Source: HFD Data Literacy Framework (modified)

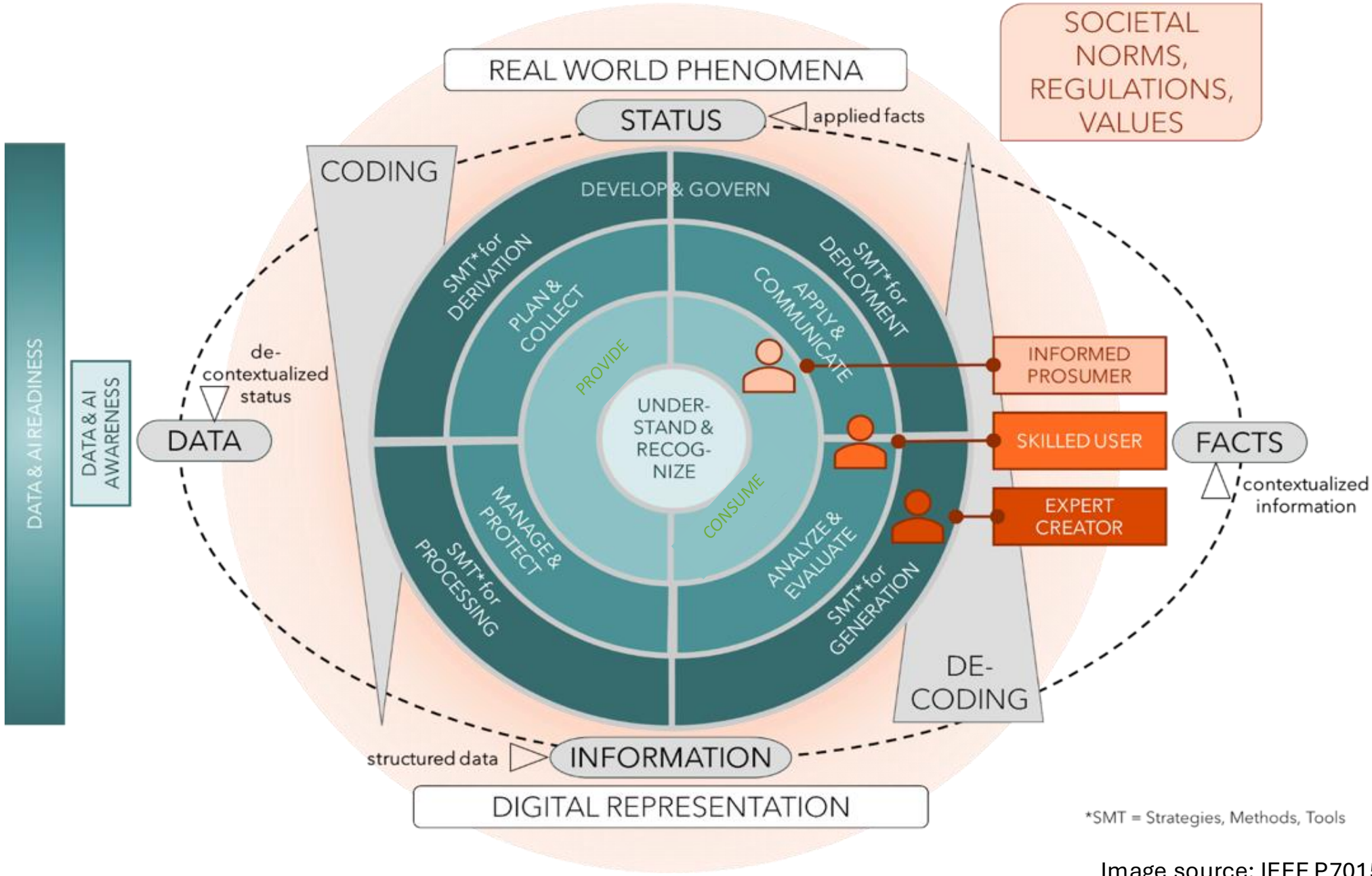


Image source: IEEE P7015 Draft Standard

IEEE P7015 COMPETENCE CATALOGUE (EXAMPLES)

Basic understanding	Understand and recognize	I am aware that humans and AI systems perceive and process data and information differently and what this means for human interaction with AI systems.
Everyday Context	Provide	I respect the intellectual property of others when sharing data and information with AI applications.
	Consume	I can critically assess origin and trustworthiness of data, information, and digital tools.
Professional Context	Manage and protect	I properly prepare data to identify and correct errors and biases, ensure quality, and improve the value of analyses.

Source: IEEE P7015 Draft Standard (modified)

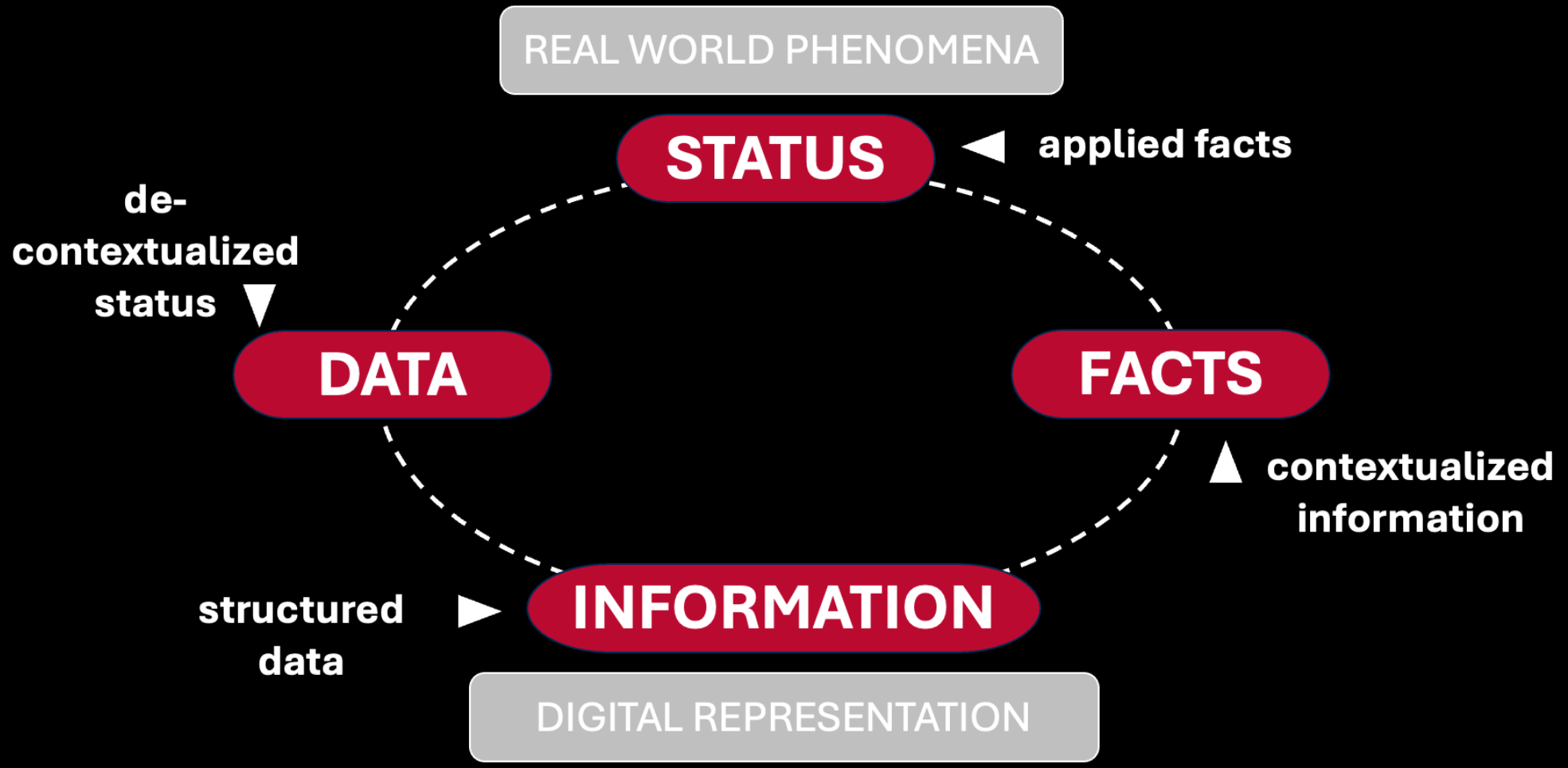
STATISTICAL THINKING will one day be as necessary for efficient CITIZENSHIP as the ability to READ AND WRITE!

Attributed to H. G. Wells, 1903

POWER

04

THE CUSTOMS‘ USE CASE: FIGHT ORGANIZED CRIME WITH DATA



Source: According to IEEE P7015/D1 (2025)

WHAT THE CUSTOMS AUTHORITY THOUGHT: OPTIMIZE EFFICIENCY WITH DATA & AI

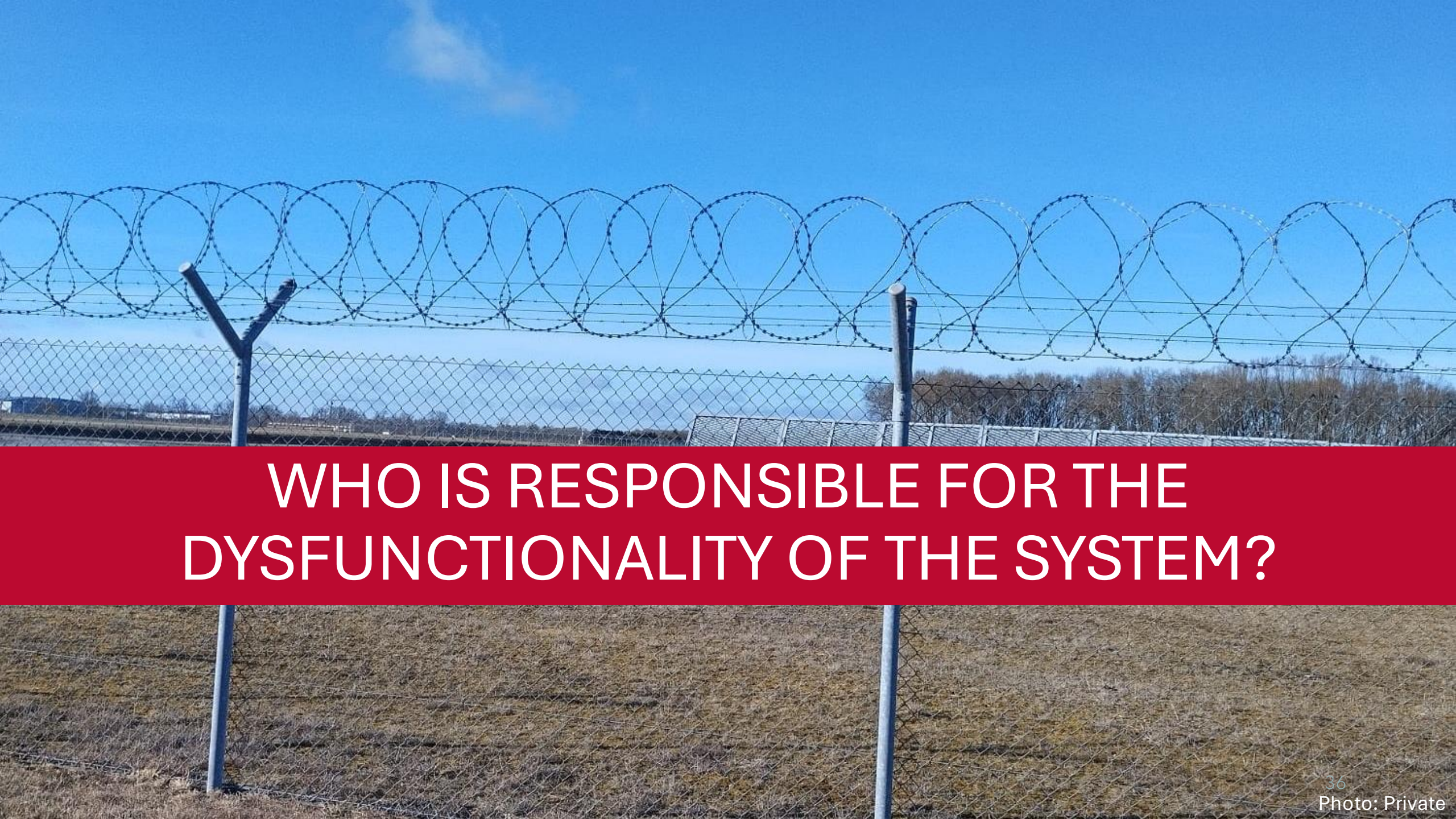
Image Source: modestas urbonas | Unsplash

WHAT THE STATISTICIANS THOUGHT: IT WILL TAKE SOME EFFORT TO FIX THE DATA

Image Source: Walter Tresa | Unsplash

WHAT THE CUSTOMS OFFICERS THOUGHT: THE DATA IS COMPLETELY USELESS

Image Source: Giancarlo Revolledo | Unsplash

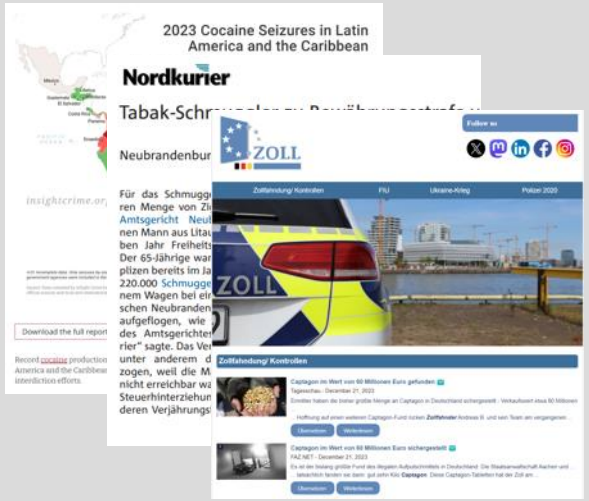


WHO IS RESPONSIBLE FOR THE DYSFUNCTIONALITY OF THE SYSTEM?

Photo: Private

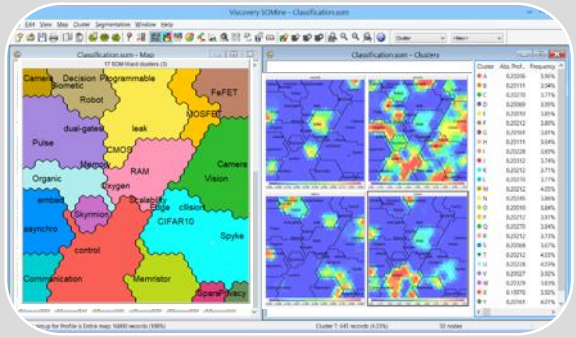
(How) can we empower people and transform FUNCTIONAL DEVIANCE into INNOVATION?

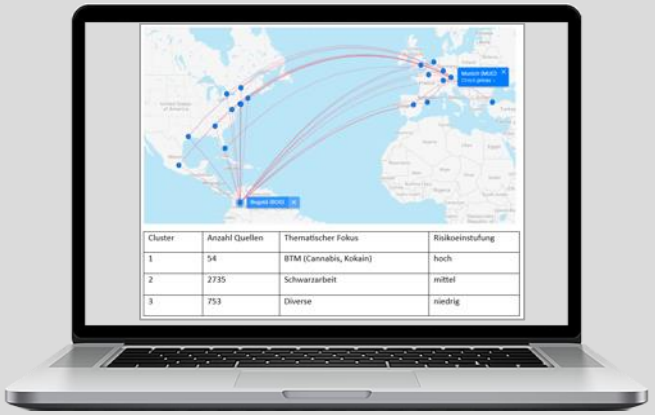
THOSE WHO ARE EXPERTS ON THE PROBLEM OFTEN ARE ALSO EXPERTS ON THE SOLUTION



AI-SUPPORTED SITUATION ANALYSIS

Datum	URL	E1	E2	E3	E4
12.03.2024	https://www.nordkur	-0.0068	0.0095	-0.0063	-0.0039
12.03.2024	https://www.suedde	-0.0074	0.0015	-0.0055	-0.0200
12.03.2024	https://www.allgeme	-0.0159	-0.0280	0.0030	-0.0206
12.03.2024	https://www.aachene	-0.0302	-0.0017	-0.0080	-0.0372
12.03.2024	https://www.idowa.d	-0.0186	-0.0133	-0.0220	-0.0045
13.03.2024	https://www.abendb	-0.0413	-0.0014	-0.0018	-0.0262
12.03.2024	https://www.spiegel.	-0.0284	0.0054	0.0145	-0.0037
26.03.2024	https://www.suedde	-0.0142	0.0238	-0.0153	-0.0222
21.12.2023	https://www.tagessc	-0.0128	0.0058	0.0013	-0.0301





Webscraping

Data Sources:
Press review, Google Alerts, incoming reports from various channels

Transformers

Vector Embeddings:
Structured representation of words and their relationships with deep learning architectures

Unsupervised Learning

Visual Clustering:
Extraction of thematic clusters and detailed analysis using self-organizing maps, knowledge graphs

Generative AI

AI-generated reports:
Visualization of routes, automated reporting with Large Language / Large Multimodal Models

TEACH BY EXAMPLES.
AND BE AN EXAMPLE.

Photo: Sebastien Bonneval | Unsplash

AI is POWER.
STATISTICAL LITERACY
can help us use it
RESPONSIBLY.