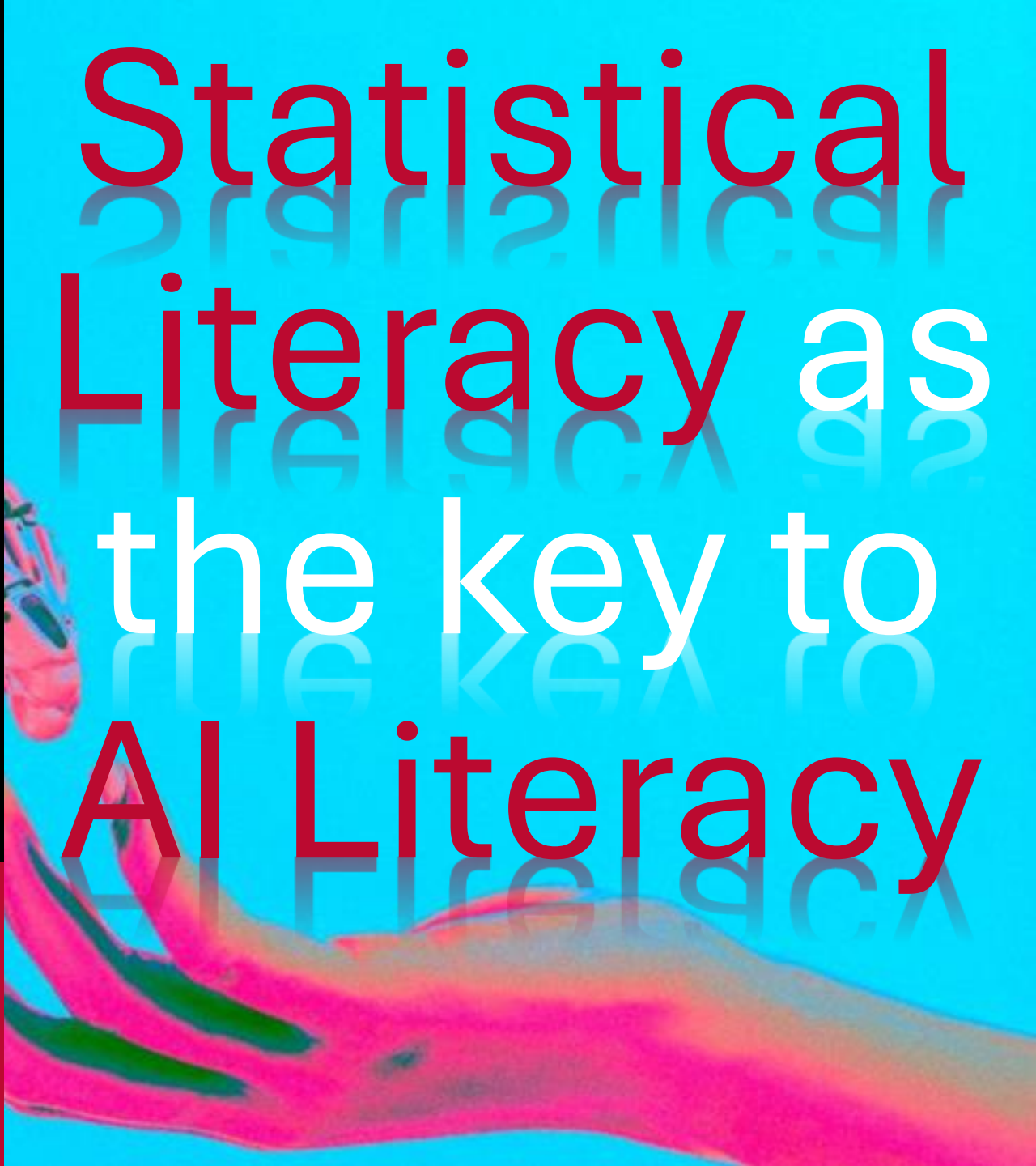


# Bridging the GAP (Part 1)

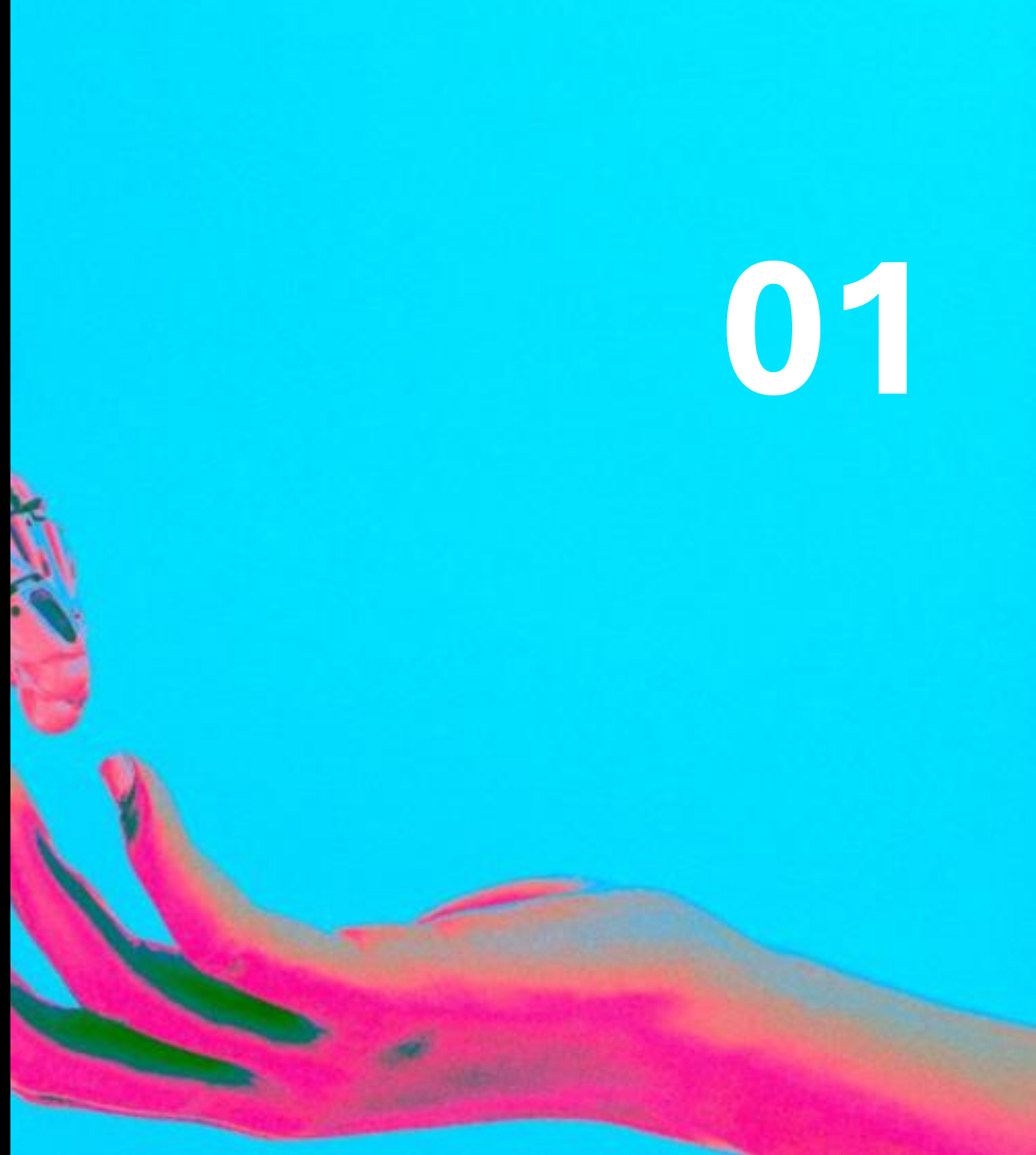
9. March 2026 | Dr. Katharina Schüller  
katharina.schueller@stat-up.com



Statistical  
Literacy as  
the key to  
AI Literacy

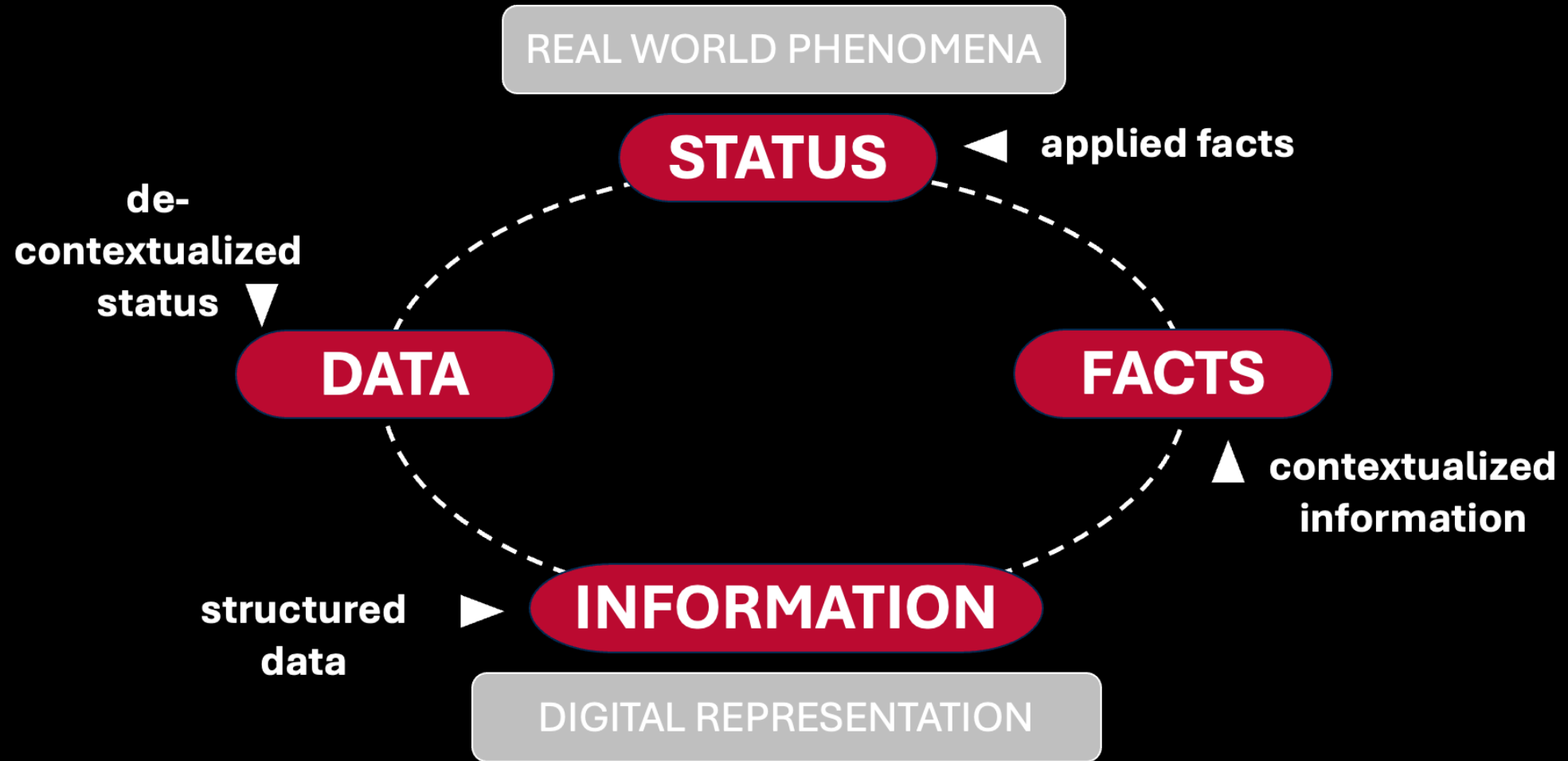
TRUST

01



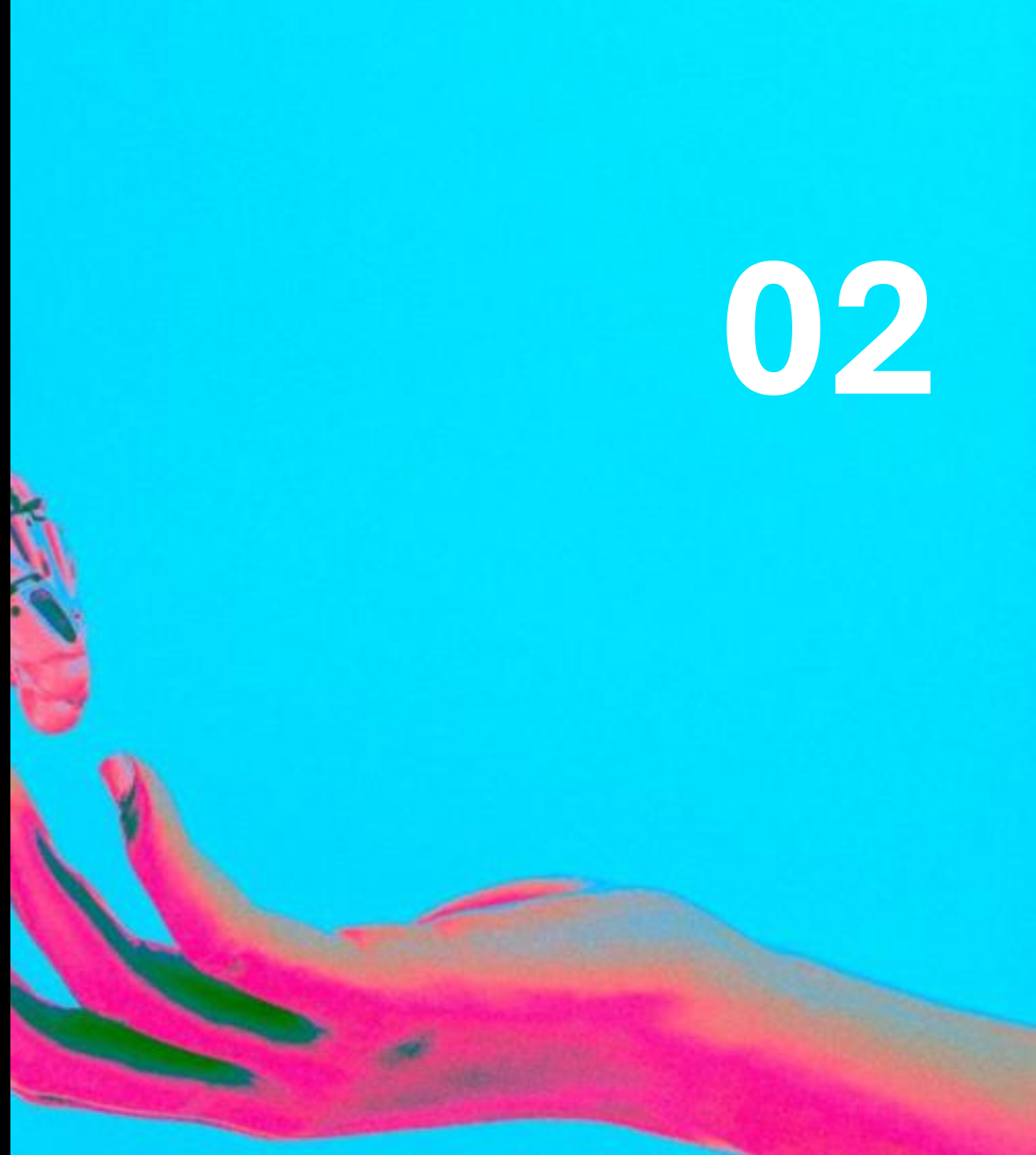
# STATISTICAL THINKING IN A NUTSHELL – P7015

## STANDARD FOR DATA & AI LITERACY

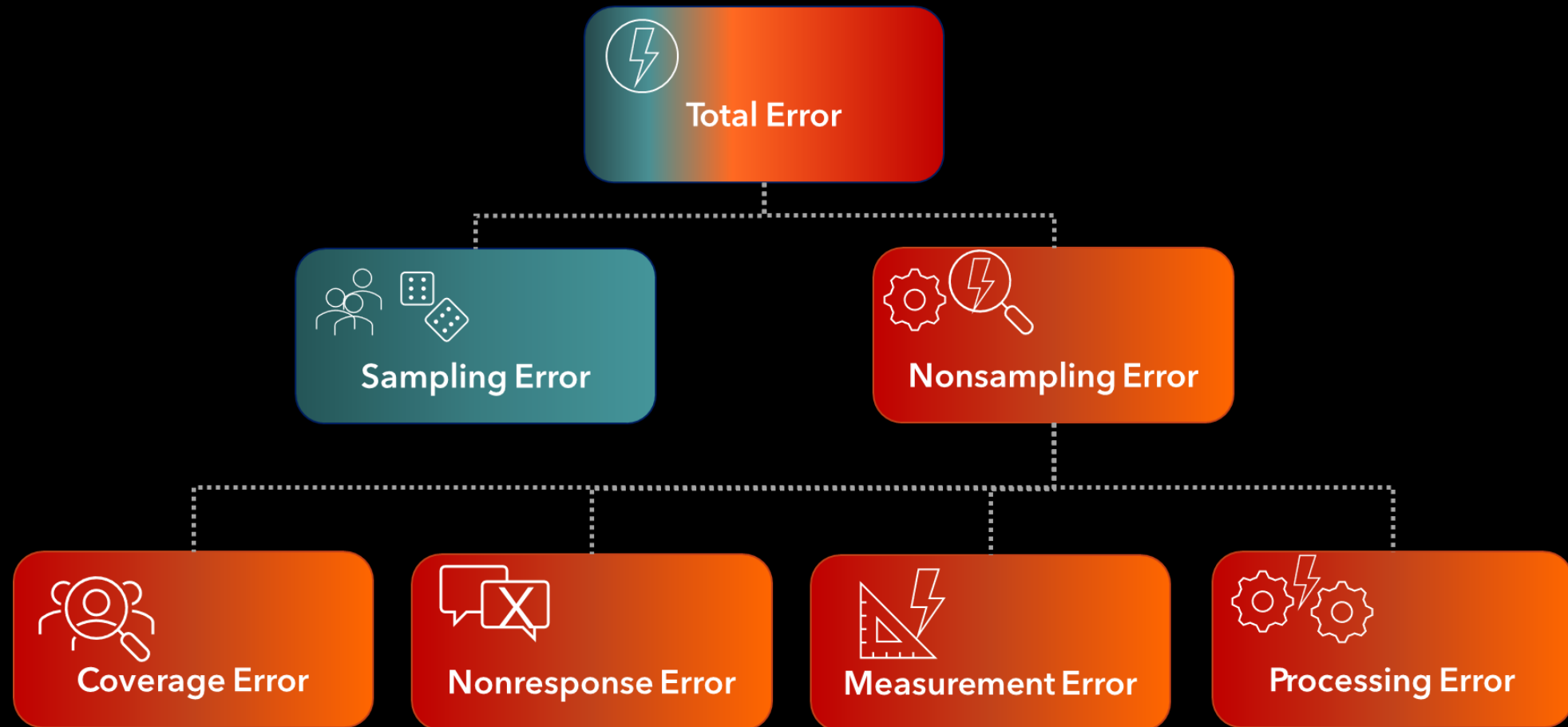


DATA

02









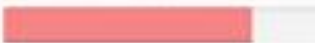











# TOTAL SURVEY ERROR FRAMEWORK



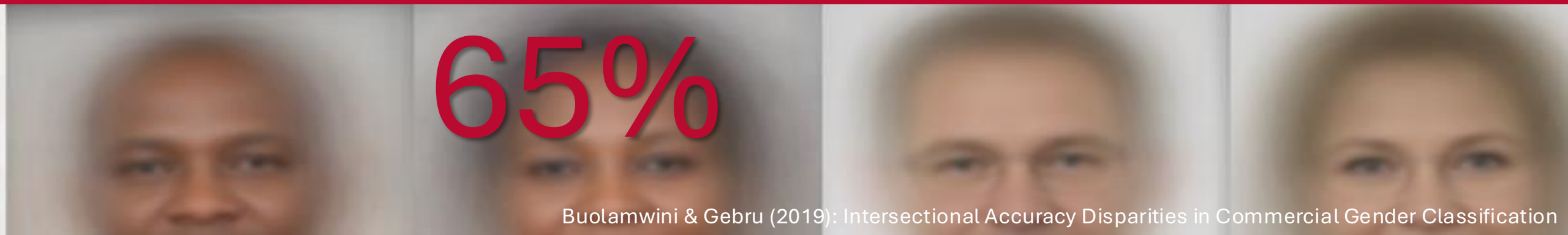


**WHAT IF THE DARK SIDE  
IS NOT LIKE THE BRIGHT SIDE?**

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%



DHH ✓

@dhh

The @AppleCard is such a fucking sexist program. My wife and I filed joint tax returns, live in a community-property state, and have been married for a long time. Yet Apple's black box algorithm thinks I deserve 20x the credit limit she does. No appeals work.

9:34 nachm. · 7. Nov. 2019 · [Twitter for iPhone](#)

9,7 Tsd. Retweets 29,3 Tsd. „Gefällt mir“-Angaben

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??!

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

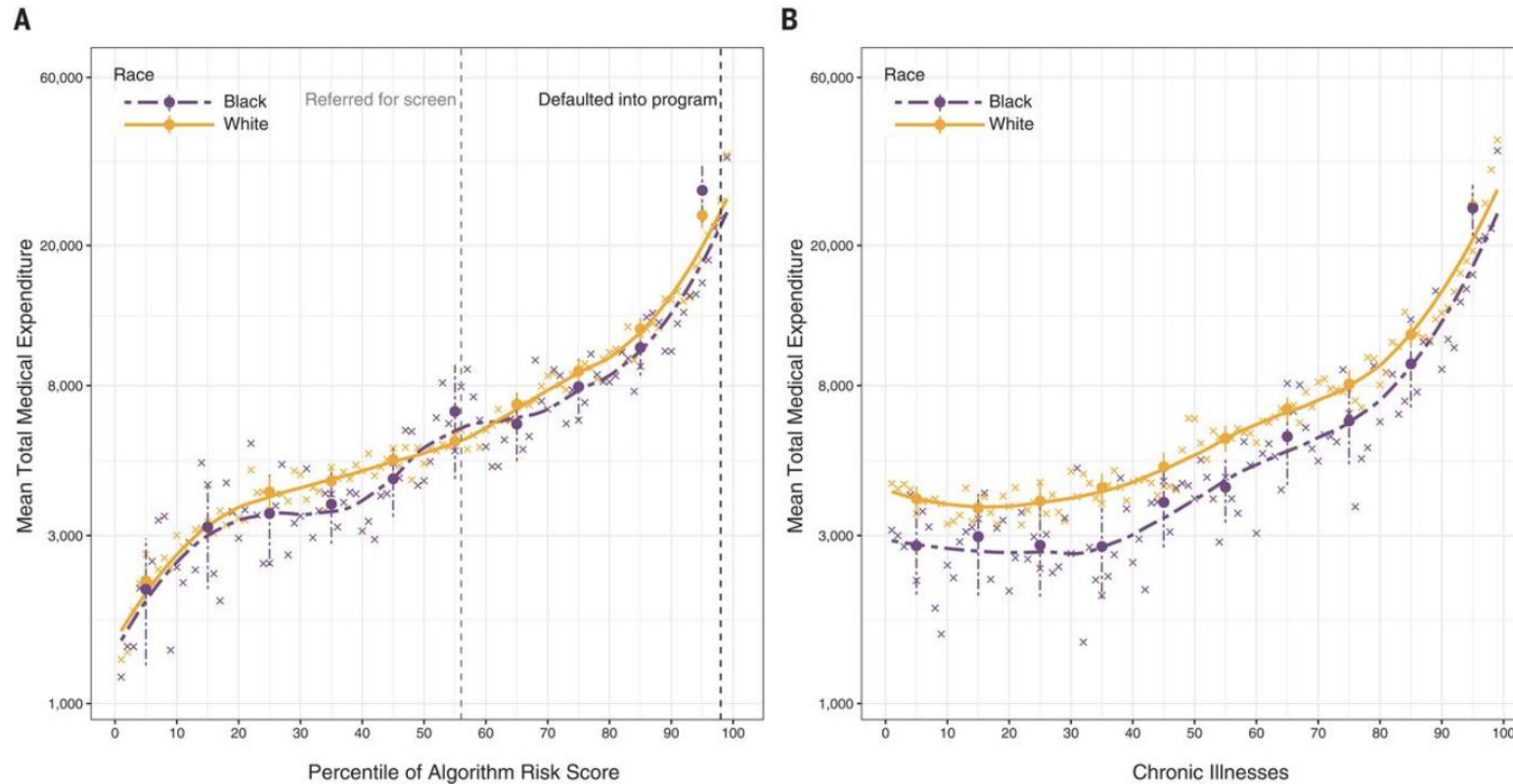


Fig. 3 Costs versus algorithm-predicted risk, and costs versus health, by race.

„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.“



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

Why can't we simply  
use **WEIGHTS** to  
adjust **BIASED DATA**?

# MIXED MODE DESIGN – GAMBLING SURVEY

## WHAT IS THE TRUTH?

	Telefon	Online*
	gewichtet**	
	%	%
Spielteilnahme insgesamt (letzte 12 Monate)	23,4 %	62,8 %
Teilnahme an Glücksspielformen (letzte 12 Monate)		
LOTTO 6aus49	12,5 %	34,4 %
Eurojackpot	7,5 %	24,0 %
Aktion Mensch	3,8 %	14,2 %
Geldspielautomaten	0,9 %	3,9 %
Kasinospiele	1,2 %	6,4 %
Sportwetten	1,4 %	8,6 %
Schweregrad der Glücksspielstörung		
keine Glücksspielteilnahme / keine erfüllten DSM-5-Kriterien	96,9 %	80,9 %
riskantes Spiel (1-3 DSM-5-Kriterien)	2,8 %	12,7 %
GS-Störung: leicht (4/5 DSM-5-Kriterien)	0,2 %	2,6 %
GS-Störung: mittel (6/7 DSM-5-Kriterien)	0,1 %	1,9 %
GS-Störung: schwer (8/9 DSM-5-Kriterien)	0,1 %	1,9 %
psychische Gesundheit beeinträchtigt (MHI-5)	11,3 %	21,7 %
riskanter Alkoholkonsum (AUDIT-C)	26,1 %	29,2 %

2.7 x

16.0 x

1.9 x

1.1 x

\* Panel effect was not analyzed. The Irish Gambling Survey (Ó Ceallaigh et al., 2023) estimated a prevalence of 1.7% - 5.9% depending on the panel, i.e., a factor of 3.5 (p. 73); panel effect was significant (p. 71).

\*\* The absolute weighting effect with regard to the degree of GS disorder is 0.0–0.7 p.p. (risky gambling, online), despite considerable weighting of several sociodemographic factors (high school diploma, telephone: -16.5 p.p.). This is consistent with empirical findings that sociodemographic factors have little disruptive effect, cf. Allami et al., 2021, p. 2975.

Source: Buth et al. (2024): Glücksspiel-Survey 2023

There are a lot of  
**SMALL DATA PROBLEMS**  
that occur in **BIG DATA.**

They don't disappear because  
you've got lots of the stuff.

**THEY GET WORSE.**



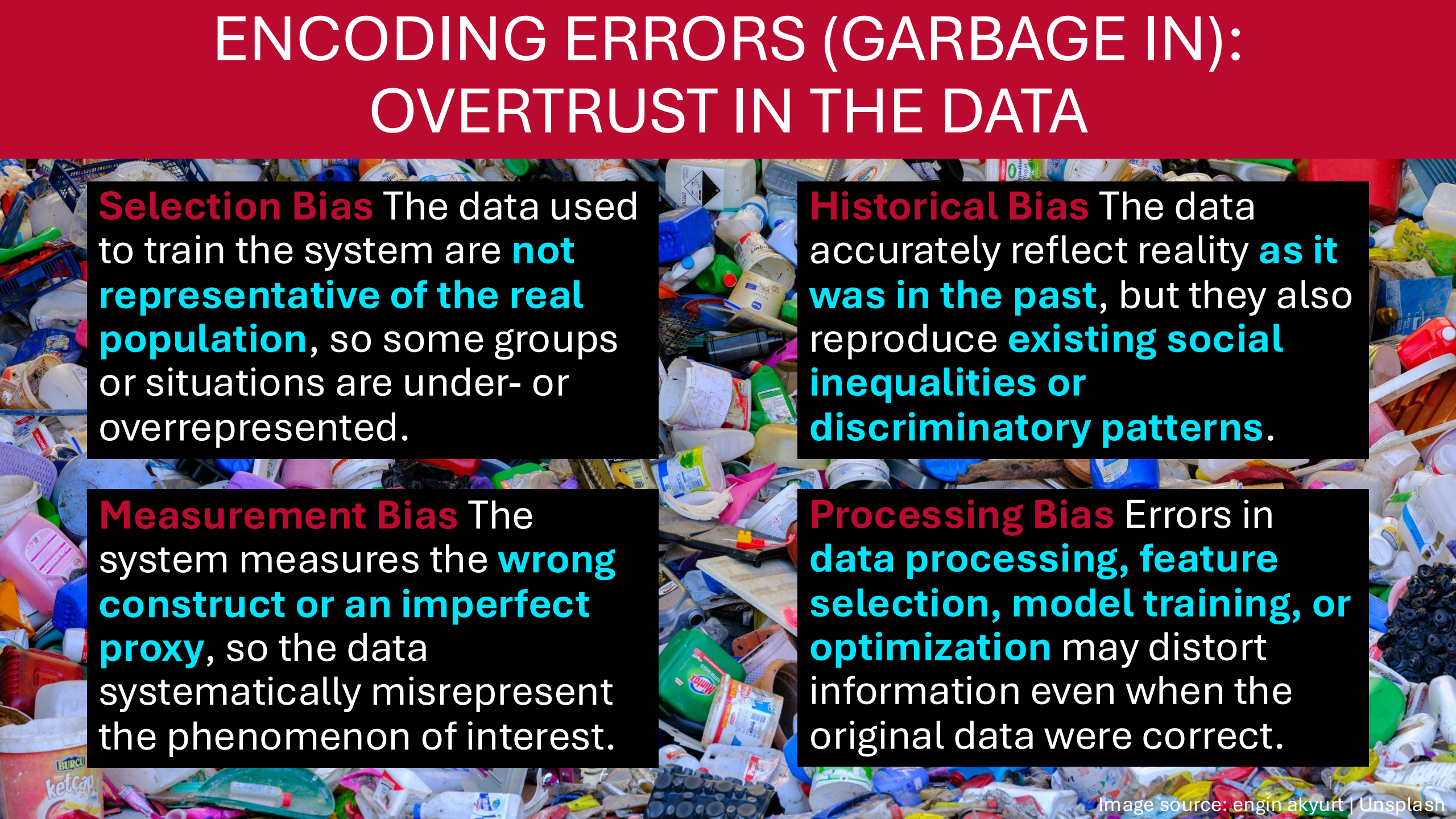
**PROBLEM-FREE GAMBLERS WERE UNDERREPRESENTED IN BOTH SURVEY MODES**



# UNCERTAIN KNOWLEDGE + KNOWLEDGE ABOUT THE EXTENT OF UNCERTAINTY



# 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.

Katharina  
Schüller

# DATEN SIND MACHT

50  
JAHRE  
campus

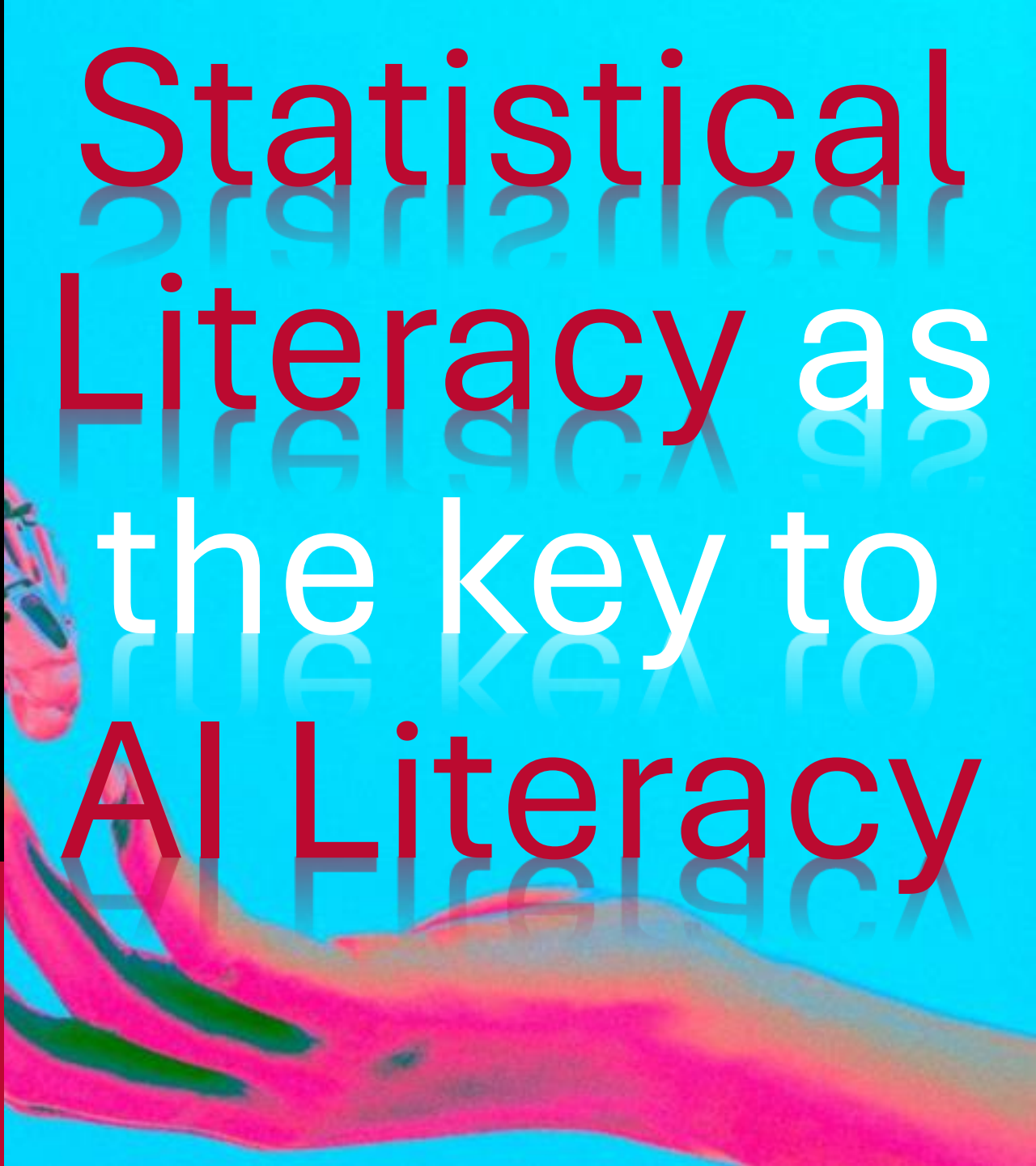
Kompetentes  
Entscheiden  
im Zeitalter  
von KI

**campus**

Nobody wants  
“DATA”.  
What they  
want are the  
ANSWERS.

# Bridging the GAP (Part 2)

10. March 2026 | Dr. Katharina Schüller  
katharina.schueller@stat-up.com



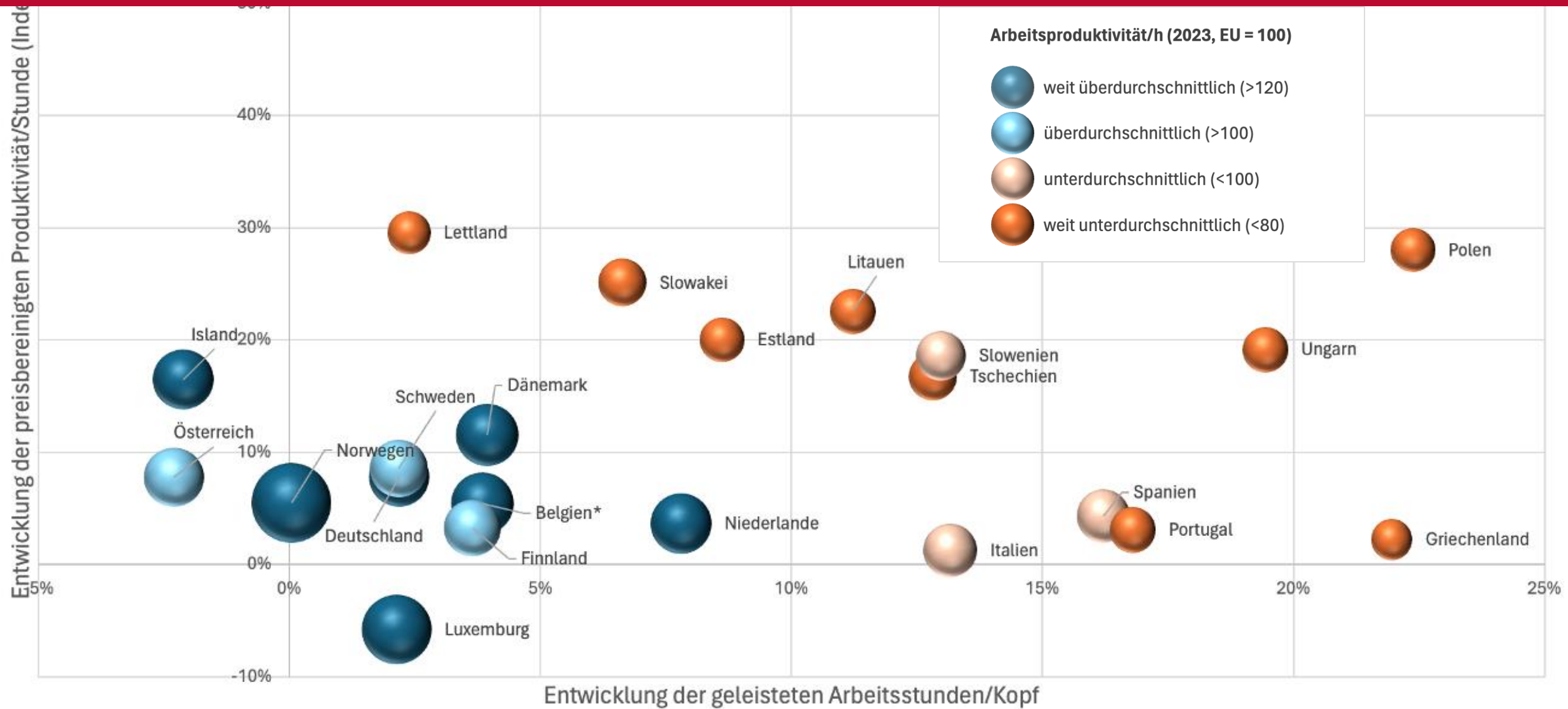
Statistical  
Literacy as  
the key to  
AI Literacy

Why can't we simply  
use **GOOD DATA** to  
build **FAIR**  
**ALGORITHMS?**

# „WE ARE (NO LONGER) USED TO WORKING LONG AND HARD HOURS.“

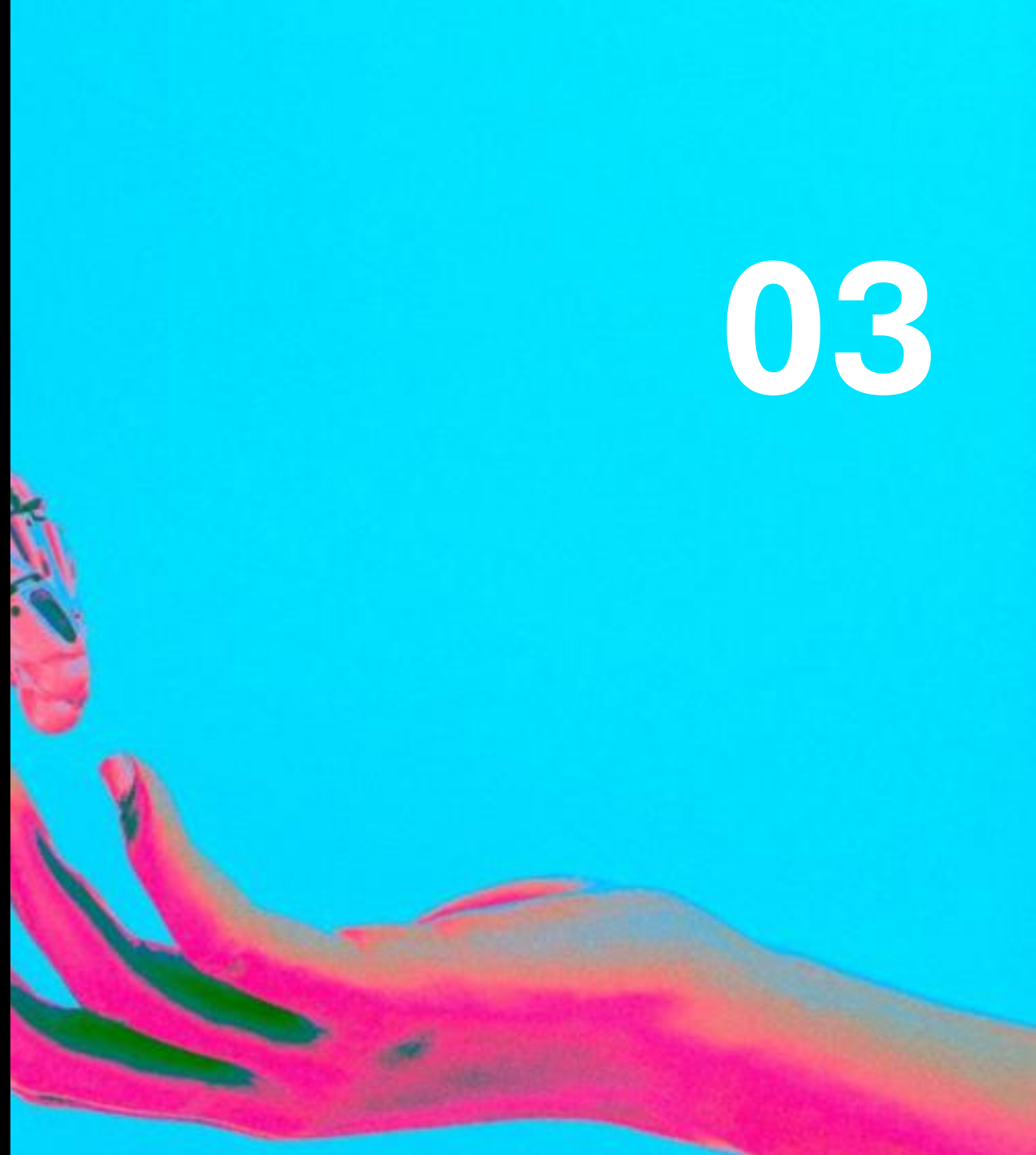


# DOES IT EVEN MAKE SENSE TO COUNT WORKING HOURS?



# MODELS

03



What you **SEE**  
is what you **GET**



**WHEN THE DESCRIPTIVE  
BECOMES THE NORMATIVE**



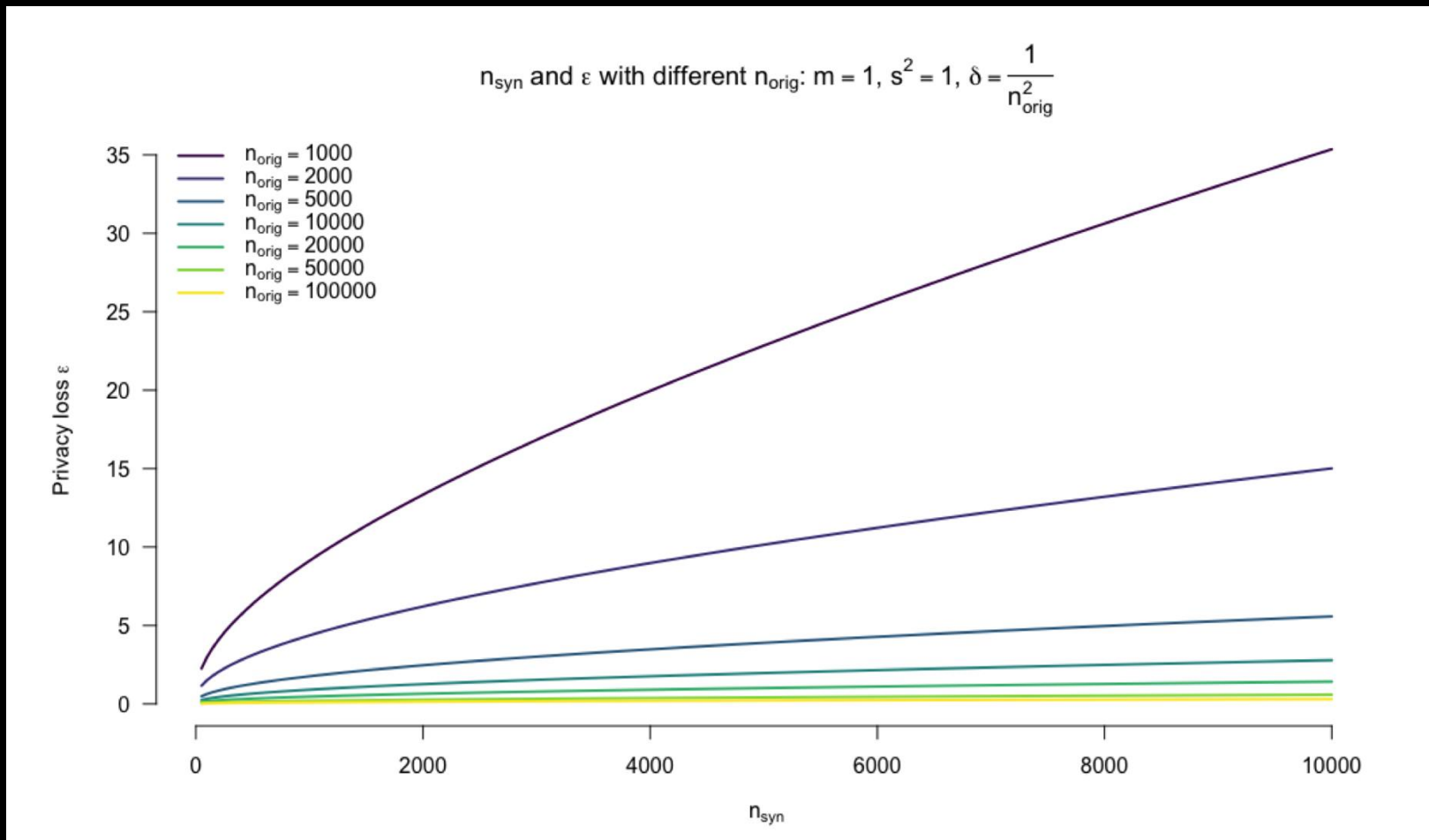
# SYNTHETIC DATA: THE TROUBLE WITH CLONES

A line of white LEGO Clone Trooper minifigures is shown in a shallow depth of field. The first figure in the foreground is in sharp focus, showing its helmet with a black visor and its white armor. The other figures in the line behind it are progressively more out of focus, creating a sense of depth. The background is a plain, light-colored surface.

# SYNTHETIC FEEDBACK LOOPS AND AMPLIFIED BIAS

Photo: Marc Belver Colomer | Unsplash

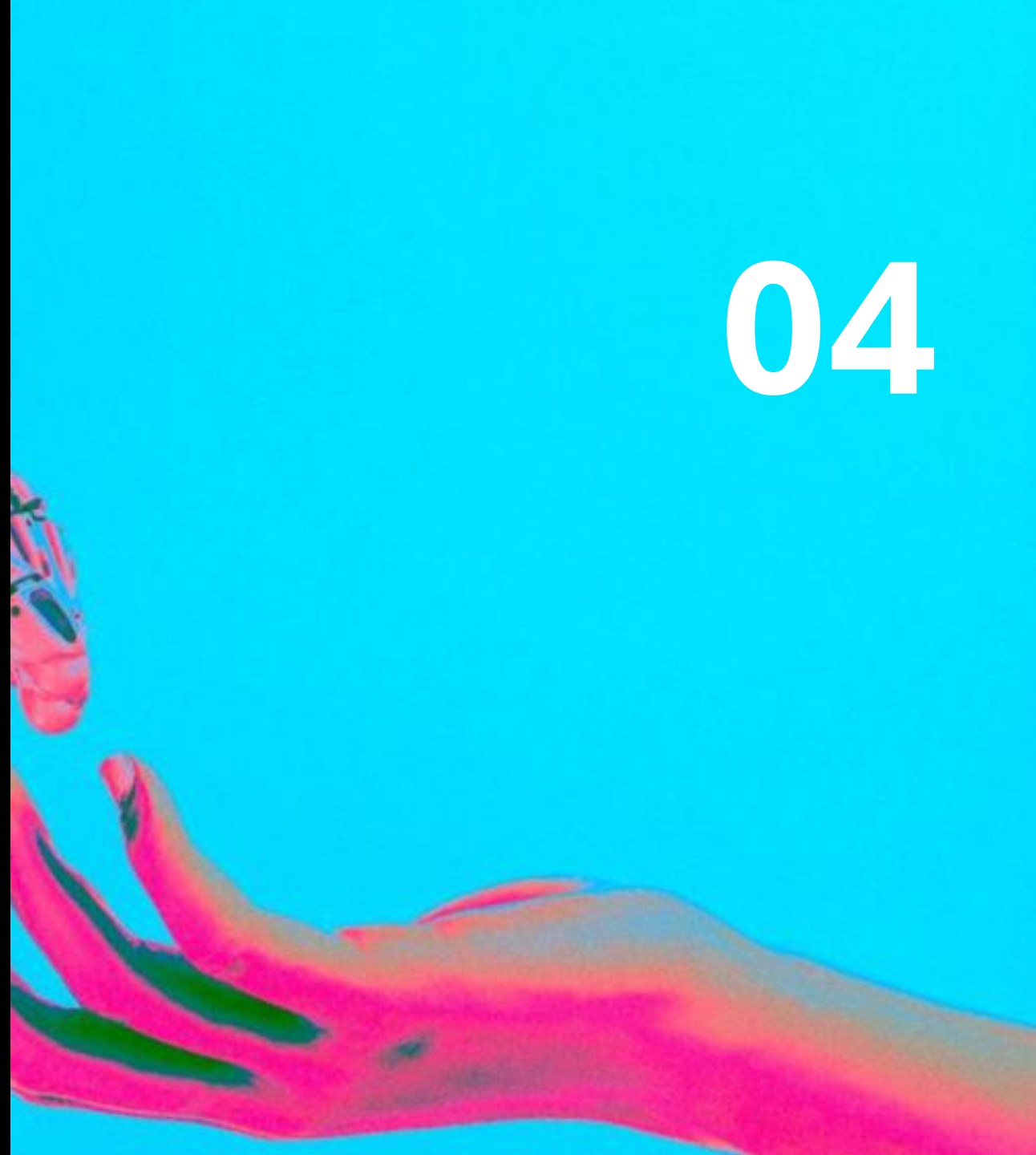
# STATISTICAL USEFULNESS OR FORMAL PRIVACY? THERE IS NO FREE LUNCH.



„We show that getting formal privacy guarantees for more realistic synthetic data models is significantly harder.“

MEANING

04





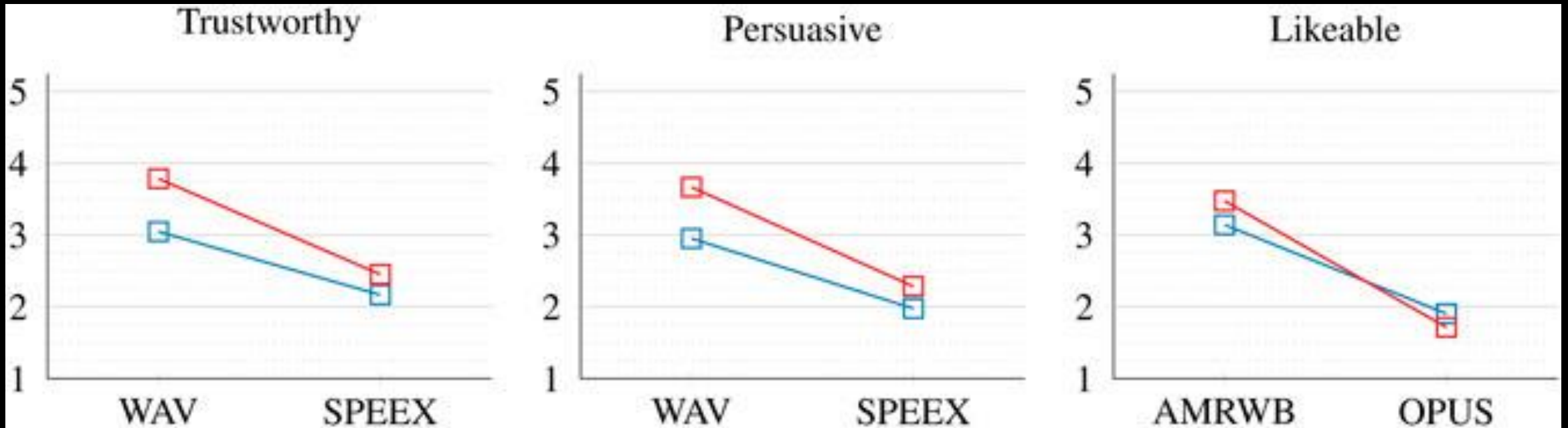
39%

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

89%

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 (—■—).

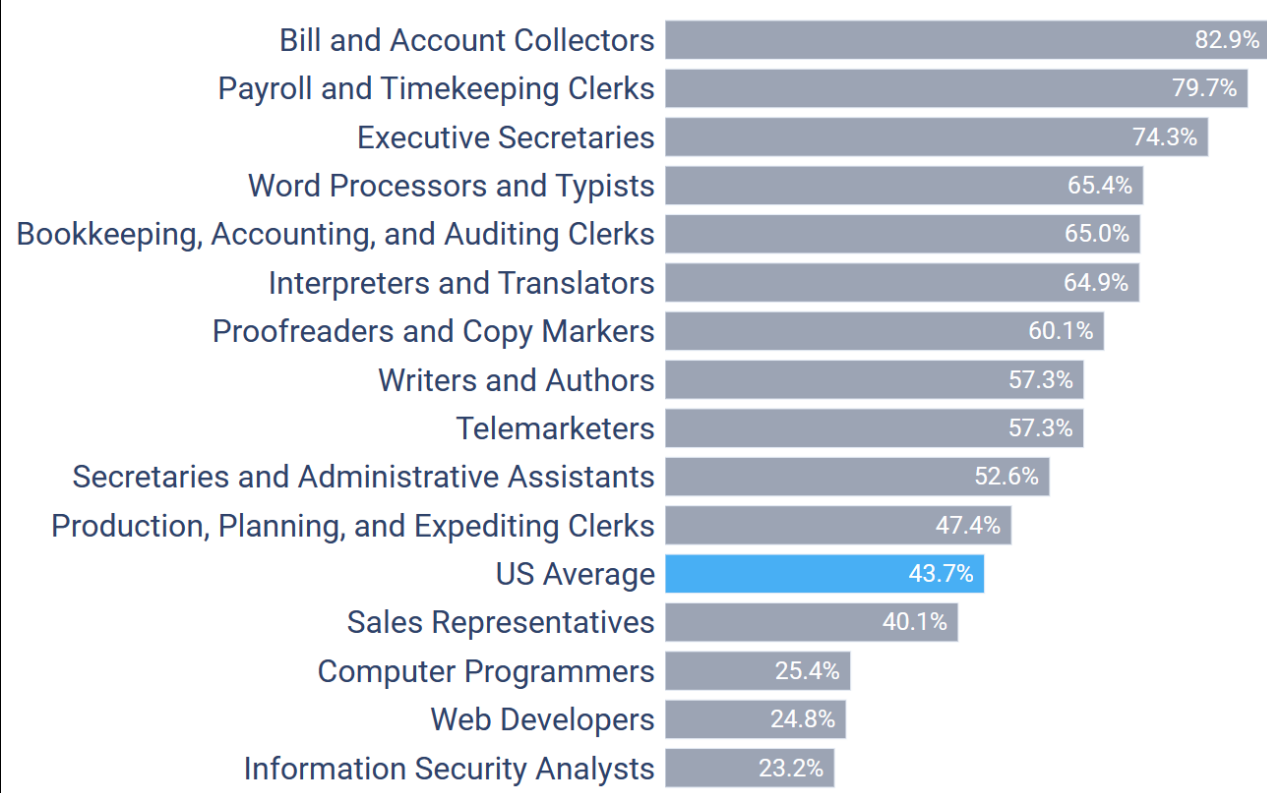
# SUPPORT THE BOSS' PRIORITY WITH AI: MORE DIVERSITY AND FAIRNESS?



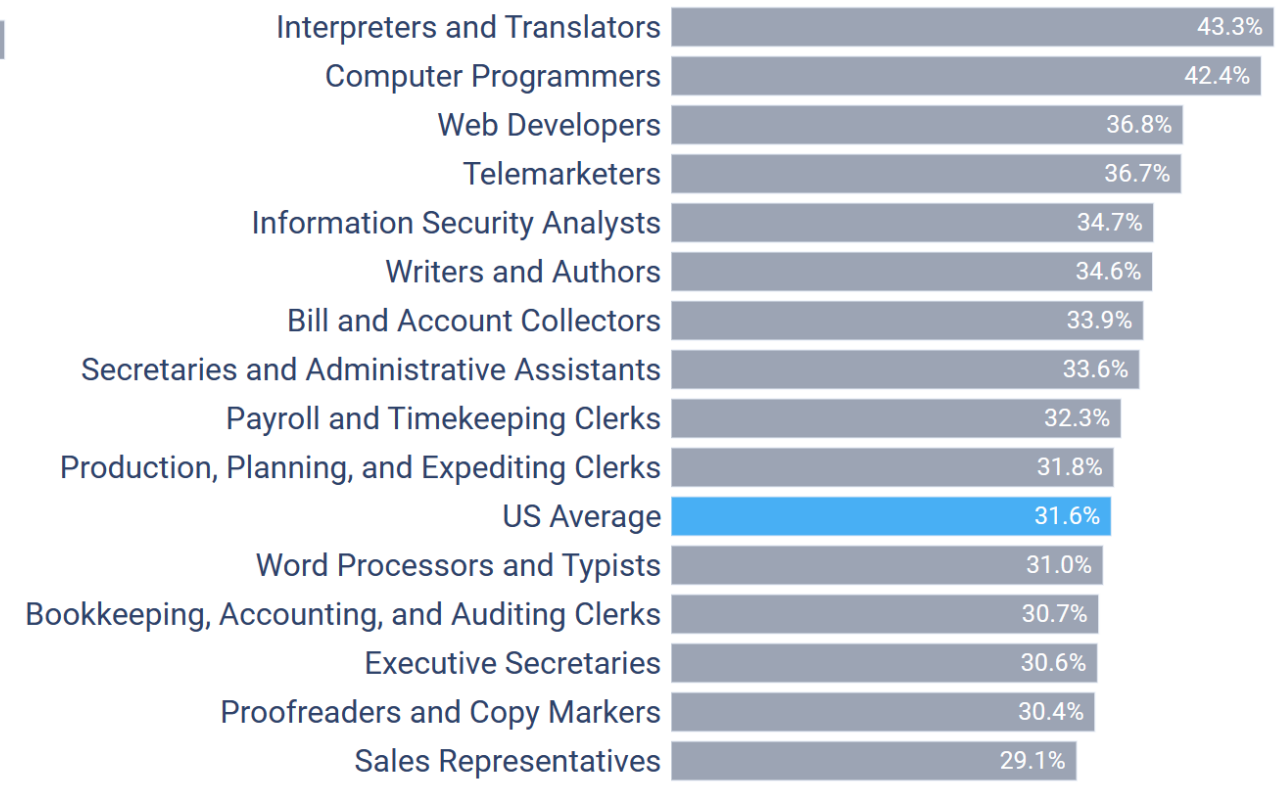
**Chef-Sache!**

# AI ENDANGERS JOBS WITH A HIGH PROPORTION OF WOMEN AND MINORITIES

Percentage of women in AI-exposed positions



Percentage of people of color in AI-exposed positions

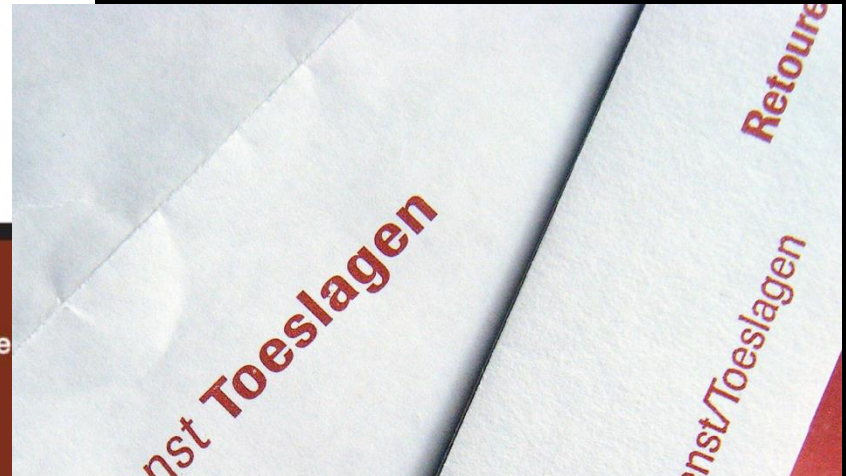


NICK WALLIS  
**THE GREAT  
POST OFFICE  
SCANDAL**  
The fight to expose a multimillion  
pound IT disaster which put innocent  
people in jail



Report

Royal Commission into the Robodebt Scheme



# ALGOOCRACY: HOW GOVERNMENT BY ALGORITHMS FAILED



# DECODING ERRORS (GARBAGE OUT): OVERTRUST IN THE RESULTS

**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.

A night sky with a red horizontal band across the middle containing white text. The sky is dark blue with many small white stars. The red band is a solid, vibrant red. The text is in a bold, white, sans-serif font.

# THINKING FAST: PATTERNS, SIGNALS, CAUSALITY

# WHEN STATISTICAL ILLITERACY MEETS GENERATIVE AI



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



BILD-KI



INFOS ZU BILDPLUS



DEBATTE



WETTER



BILDPLAY



MARKTPLATZ



ZEITUI

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

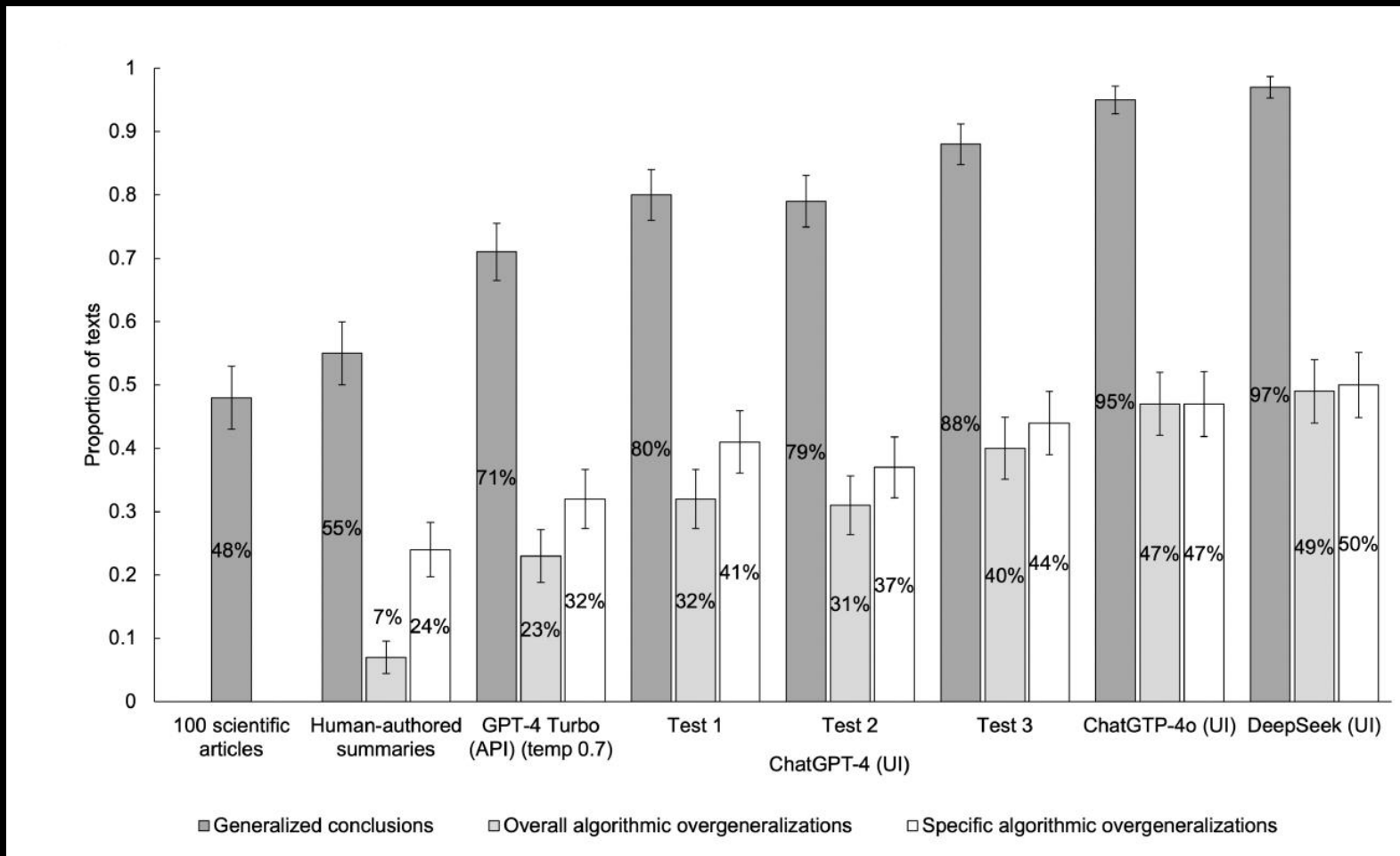
# DAS sind die gefährlichsten Straßen Deutschlands

3 in Hannover, 2 in Hamburg, 2 in Berlin

„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



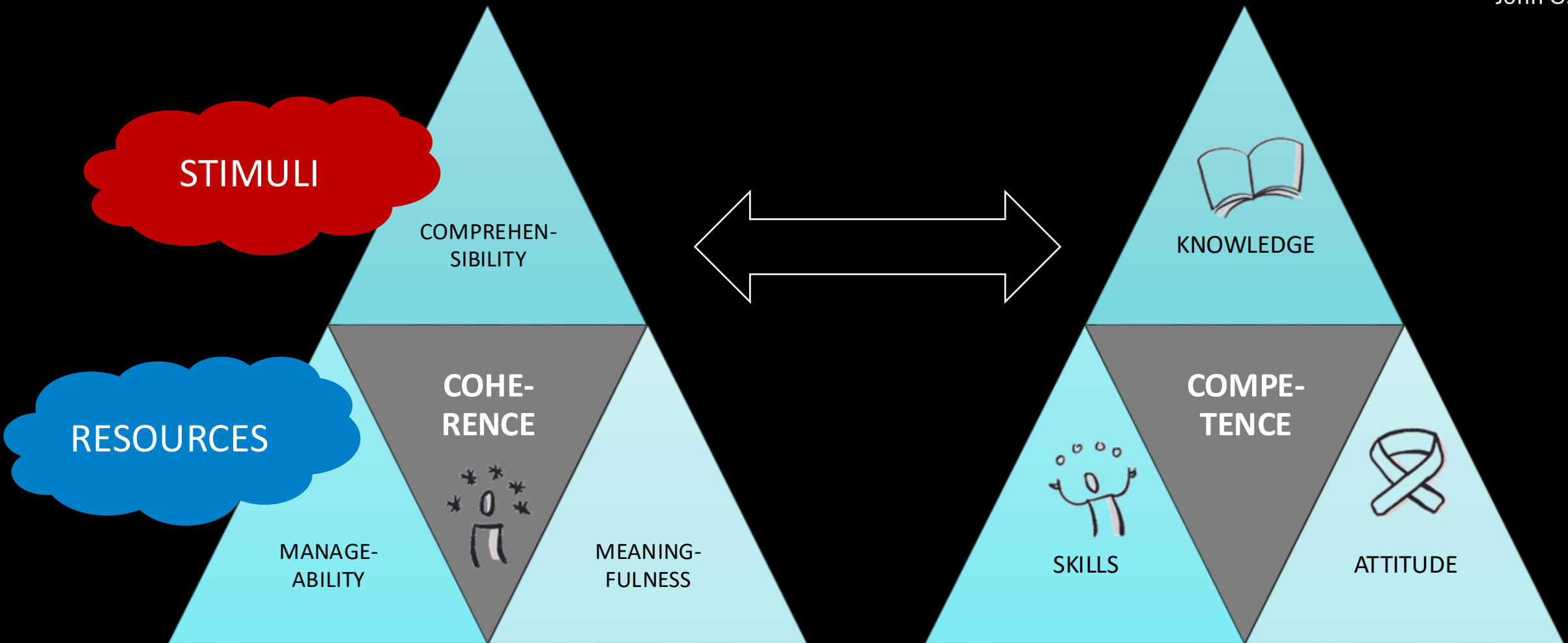
„Our results indicate a strong bias in many widely used LLMs towards overgeneralizing scientific conclusions, posing a significant risk of large-scale misinterpretations of research findings.“



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

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

John C. Havens

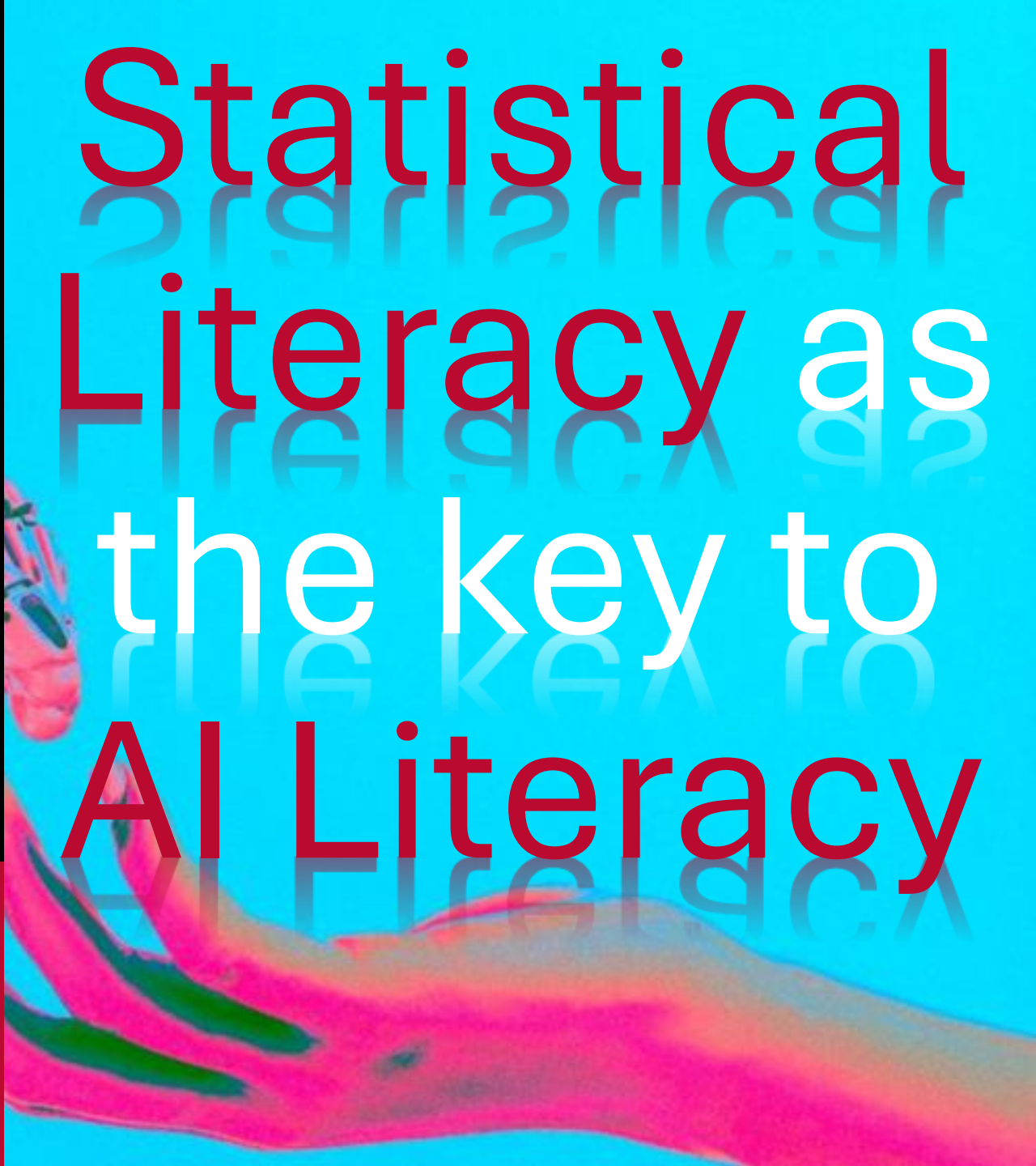


Antonovsky (1987): Unraveling the mystery of health. How people manage stress and stay well.

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

# Bridging the GAP (Part 3)

10. March 2026 | Dr. Katharina Schüller  
katharina.schueller@stat-up.com

A hand holding a pen over a document with statistical text. The background is a light blue gradient with a faint image of a hand holding a pen over a document. The text is overlaid on this background.

Statistical  
Literacy as  
the key to  
AI Literacy

LITERACY

05



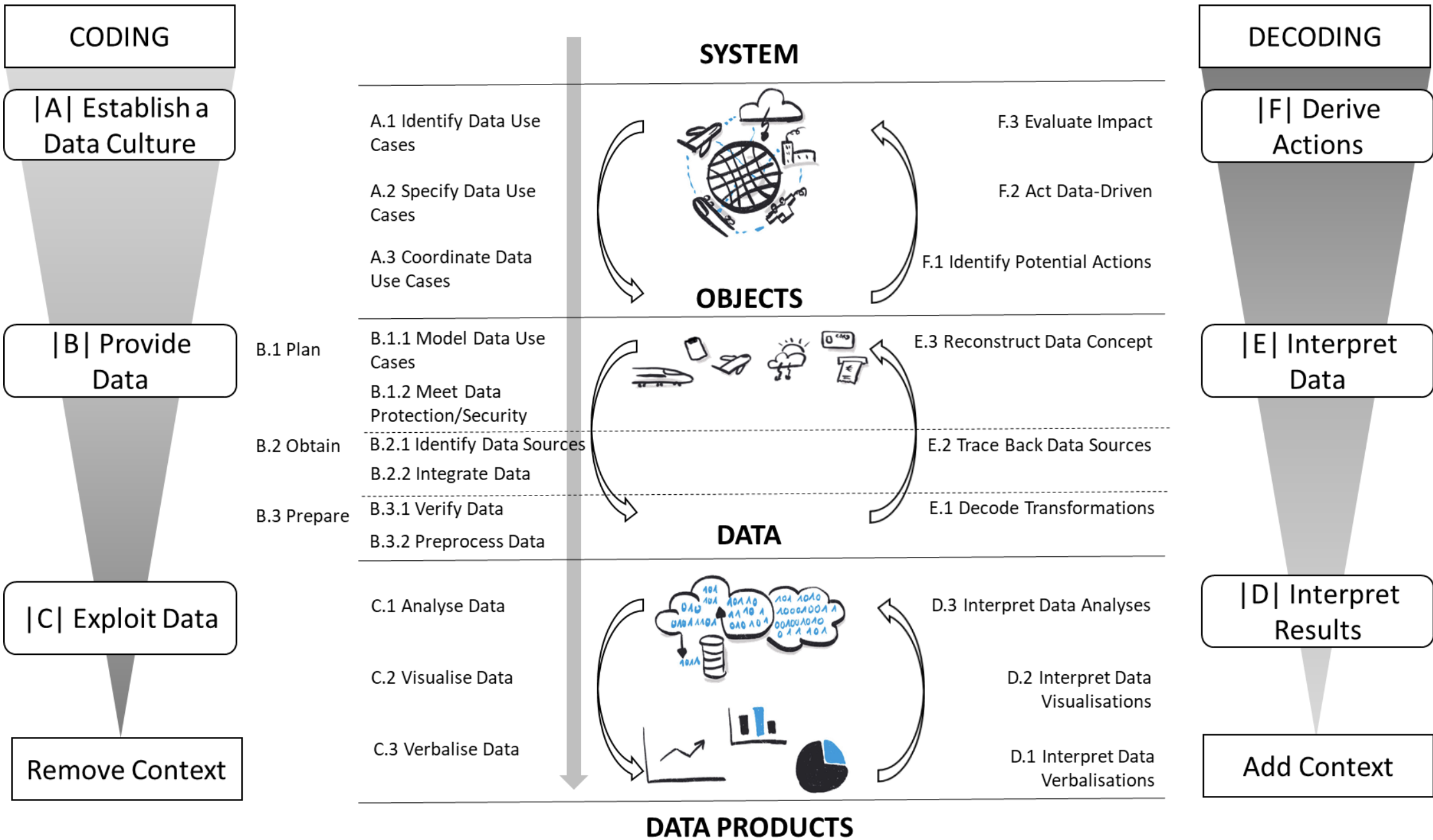
# DIGITAL INTELLIGENCE (DQ): IEEE 3527.1



- 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**



# 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



# DATA LITERACY CHARTA<sup>®</sup>

**Together with numerous partners**, the Stifterverband jointly initiated the Data Literacy Charter in January 2021. It formulates a common understanding of data literacy and its importance for educational processes. The Charter is in line with the German Federal Government's data strategy and with the Berlin Declaration on the Digital Society.

*Auhors:*

*Katharina Schüller, Henning Koch, Florian Rampelt*

Swiss Data Literacy  
Charter

[swiss-academies.ch](http://swiss-academies.ch)

2021: GERMAN DATA LITERACY CHARTER  
2025: SWISS DATA (& AI) LITERACY CHARTER

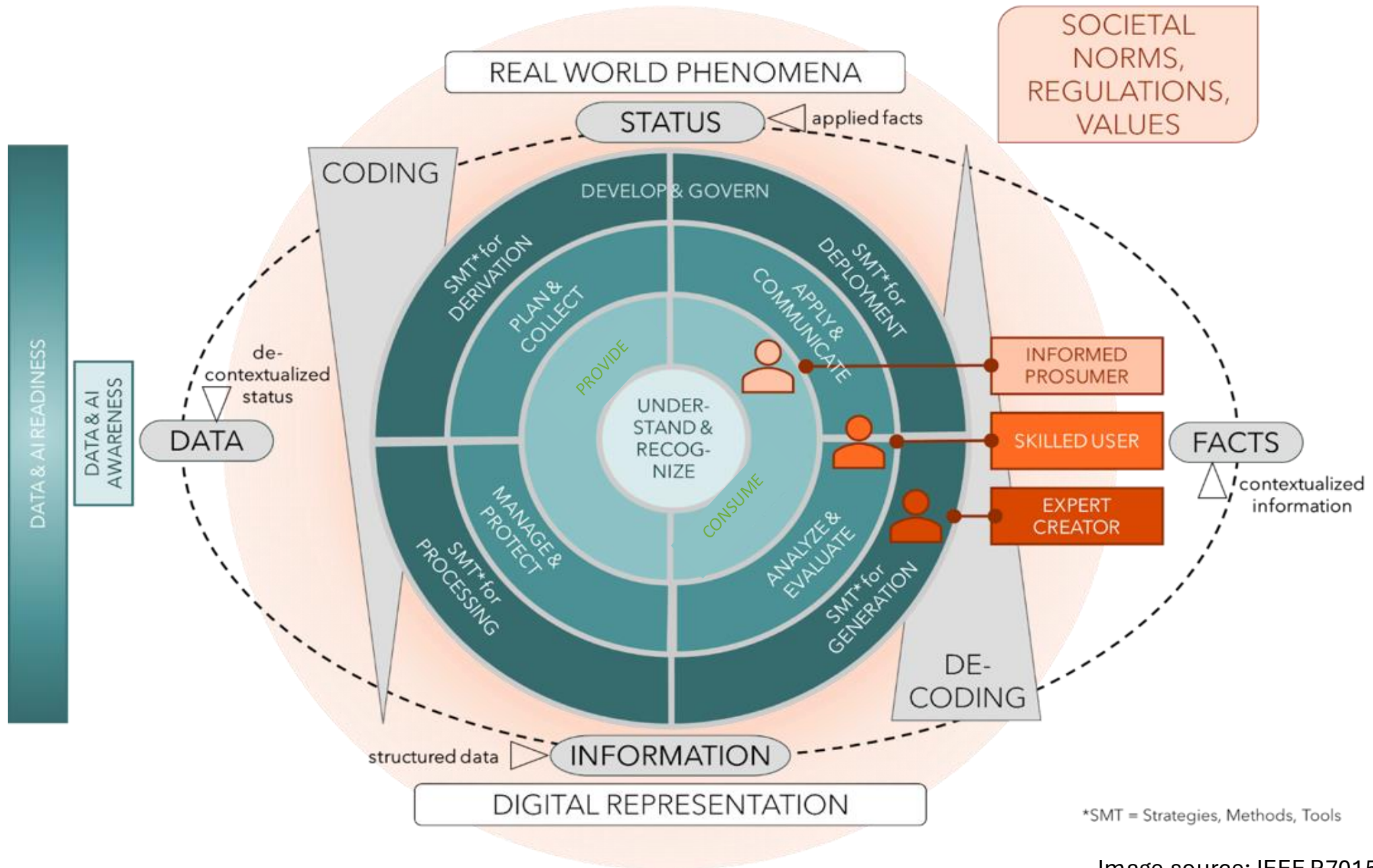


Image source: IEEE P7015 Draft Standard

# 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

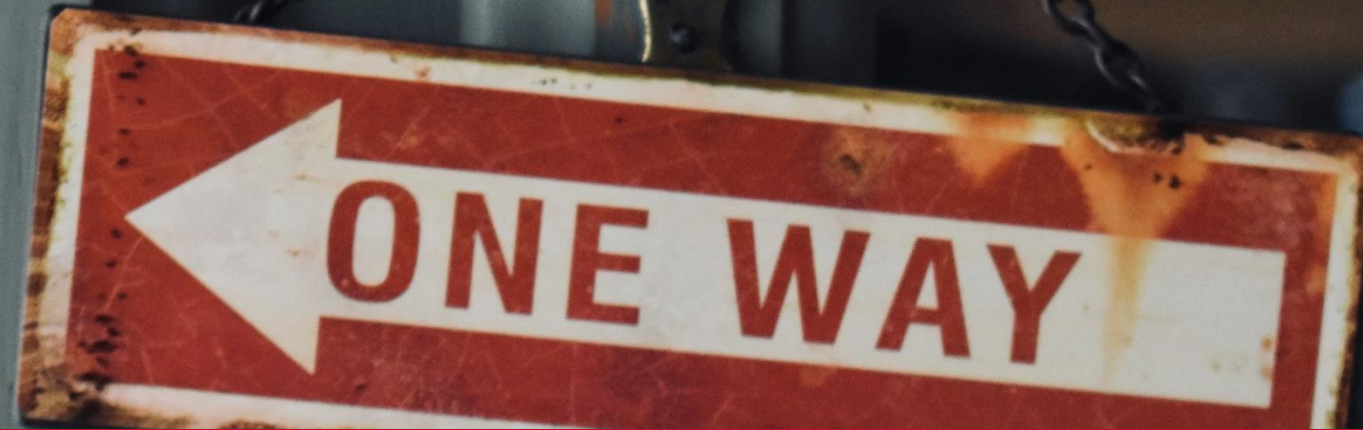
Manage and protect

I properly prepare data to **identify and correct errors and biases**, ensure quality, and improve the value of analyses.



# BOLD PROMISES OR STARK REALITY: EVALUATING AI TOOLS

Image Source: kind and curious | Unsplash



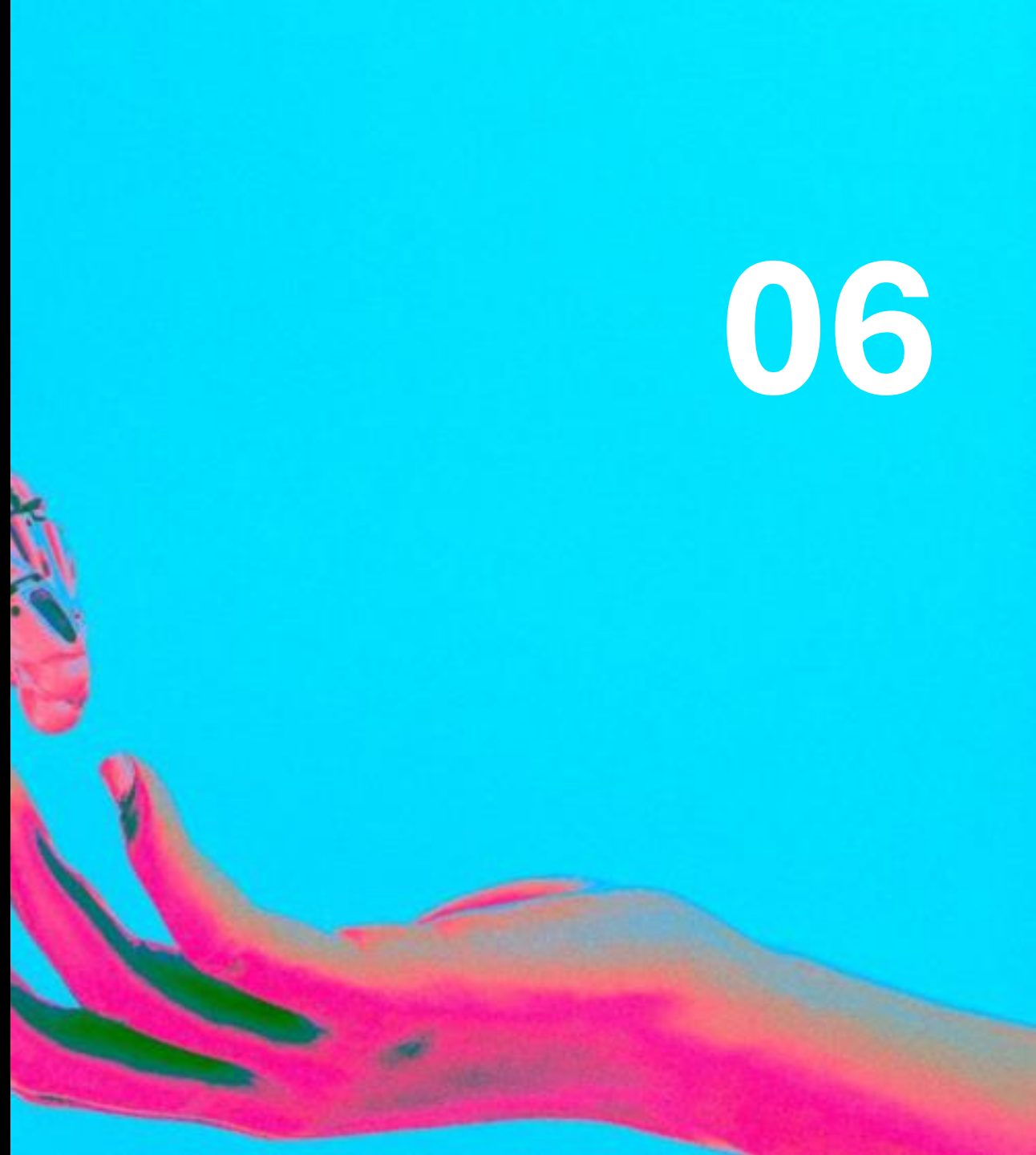
**UNCERTAINTY IS HARDER TO SELL  
THAN CERTAINTY**



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

POWER

06





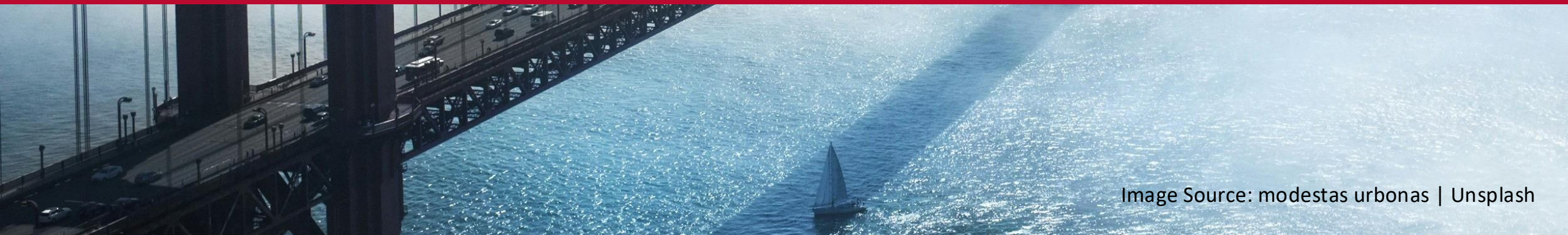
“IT FEELS LIKE THOSE PEOPLE UP THERE ARE WORKING AGAINST US”







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



# BEFORE DATA CLEANING: NEGATIVE INSPECTION (Y/N)

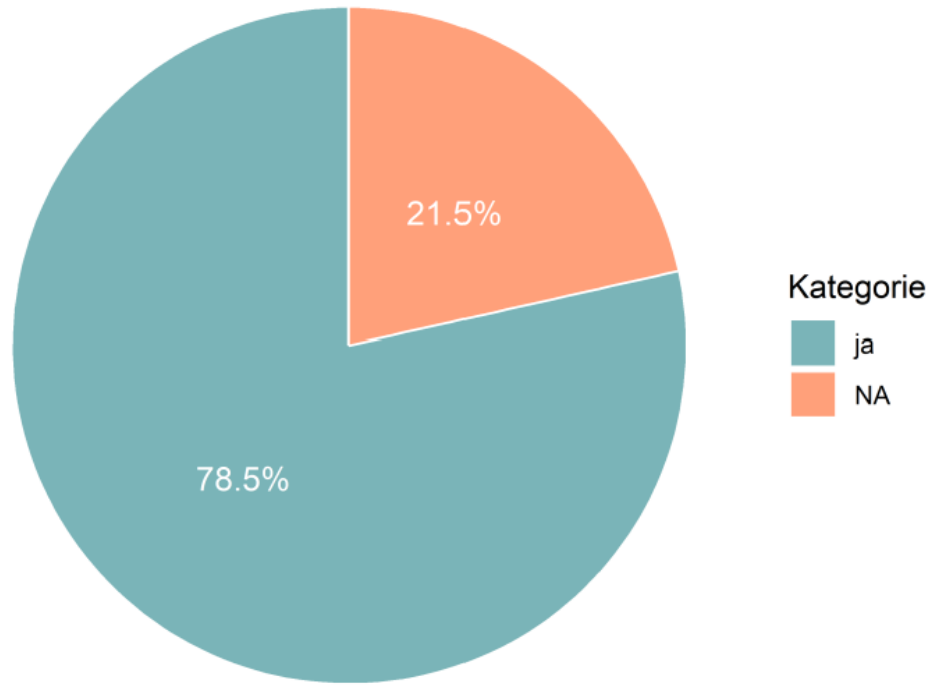
---

<b>Negativkontrolle</b>	<b>Anzahl</b>
JA	258.677
ja	78.452
NA	5.075
NEIN	9.531
Nein	29.079
ja	150
nein	3.071

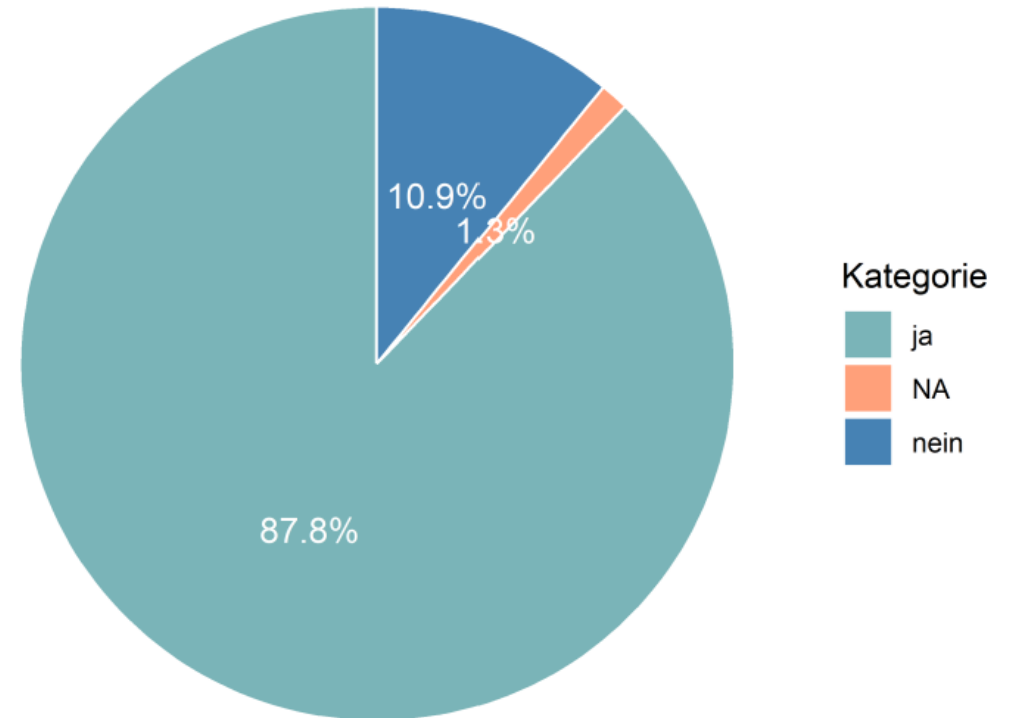
---

# AFTER DATA CLEANING: RESULTS FROM DIFFERENT SYSTEMS

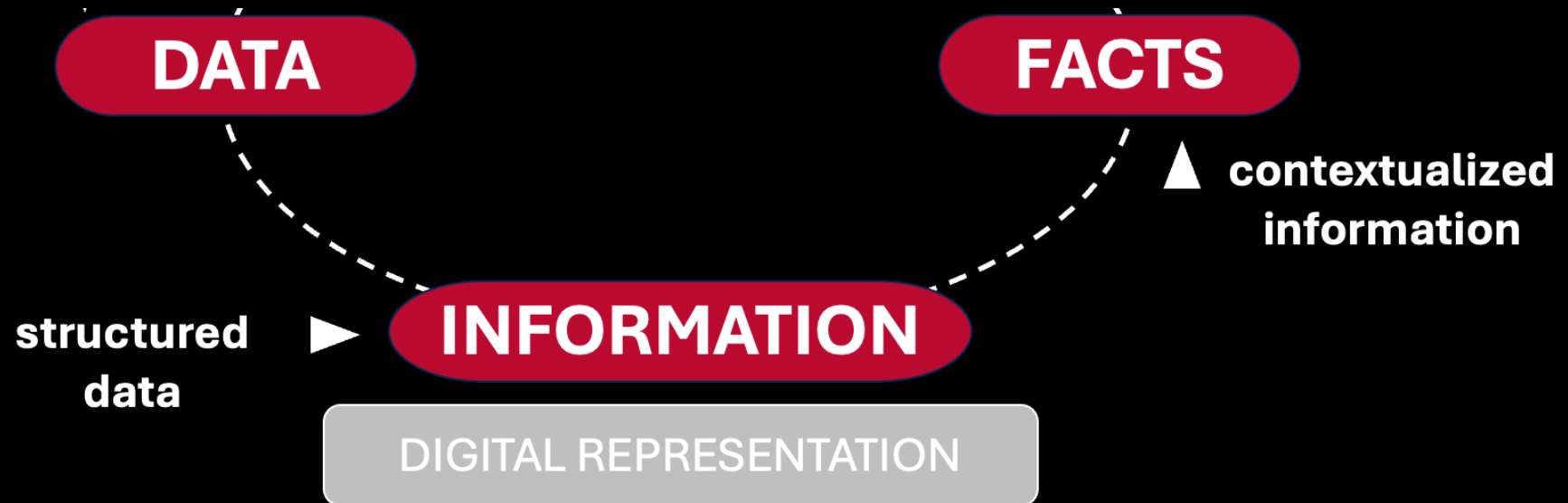
## Web Form



## Upload



# INVESTIGATE DIGITAL REPRESENTATIONS: WHAT DETERMINES DATA QUALITY?





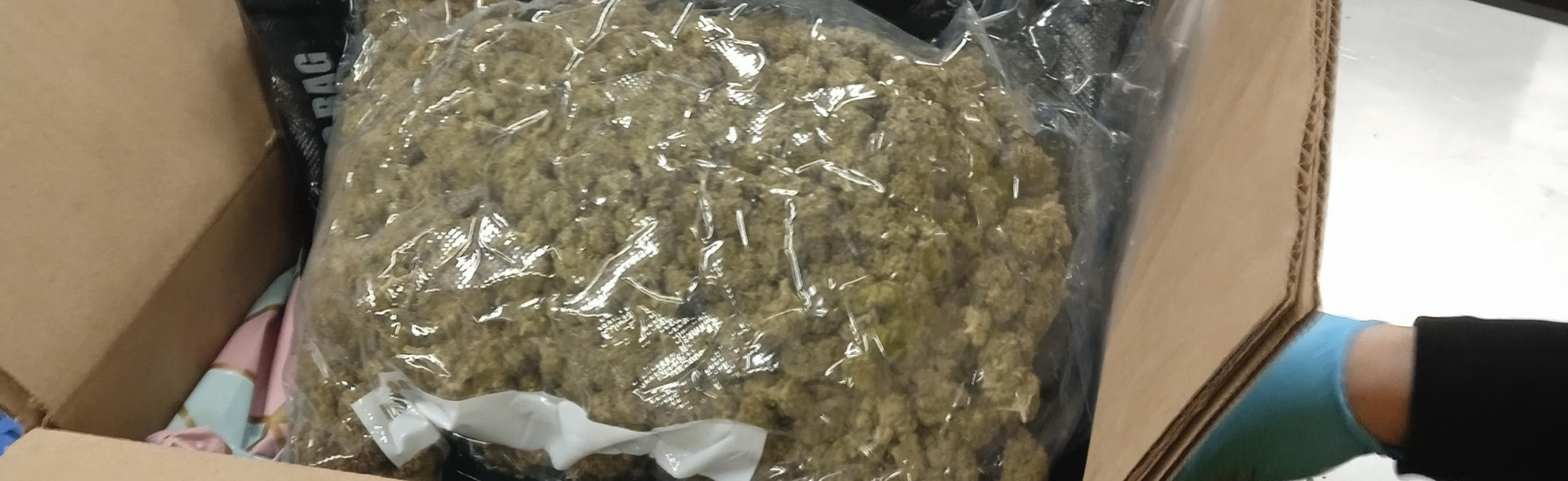
**WHAT THE STATISTICIANS THOUGHT:  
IT WILL TAKE SOME EFFORT TO FIX THE DATA**



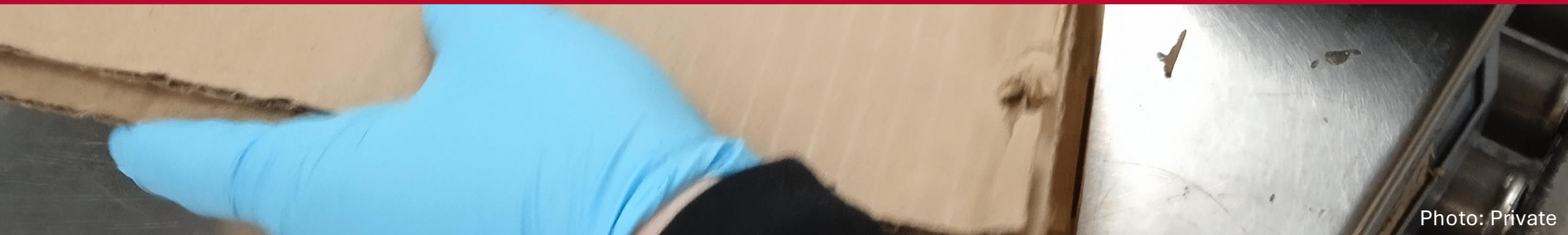


STAGE 1:  
„RISK SCORE“ = PROBABILITY

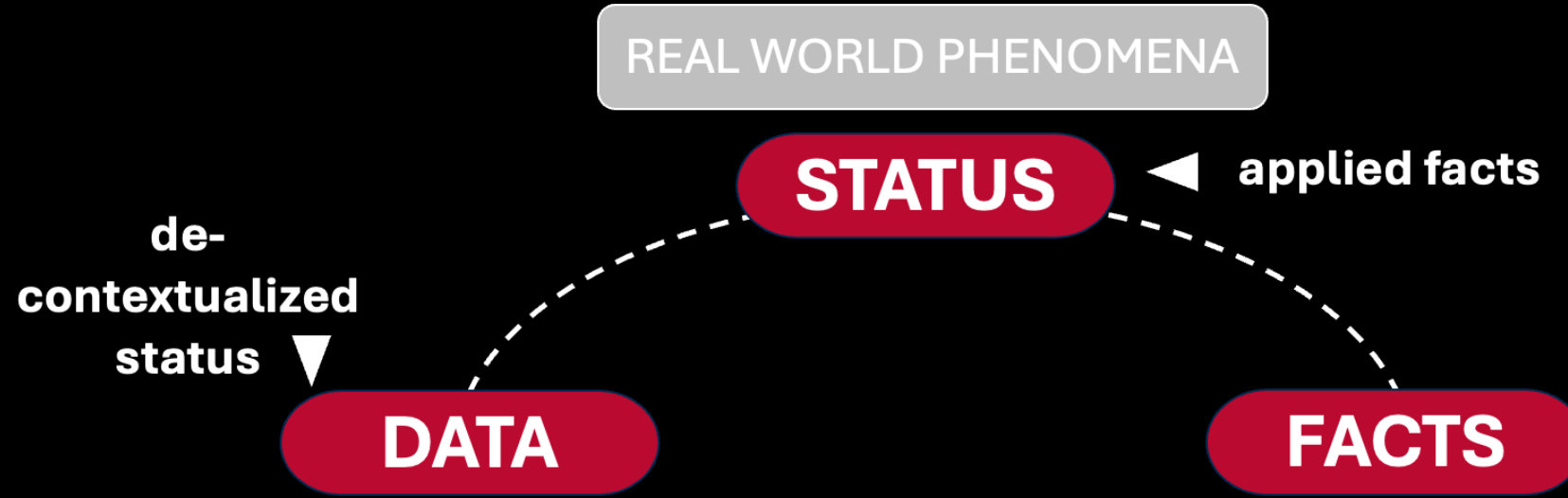




**STAGE 2:  
„RISK SCORE“ = INTUITION**



# INVESTIGATE REAL WORLD PHENOMENA: WHAT DETERMINES HUMAN BEHAVIOR?





**„RISK“ IS AN INPUT FOR, NOT AN OUTPUT OF  
STATISTICAL ANALYSIS**



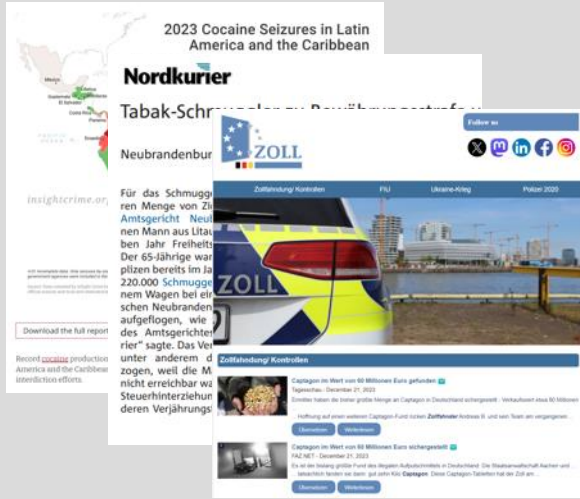
**WHAT THE CUSTOMS OFFICERS THOUGHT:  
THE DATA IS COMPLETELY USELESS**



**WHO IS RESPONSIBLE FOR THE  
DYSFUNCTIONALITY OF THE SYSTEM?**

(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



## Web scraping

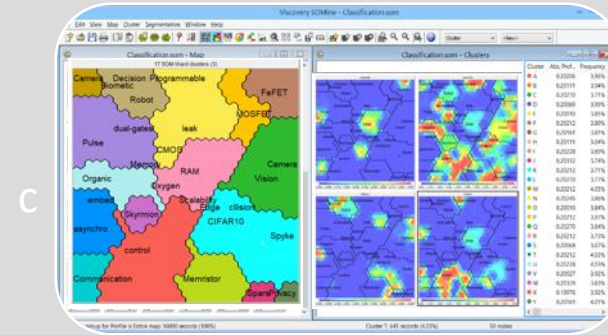
Data Sources:  
Press review, Google Alerts,  
incoming reports from  
various channels

## AI-SUPPORTED SITUATION ANALYSIS

Datum	URL	E1	E2	E3	E4
12.03.2024	https://www.nordkurier.de/...	-0.0068	0.0095	-0.0063	-0.0039
12.03.2024	https://www.suedde.de/...	-0.0074	0.0015	-0.0055	-0.0200
12.03.2024	https://www.allgemeine.de/...	-0.0159	-0.0280	0.0030	-0.0206
12.03.2024	https://www.aachener.de/...	-0.0302	-0.0017	-0.0080	-0.0372
12.03.2024	https://www.idoweb.de/...	-0.0186	-0.0133	-0.0220	-0.0045
13.03.2024	https://www.abendblatt.de/...	-0.0413	-0.0014	-0.0018	-0.0262
12.03.2024	https://www.spiegel.de/...	-0.0284	0.0054	0.0145	-0.0037
26.03.2024	https://www.suedde.de/...	-0.0142	0.0238	-0.0153	-0.0222
21.12.2023	https://www.tagesschau.de/...	-0.0128	0.0058	0.0013	-0.0301

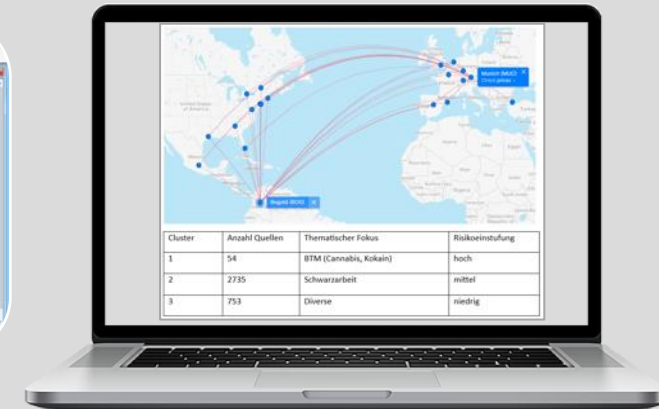
## Transformers

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

AI is POWER.

STATISTICAL LITERACY

can help us use it

RESPONSIBLY.