Applied Data Science Project
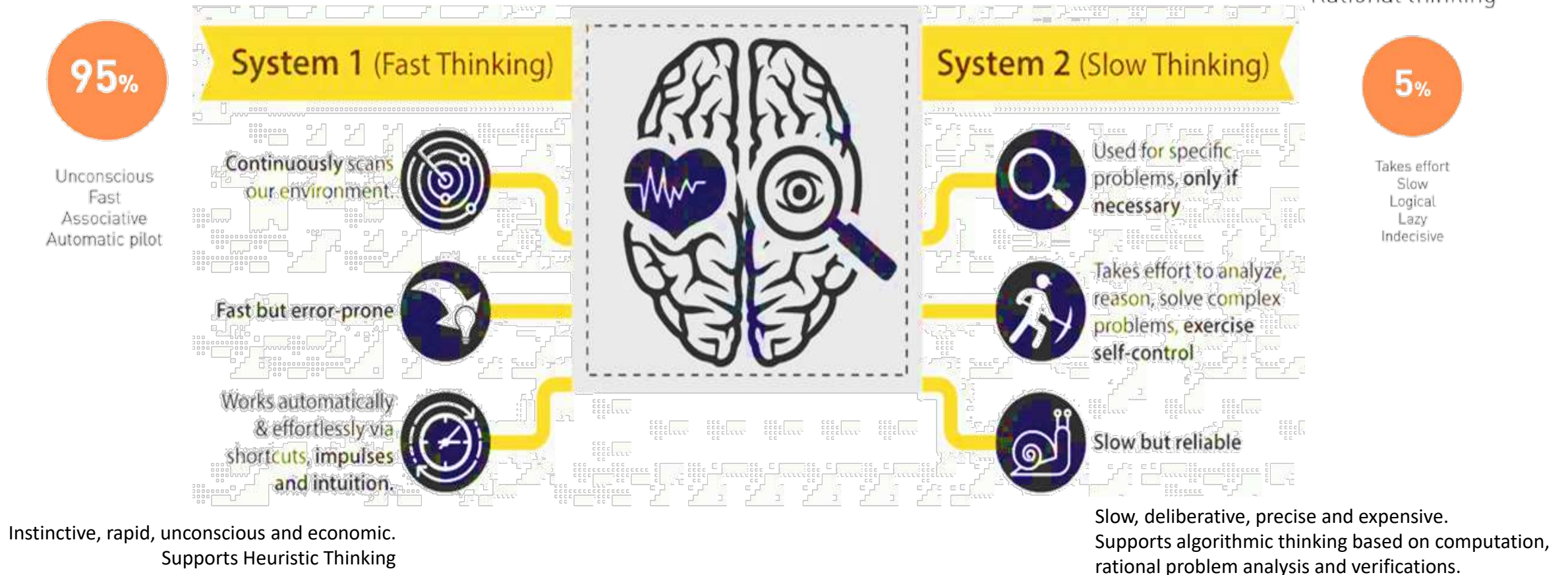
L22 – Biases, Stereotypes and Personas

2 cognitive systems

Intuition & instinct

Rational thinking

95%

Unconscious
Fast
Associative
Automatic pilot

5%

Takes effort
Slow
Logical
Lazy
Indecisive

System 1 (Fast Thinking)

Continuously scans our environment.

Fast but error-prone

Works automatically & effortlessly via shortcuts, impulses and intuition.

System 2 (Slow Thinking)

Used for specific problems, **only if necessary**

Takes effort to analyze, reason, solve complex problems, exercise self-control

Slow but reliable

Instinctive, rapid, unconscious and economic.
Supports Heuristic Thinking

Slow, deliberative, precise and expensive.
Supports algorithmic thinking based on computation,
rational problem analysis and verifications.

The conflict between the two systems causes our systematic errors
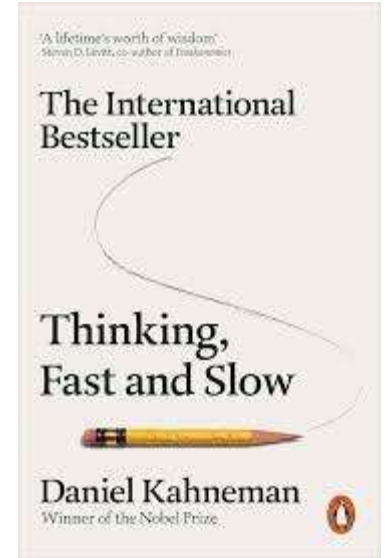(BIAS)

2 cognitive systems

*"This is the essence of intuitive heuristics:
when faced with a difficult question,
we often answer an **easier one** instead, usually without
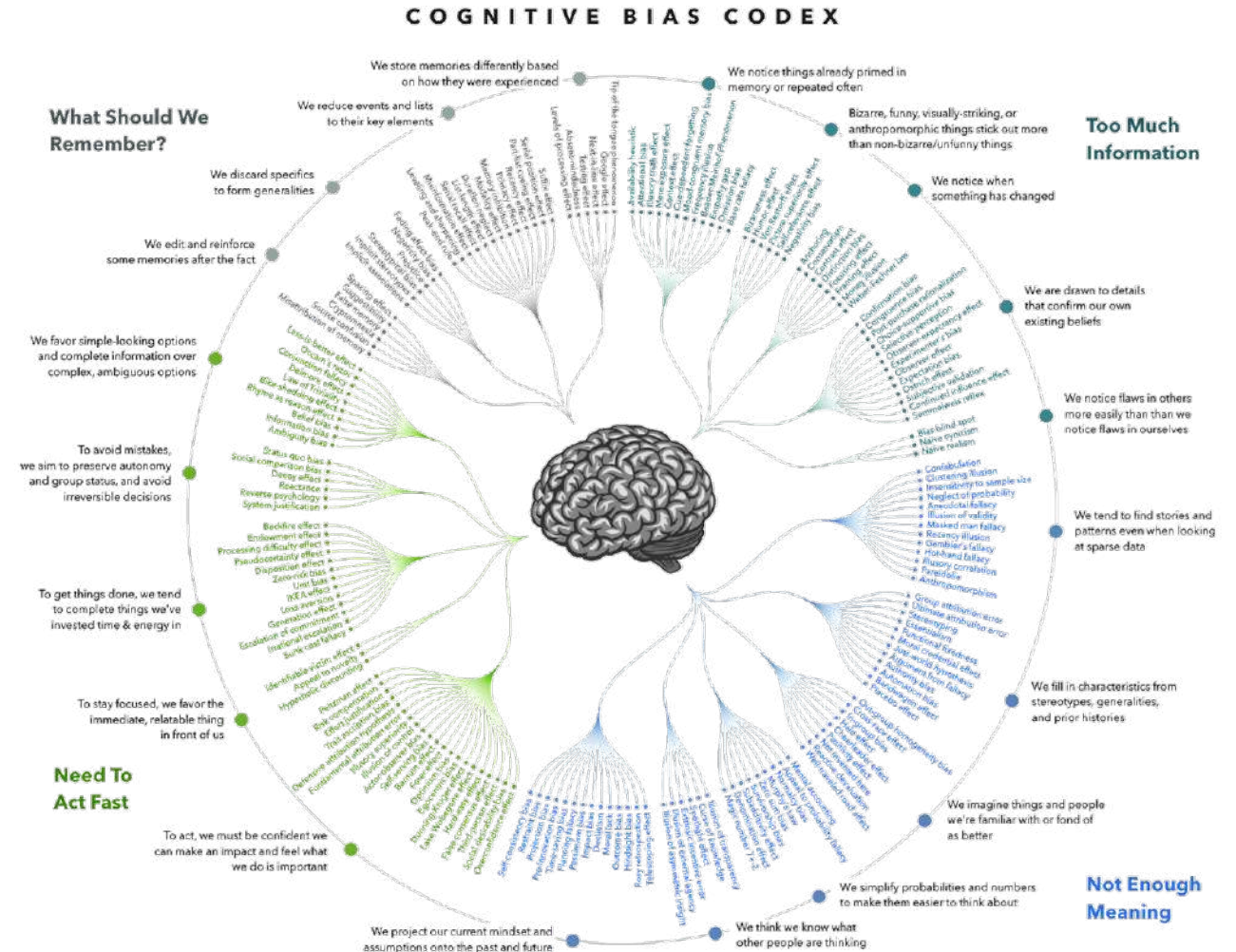noticing the substitution."*

Daniel Kahneman, Thinking, Fast and Slow

Worth reading

Daniel Kahneman.
Nobel prize for Economics, 2002
Pensieri lenti e veloci. Mondadori, 2019

Bias*

**Systematic errors of interpretation,
that shape our judgments,
in ways that do not correspond to reality (prejudices).**

The cognitive biase are based on prejudices or emotional states, and **reinforced by the characteristics of the information**:
- excess of information
- lack of information (COMPENSATION)

They results in **heuristics (decisions)** that may be incorrect and not adequate to the situation

COGNITIVE BIAS CODEX

DESIGNHACKS.CO · CATEGORIZATION BY BUSTER BENSON · ALGORITHMIC DESIGN BY JOHN MANOOGIAN III (JM3) · DATA BY WIKIPEDIA

The most common biases

Confirmation bias
the most common unconscious mechanism
to find evidence (select, accept data) in favour of our opinion
and repulsion towards the unknown (echo chambers)

Exposure effect
confidence in data that are available or that we've been
recently exposed

Outcome bias
we make decisions only on past experiences
«**we have always done in this way**»

Polarization pattern
tendency to see significant data relationships, even when
values are random (we are wired to see models even where do
not exist)

T 05 - Valutazione

The most common biases

PROPORTIONALITY BIAS

OUR TENDENCY TO BELIEVE THAT...

BIG EVENTS   must have   BIG CAUSES

SHAKE   SHAKE   SHAKE
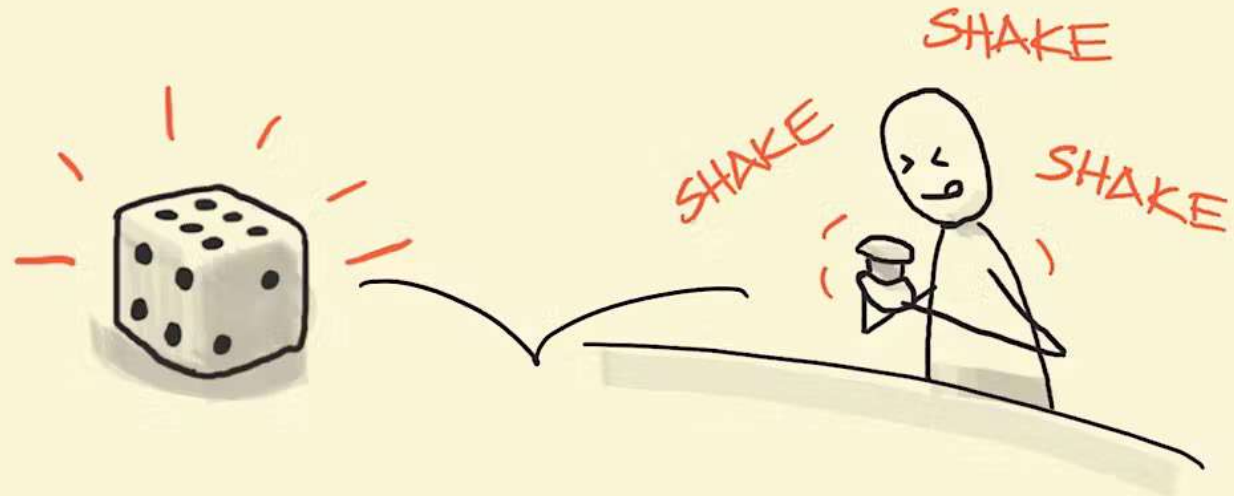
ONE DRIVER OF CONSPIRACY THEORIES

sketchplanations

The most common biases
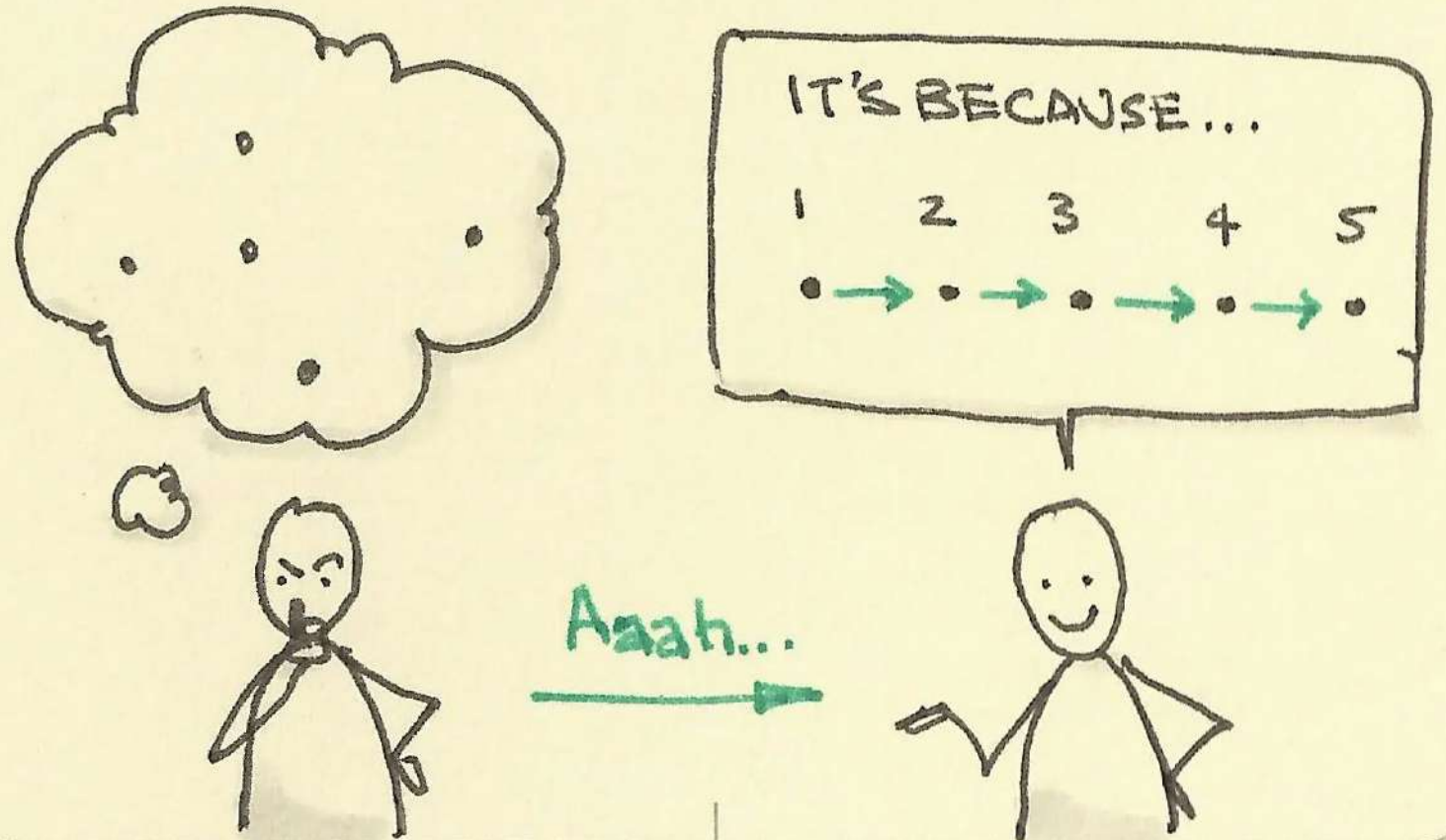
Most common biases

Automation bias

our tendency to favour outputs generated by automated systems and to ignore contradictory information made by non-automated systems, even when correct.

Defect of knowledge

we attribute the same degree of our knowledge on the topics in question

Stereotypes

rigid and generalised opinions, not based on direct experience and regardless of the assessment of individual cases)

It can result in certain subgroups of the population less likely to be represented in the data and outpusts.

Compensation mechanisms

We all tend to **group data, info, events into categories** to make sense of the abundant flow of information we are surrounded by.

Resignation effect

It happens when, in front of a large amount of information difficult to critically evaluate, people feel overwhelmed and **give up trying to distinguish between accurate information and misinformation**.

Over time, it decreases the self-confidence in recognizing disinformation.

SCIENCE ADVANCES | RESEARCH ARTICLE

PUBLIC HEALTH

AI model GPT-3 (dis)informs us better than humans

Giovanni Spitale, Nikola Biller-Andorno, Federico Germani*

Artificial Intelligence (AI) is changing the way we create and evaluate information, and this is happening during an infodemic, which has been having marked effects on global health. Here, we evaluate whether recruited individuals can distinguish disinformation from accurate information, structured in the form of tweets, and determine whether a tweet is organic or synthetic, i.e., whether it has been written by a Twitter user or by the AI model GPT-3. The results of our preregistered study, including 697 participants, show that GPT-3 is a double-edge sword: in comparison with humans, it can produce accurate information that is easier to understand, but it can also produce more compelling disinformation. We also show that humans cannot distinguish between tweets generated by GPT-3 and written by real Twitter users. Starting from our results, we reflect on the dangers of AI for disinformation and on how information campaigns can be improved to benefit global health.
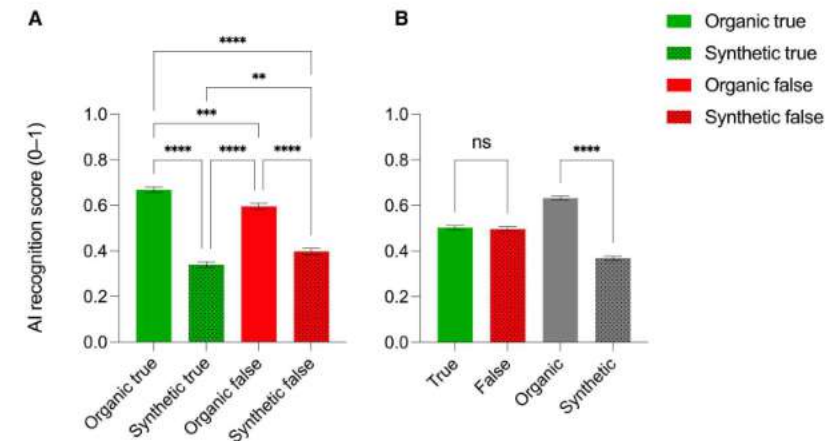

Fig. 3. Human respondents cannot distinguish organic versus synthetic tweets but recognize their origin better when they are generated by Twitter users. (A) AI recognition score for organic true (green bars), synthetic true (green dotted bars), organic false (red bars), and synthetic false (red dotted bars) tweets. AI recognition score (0 to 1) indicates the probability that human respondents can identify whether a tweet is produced organically (i.e., by a Twitter user) or synthetically (i.e., by GPT-3). Human respondents recognize whether organic true tweets are organic or synthetic tweets more effectively than all other type of tweets, whereas synthetic true tweets are recognized correctly the least. (B) Human respondents cannot predict whether true or false tweets (i.e., accurate tweets or disinformation tweets, green versus red bars) are produced by Twitter users or by GPT-3, and the truthfulness of the information does not have an impact on the AI recognition score. Regarding organic versus synthetic tweets (grey versus grey dotted bars), human respondents recognize whether tweets are generated by humans or GPT-3 better when they are organic (i.e., generated by Twitter users), when compared with synthetic tweets (i.e., generated by GPT-3). The AI recognition score (0 to 1) is the average score for all 697 respondents (1, 100% correct answers; 0, 0% correct answers); ordinary one-way ANOVA multiple-comparisons Tukey's test, $n = 697$; ns, $P > 0.05$; **$P < 0.01$, ***$P < 0.001$, and ****$P < 0.0001$. Bars represent SEM.
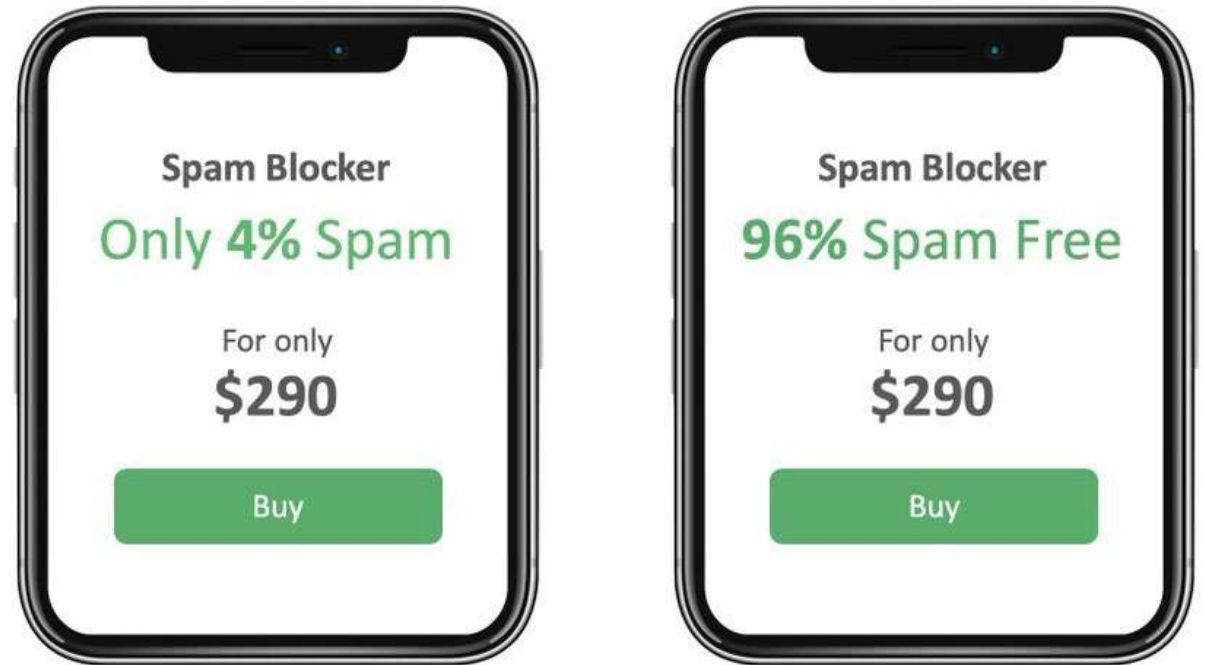
Framing effect

It concerns how information is presented.
Since the context determines our choices,
we are influenced by the way in which options are proposed.

Which is your preference?

Which is your preference?

Framing effect

It concerns how information is presented.
Since the context determines our choices,
we are influenced by the way in which options are proposed.

Framing effect in communication

Hospital reports in the US show mortality rates, while survival rates in the UK

**Death rate
of a surgical procedure
5%**

**Survival rate of a
surgical procedure
95%**

**20 deaths out of 400
patients who underwent
surgery**

The phenomenon quantified is the same,
but the way it is offered changes our risk perception

What's the worst?
What's the difference?

Biases in the design and development process

Sampling bias

It occurs when the data collection process affects the composition of the sample and distorts the results.

Selection bias: the sample differs systematically from the reference population

Self-bias : when people that design/develop and assess the solution coincide

Clustering bias

when we confuse small coincidences within a small dataset as a commonality.

- We find a small trend in a sea of possibilities
- We assume that it is a widespread phenomenon within our data sets.

Doubts, risks, countermeasures and explanations should be included in the METHODOLOGICAL NOTE accompanying the datasets

We all, as users and developers, have in common cognitive characteristics:

- **We don't see everything**

- **Our search for meaning can conjure illusions.** We complete the missing data with assumptions

- **Quick decisions can be seriously flawed.**
  Some of the quick reactions and decisions we jump to are unfair, self-serving, and counter-productive.

- **Our memory reinforces errors.**
  Some of the stuff we remember affects how we select information and take decisions.

- **Information overload** sucks, so we aggressively filter. Noise becomes signall.

- **Lack of meaning** is confusing, so we fill in the gaps. Signal becomes a story.

- **Stories become decisions**.This isn't getting easier, so we try to remember the important bits.

Algorithmic bias

When the algorithm favours some results over others,
it often reinforces **privileges** held by dominant social groups.

"*Bias in algorithms can emanate from **unrepresentative or incomplete** training data or the reliance on flawed information that reflects **historical inequalities**. If left unchecked, biased algorithms can lead to decisions which can have a **collective, disparate impact on certain groups** of people even **without the programmer's intention** to discriminate.*"

Lee, Resnick and Barton

There is a power and **informational asymmetry** between developers and users, which end up deploying algorithms that function in a "black box" style and whose criteria and methods are unknown to users.

Algorithmic bias

- Racial prejudice in the USA in the **system of predicting the risk of recidivism to decide on a prison sentence or probation.**
ProPublica (investigative journalism agency) demonstrated the error of the algorithm (assigned twice the rate of recidivism to black people)

- Gender bias in financial services. When Apple e Goldman Sachs launched a new type of credit card, several customers noticed that the **software granted men 10 to 20 times the amount of credit**.

In both cases, the companies denied the allegations but refused to disclose the procedures and data used.

PROPUBLICA   Donate

Bernard Parker, left, was rated high risk; Dylan Fugett was rated low risk. (Josh Ritchie for ProPublica)

Machine Bias
There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica
May 23, 2016
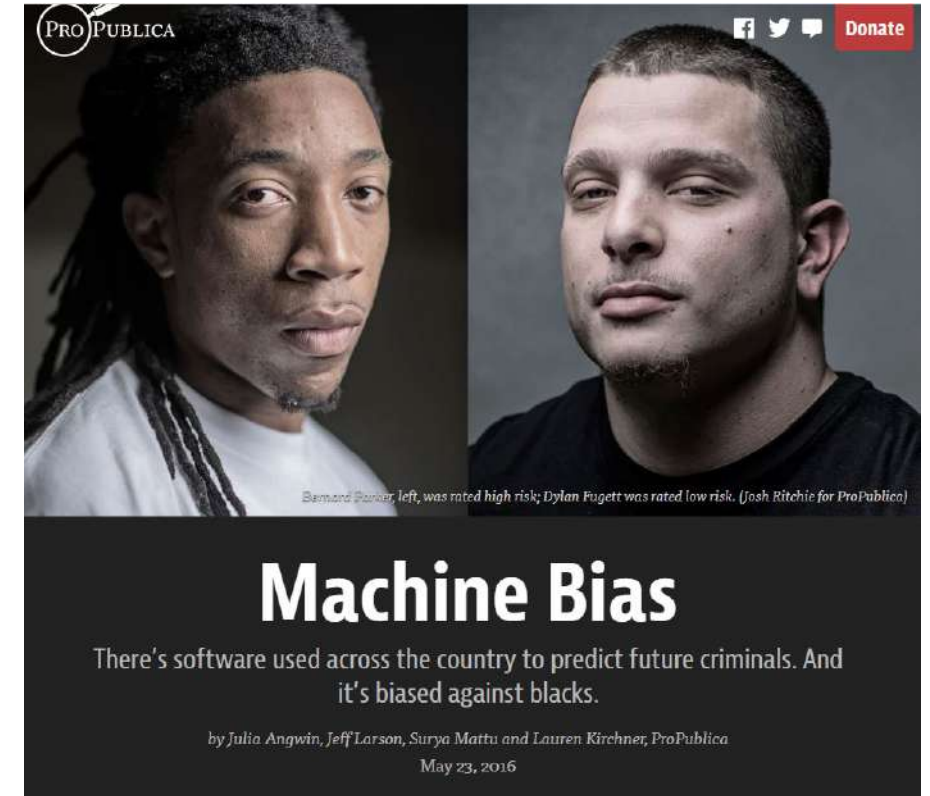
TIME

IDEAS • THE ART OF OPTIMISM

Artificial Intelligence Has a Problem With Gender and Racial Bias. Here's How to Solve It

Gender Shades

MIT Media Lab ✓
61.700 iscritti

https://youtu.be/TWWsW1w-BVo

Impacts on individuals

Disproportionately affects certain groups, without an acceptable rationale

HR → A recruitment system trained on the past hiring decisions would learn about managers' assessment criteria or preferences.

Even though discriminatory features such as ethnicity and gender are not inputted, the result may be **implicitly affected by correlation with other data**.
e.g. ethnicity and neighborhood

Or **by proxy**
e.g. performance = nr. of hours worked/week

but fault can be prevented by identifying errors and biases to create more reliable and fair systems

The combination of AI and Big Data enabling automated decision-making poses relevant ethic issues related to fairness and/or discrimination.

+

- Better performance in processing of large amount of data

- Prevention of **confirmation bias** consequences

−
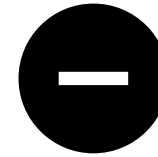
Biased results resulting in discriminating decisions due to:
- ML systems trained on past human judgements reproducing **prejudices and errors**
- Data set that does NOT reflect the **statistical composition of the population**
- Automated decisions based on multiple factors but **non-predefined criteria**.

| Medical diagnosis Financial investments | Impacts on individuals | HR Security |

links
PASSION FOR INNOVATION

Politecnico di Torino

Worth readings
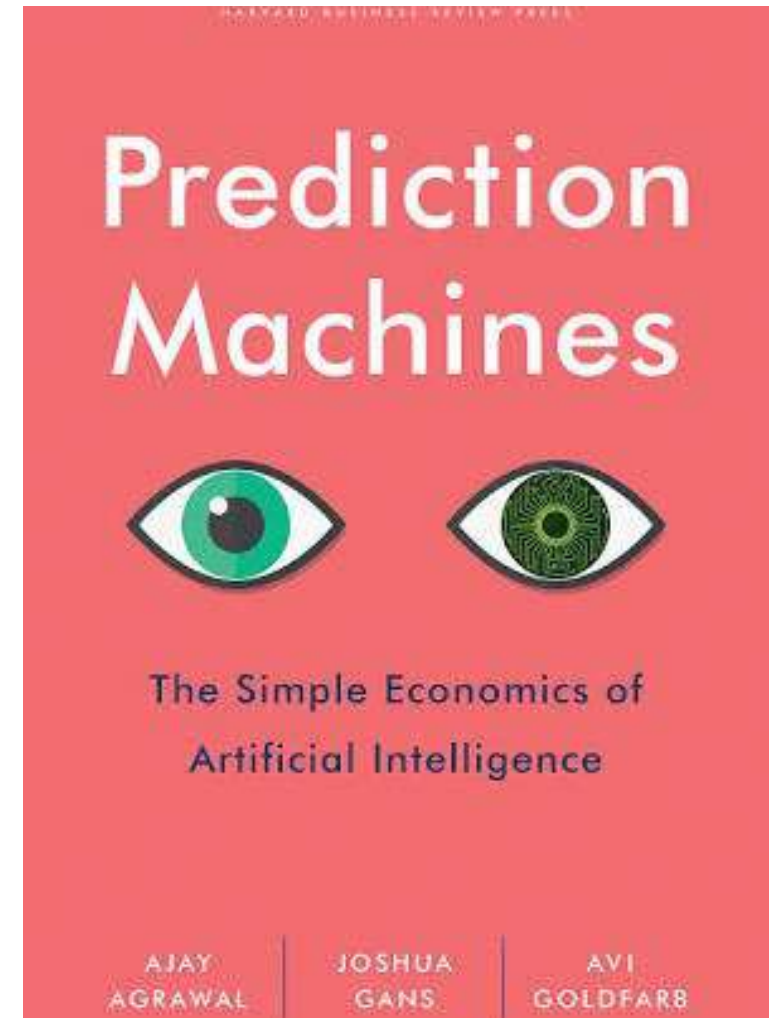
A. Agrawal, J. Gans, A. Goldfarb
Prediction Machines. The Simple Economics of Artificial Intelligence. 2018
https://www.predictionmachines.ai/

How much we are biased?

Free online test by <u>Harvard</u> University.

https://implicit.harvard.edu/implicit/user/uk/uk.static/selectatest.html

Project Implicit

Religion IAT — *Religion* **('Religions' IAT).** This IAT requires some familiarity with religious terms from various world religions.

Age IAT — *Age* **('Young - Old' IAT).** This IAT requires the ability to distinguish old from young faces. This test often indicates that participants have automatic preference for young over old.

Weight IAT — *Weight* **('Fat - Thin' IAT).** This IAT requires the ability to distinguish faces of people who are obese and people who are thin. It often reveals an automatic preference for thin people relative to fat people.

Arab-Muslim IAT — *Arab-Muslim* **('Arab Muslim - Other People' IAT).** This IAT requires the ability to distinguish names that are likely to belong to Arab-Muslims versus people of other nationalities or religions.

Countries IAT — *Countries* **('UK - United States IAT').** This IAT requires the ability to recognise photos of national leaders and other national icons. The results revealed by this test provide a new method of appraising nationalism.

Skin-tone IAT — *Skin-tone* **('Light Skin - Dark Skin' IAT).** This IAT requires the ability to recognize light and dark-skinned faces. It often reveals an automatic preference for light-skin relative to dark-skin.

Weapons IAT — *Weapons* **('Weapons - Harmless Objects' IAT).** This IAT requires the ability to recognize White and Black faces, and images of weapons or harmless objects.

Race IAT — *Race* **('Black - White' IAT).** This IAT requires the ability to distinguish faces of European and African origin. It indicates that most participants have an automatic preference for white over black.

Sexuality IAT — *Sexuality* **('Gay - Straight' IAT).** This IAT requires the ability to distinguish words and symbols representing gay and straight people. It often reveals an automatic preference for straight relative to gay people.

Gender-Science IAT — *Gender - Science.* This IAT often reveals a relative link between liberal arts and females and between science and males.

Disability IAT — *Disability* **('Disabled - Abled' IAT).** This IAT requires the ability to recognize symbols representing abled and disabled individuals.

Transgender IAT — *Transgender* **('Transgender People – Cisgender People' IAT).** This IAT requires the ability to distinguish photos of transgender celebrity faces from photos of cisgender celebrity faces.

Gender-Career IAT — *Gender - Career.* This IAT often reveals a relative link between family and females and between career and males.

Copyright © Project Implicit

Check for stereotypes
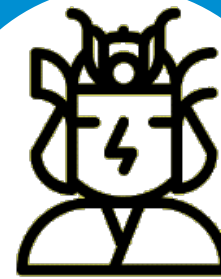
Stereotype vs archetype

Stereotypes are over simplified, generalised ideas about a group of people. They can be positive or negative, but they are often **based on inaccurate or incomplete information**.
- stereotypes can lead us to make not accurate assumptions (e.g. all gamers are young, male and antisocial)

Archetypes are universal symbols or **patterns** that are found in stories and data. They represent fundamental human experiences and motivations.
- archetypes can help us to understand the underlying needs and desires of users.

Teenagers are rebellious and irresponsible.

Women are bad drivers

All Italians are passionate and loud.
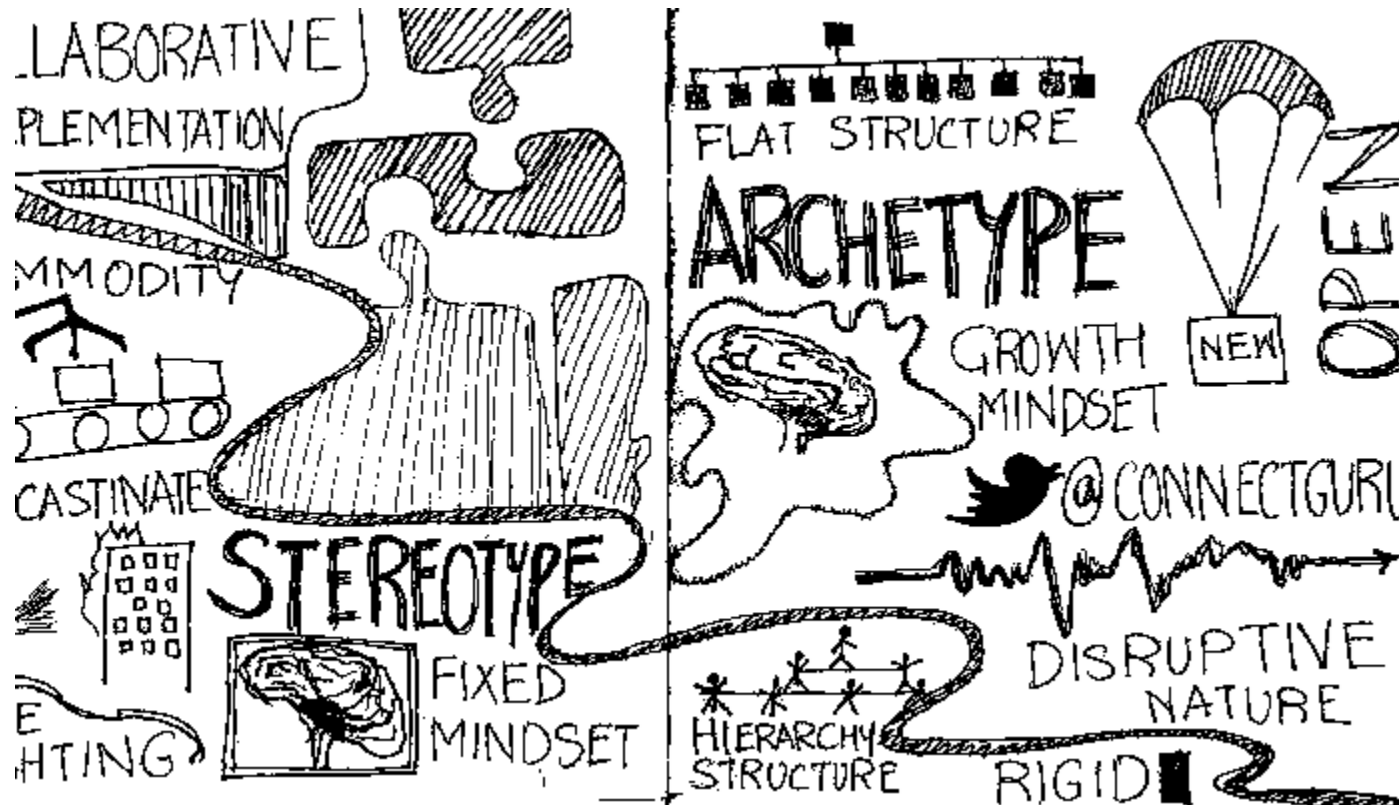
The **Hero** is a character who embarks on a journey, faces challenges, and...

The sage: Yoda in "Star Wars.

The Trickster: Loki in Norse mythology.

Again the categories.

The world doesn't need categories. It's human beings who need them. We build categories to navigate this complex and contradictory world, to somehow understand it and come to an agreement on it.
We need categories.
Anyone who tried to perceive everything on this earth without filters and without categories would be overwhelmed by a flood of stimuli and would end up drowning. We need categories. Organizing and categorizing our environment helps us humans to identify patterns, make quick decisions, and react to situations of danger, for example. In these moments, we draw on images and situations we have stored long before. So, looking at the world through categories is a necessity. But when do the categories we build to understand the world become cages? When does our freedom become a lack of freedom for others? It is faith in absolutes that transforms categories into cages—the arrogant belief that a single narrow and limited perspective on this world is complete, exhaustive, and universal. The hubris of believing we can fully understand another human being in their complexity once and for all. Or even that we've definitively understood an entirely artificial category of human beings.

More than 70 million human beings become THE REFUGEE.
1.9 million people become THE MUSLIM.
Half the world's population becomes THE WOMAN.

Dataset Examination

1) Explore your dataset to identify potential biases:
   Search for missing data or underrepresented variables and stereotypes in:
   - **sampling**
   - **data collection**
   - **labelling**

2) Search for this information:
   - **Who** created the content?
   - **What** is the content?
   - **When** was the content created?
   - **How** was the content created?
   - **Why** was the content created?
   - **What** do they count?
   - **What do these data not tell us**?

3) Check for representation across different stakeholders and demographic groups.
   - Are there features that could unfairly disadvantage certain groups or individuals or cause risks or unwanted effects?
   - Have you added features based on assumptions that might not hold for all data points?
     (E.g.: Including a zip code as a feature in a model could introduce socio-economic or racial bias if certain zip codes correlate strongly with demographics).

4) Describe the possible impact on the project and outcomes

5) Identify actions to mitigate the identified biases.
   - **Are your metrics fair**? How does the model performance differ across various groups?
     (E.g. if accuracy is your primary metric, but accuracy varies greatly between groups, then accuracy might be not the only metric to consider)

Which stereotypes can affect your project?

What categories are represented in your dataset?
Are any key typologies underrepresented?
How was the data collected?
Could the collection method exclude certain information?

Project goals	Possible stereotypes	Background	Possible archetypes
Predictive model for Humanitarian Aid	"immigrants primarily hold low-wage jobs and hurt the economy"	Germany calls for more immigrants to fix its shrinking economy, Financial time, Reuters (2023)	Employers, Employee, Candidates
Urban Air Quality Assessment and High-Resolution Temperature Mapping	Non-experts rely on basic sensory cues to perceive air quality, such as visibility, smell, or feel; neighbourhood halo effect;	Air pollution perception bias: Mismatch between air pollution exposure and perception of air quality in real-time contexts (2019)	Citizens, CEO of industries, Physicians, Public officers
Heat Forecast	People don't see heatwaves as a pressing issue.	5 things we've learnt about people's experiences of heatwaves (2018)	Frail citizens (elderly, pregnant, children, chronic patients), Red cross and responders Physicians, Public officers
Pre-training language model on Electronic Health Records **Incorporating Patient Preference Studies into clinical research and decision models**	Black patients are more likely than White patients to be described in negative terms	Electronic Health Record Notes May Be Perpetuating Biases (2022)	Patients (various), Physicians, Medical institutions, Insurance companies

How to Measure Data Quality — 13 Metrics

Objective Data Quality Metrics

The most common data quality metrics can be broken down into the following categories:

1.**Accuracy** How accurately does each available data field represent reality? This is also commonly referred to as the validity of data.

2.**Coverage** – What percentage of the events or objects of interest have records? For example, if you care about all companies in North America, what percent of North American companies are represented in the dataset?

3.**Completeness** – Of all provided records, what percentage of the available fields have a value?

4.**Integrity** – If there are relationships present in the data, how often are the expectations between related attributes violated? For example, the total funds raised by a company should always equal the sum of individual fundraising events for that company, or foreign keys should always point to records that exist (referential integrity).

5.**Consistency** – How consistent is the data in format and structure within and across datasets?

6.**Duplication** – What percentage of all records are duplicates?

7.**Precision** – How exact is the data? What is the level of detail of unstructured data like text or images? What is the delivery frequency of the data provided?

8.**Timeliness** – What is the probability that the data represent the values in the real world at any given time? Note that we're **not** interested in the time lag between an event happening in the real-world and the event showing up in the dataset. In practice, this is extremely hard to verify and the business often cares more about the dataset being in sync with the source, rather than the time-lag itself.

9.**Accessibility** – The number of business processes or personnel that can access and benefit from the data.

Subjective Data Quality Metrics
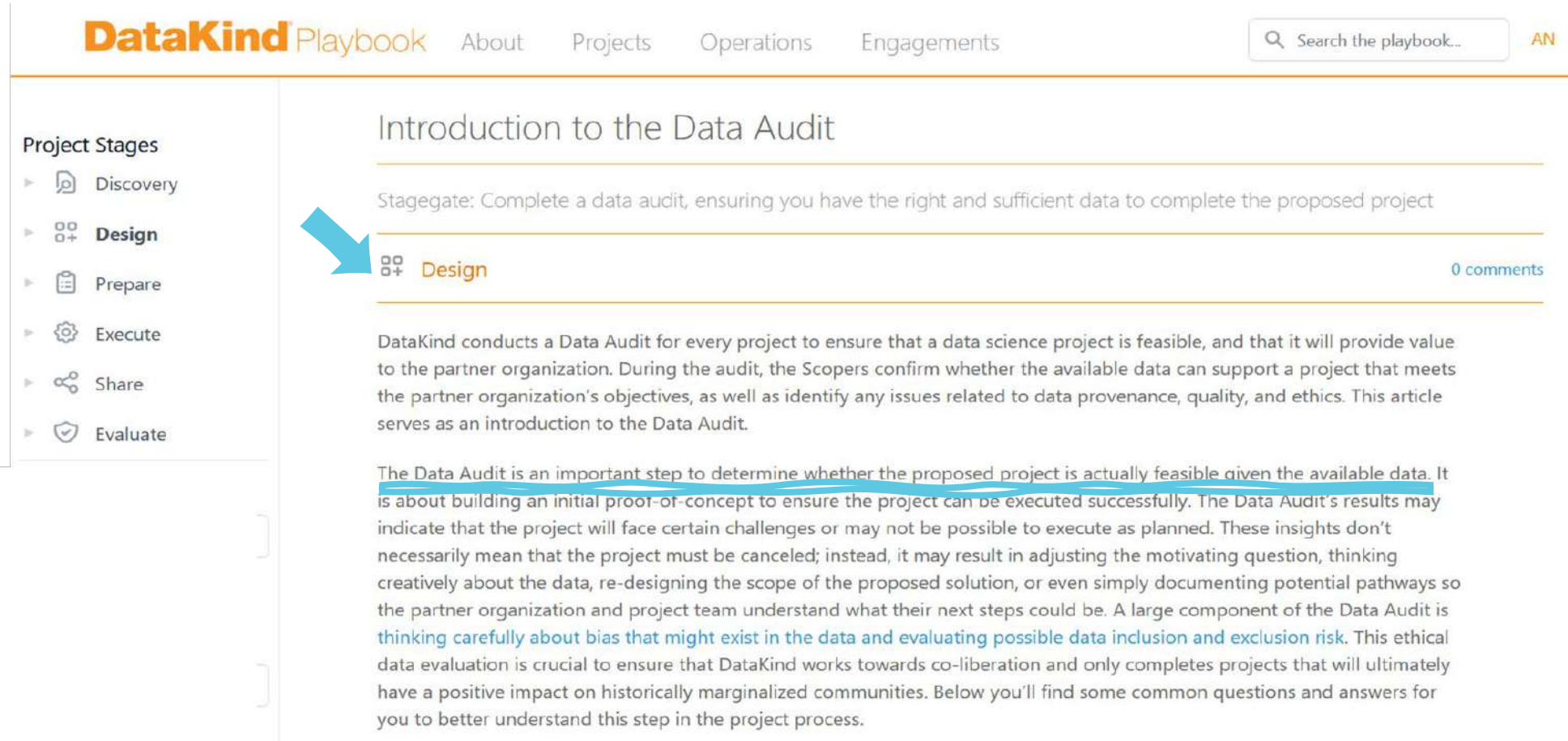
Not all aspects of data quality can be considered in isolation of their relationship with the data users. Some quality metrics are purely subjective but have a significant impact on the utilization of the data assets. These metrics are typically measured through user surveys.

1.**Believability** – Do users trust the data they are looking at, or is it being circumvented or substituted with alternate sources of similar information?

2.**Usability** – How easily can value be extracted from the data to perform some business function?

3.**Objectivity** – How impartial is the source of the data in the eyes of users?

4.**Interpretability** – How understandable is the data? Is there sufficient documentation to support the raw data?

Data audit toolkit

A Six-Step Playbook for Doing Data Science & AI for Good

- Identifying problems

- Understand the data

- Build proof-of-concept models

- Implement models at scale

- Evaluate the project's ethical implications
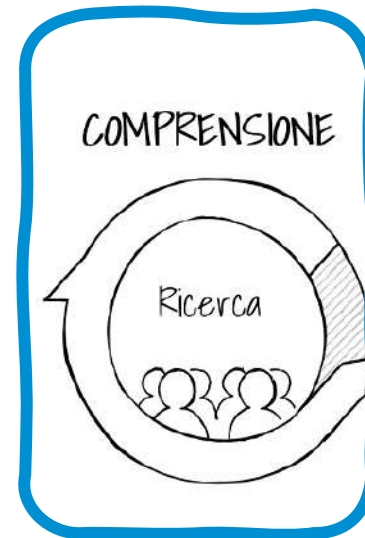

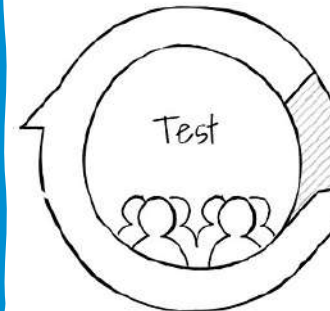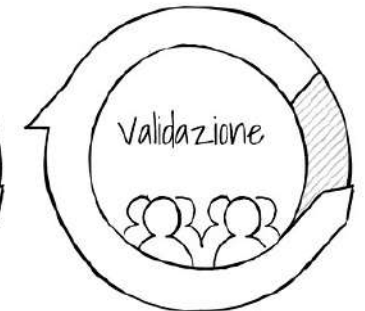https://playbook.datakind.org/playbook/articles/193

HCD | THE USERS PERSONAS

Empathy in design
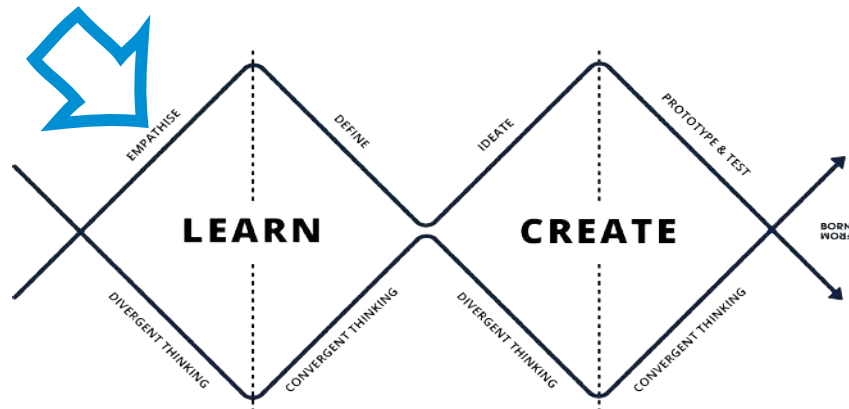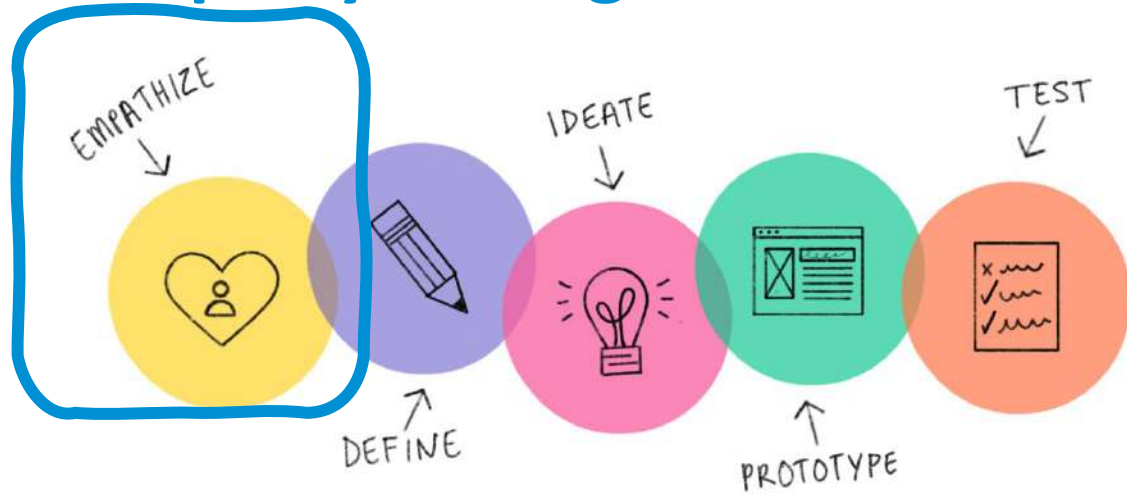
Empathy in design

"Deep understanding of the problems and realities of the people you are designing for."
In other words:
- Learn about people's **difficulties**, **latent needs** and **desires**
- Understand their **behaviors and tasks**
- Understand their **environment**, **roles** and **interactions**

GOALS
PAIN POINTS
OPPORTUNITIES

Ok, but why?
- To identify **effective solutions** to real problems
- To be able to iteratively **test and improve** the solutions
- To **provide positive experiences** for a wider audience
- To cope with **complex challenges**

Emphatise
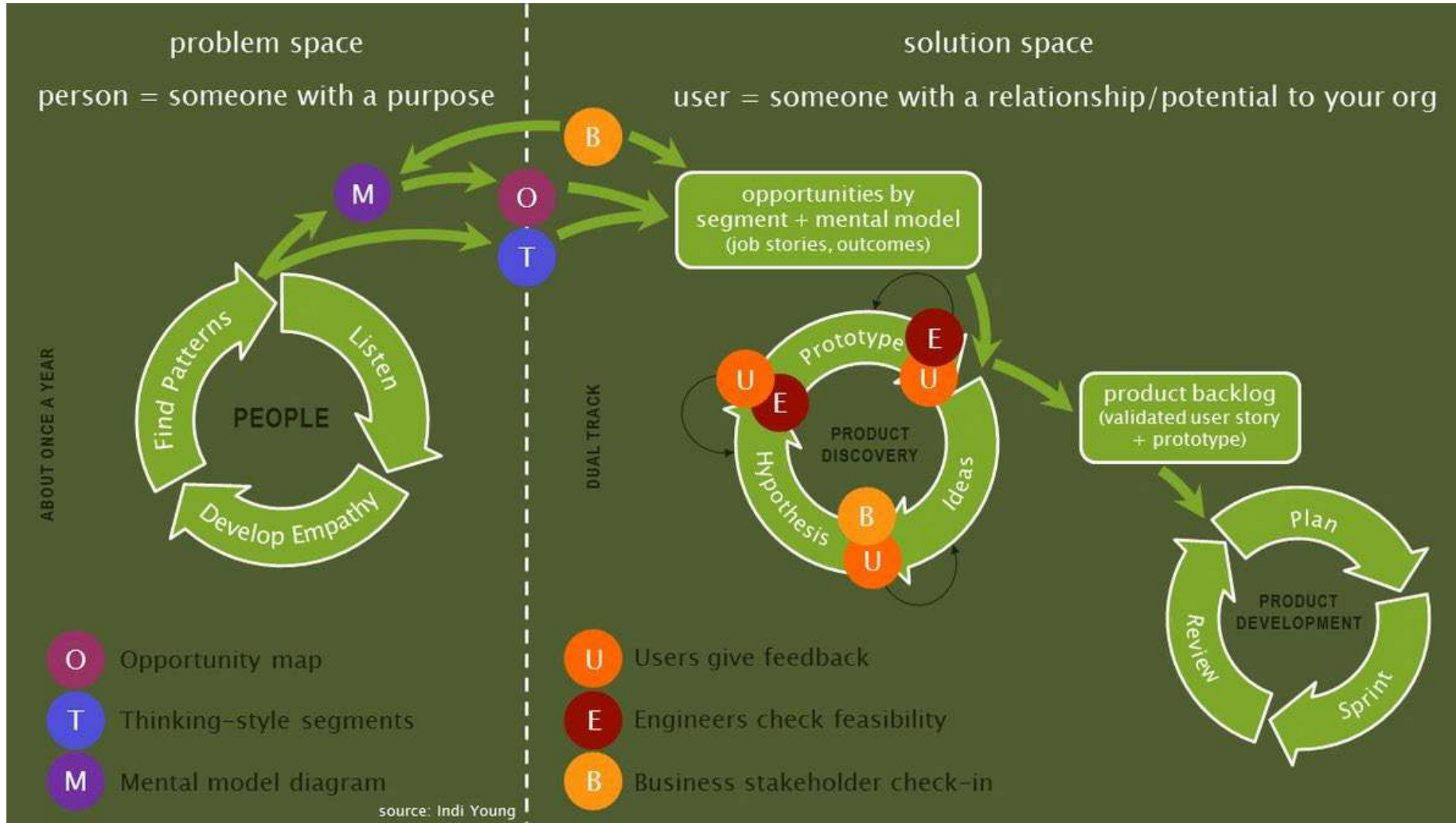
Young, I. Practical Empathy
For collaboration and creativity in your work 2025
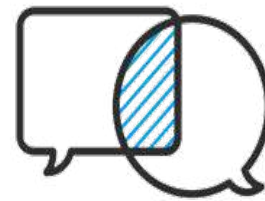
Techniques to empathise

DATA COLLECTION

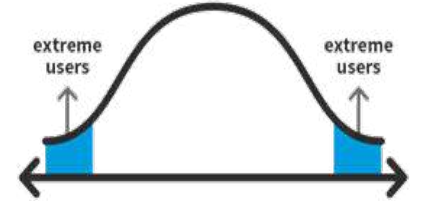Assume a Beginner's Mindset | Photo- & Video-Based Observations | Personal Photo & Video Journals | Conduct Interviews with Empathy | Bodystorm | Engage with Extreme Users
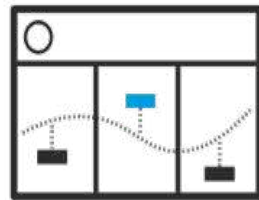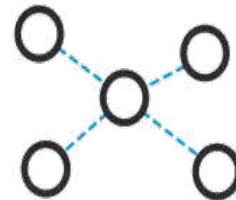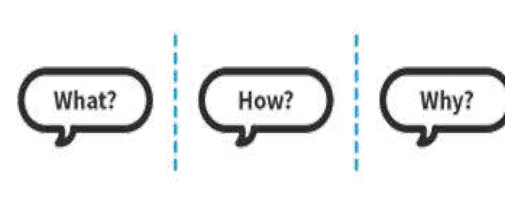
+

DATA DISPLAY

Personas | Journey Mapping | Embrace Analogies | The What-How-Why Method | Capture & Share Inspirational Stories

User Personas

Design technique was introduced In 1999 by Alan Cooper, aiming at *capture, communicate and use the research findings*

Personas are **data-driven portraits** of **archetypical stakeholders**
that help designers and developers focus on the needs and goals of target users throughout the product development process.
- based on user research, they are not meant to be literal descriptions of any individual user.
- help team project members to overcome their biases by forcing them to think about their users as individuals with their own unique needs and goals.

Grounded in real user research, Personas layout includes:
- Research findings encapsulated in many individual user portraits
- **Users' goals and needs supporting the ddep understanding of them by the sceintists and dev people**.
- **Data and features prioritised** based on a clear understanding of which user groups will benefit.

A. Cooper and P. Saffo, The Inmates Are Running the Asylum, London, U.K.:Macmillan, 1999.

UX24/7. eGUIDE INTERNATIONAL USER RESEARCH. https://ux247.com/publications/

The User Personas

PRO: **PERSONAS**
- enable designers and developers to **empathise** with these imaginary users and **understand better** their goals and needs, taking on the perspective of underrepresented or easily overlooked users.
  For example, Personas explicitly designed to represent **human diversity**, known from gender difference research, have been successfully used to detect gender-inclusiveness issues in software.
- **aid the communication within the team** (i.e., the term 'user' can mean different things to different people within the group)**,** making implicit assumptions of users explicit.
- support the communication with the stakeholders, adopting **a common language about users**
- closely **approximate the mental model of various end users,** which results in a focus on the user priorities and a meaningful feature set.
- Help to **avoid self-referential projects** based on the user's (and not developers') goals, motivations, and skills.
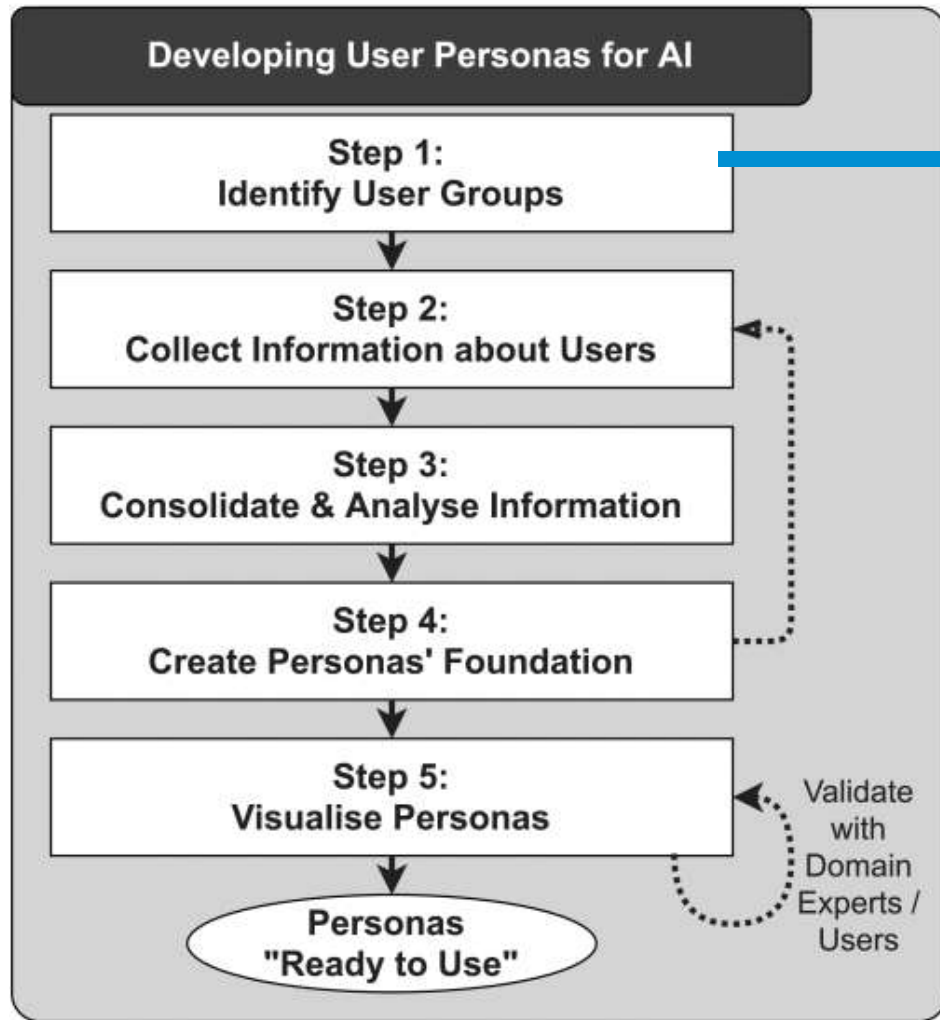
CONS: **PERSONAS**
- are prone to activate and reinforce stereotypes. For this reason, it is necessary to ensure that the diversity of people is accounted for

Design Personas for AI

STAKEHOLDERS MAP
User Groups for AI Application in Computational Pathology

A. Holzinger, M. Kargl, B. Kipperer, P. Regitnig, M. Plass and H. Müller, "Personas for Artificial Intelligence (AI) an Open Source Toolbox," in *IEEE Access*, vol. 10, pp. 23732-23747, 2022

Design Personas for AI

A. Holzinger, M. Kargl, B. Kipperer, P. Regitnig, M. Plass and H. Müller, "Personas for Artificial Intelligence (AI) an Open Source Toolbox," in *IEEE Access*, vol. 10, pp. 23732-23747, 2022
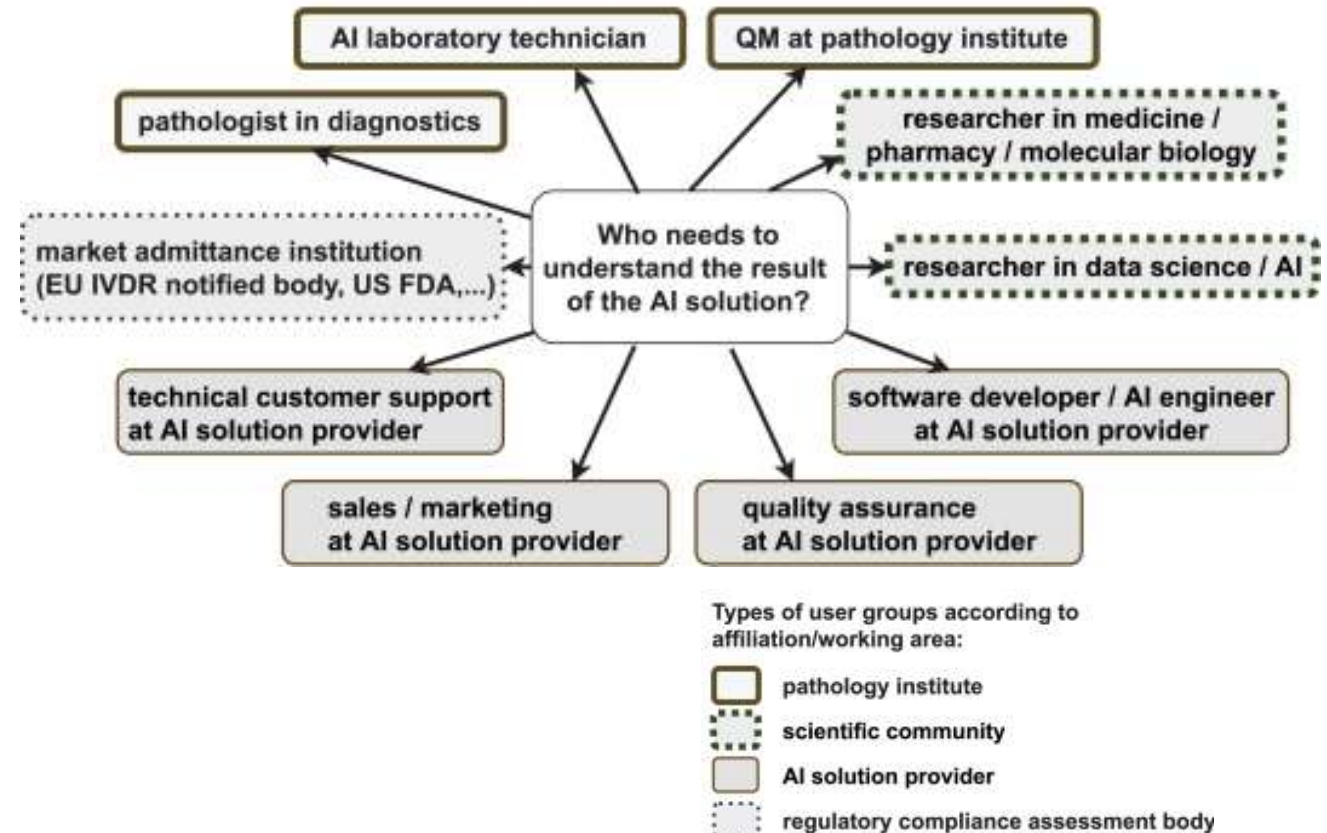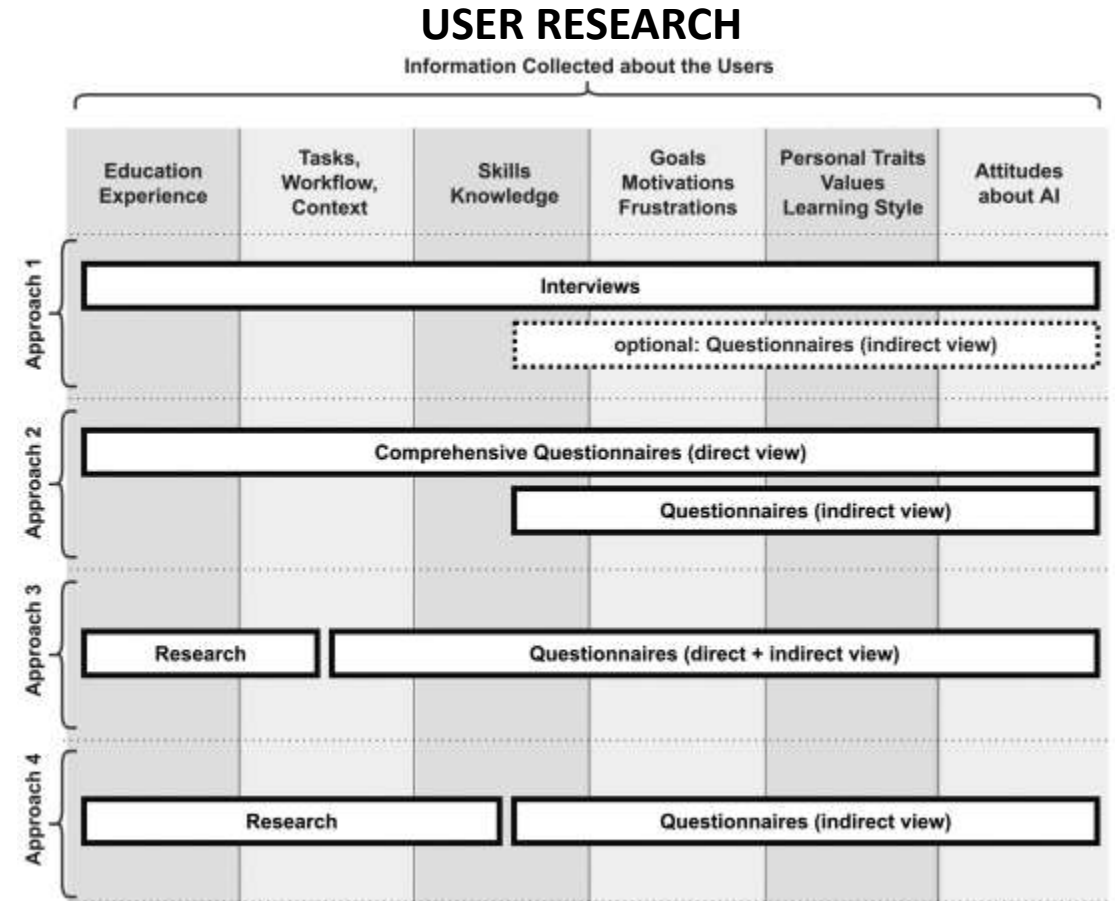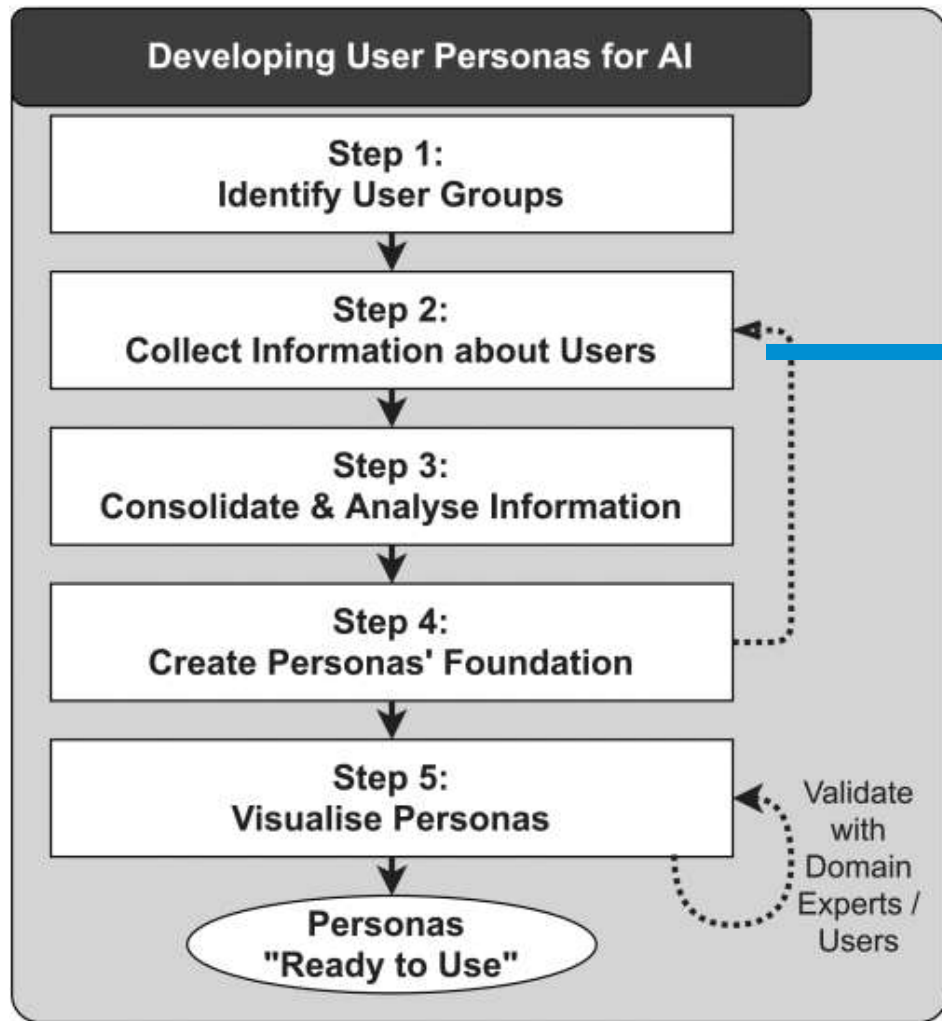
What to search → know?

- **Demographics**: age, gender, geographical location of the users. Sources: social media analytics, website analytics, previous research, competitive research.

- **Motivation**: why are the users using our product? Sources: previous research, competitive research, first-hand experience with users, scientific literature.
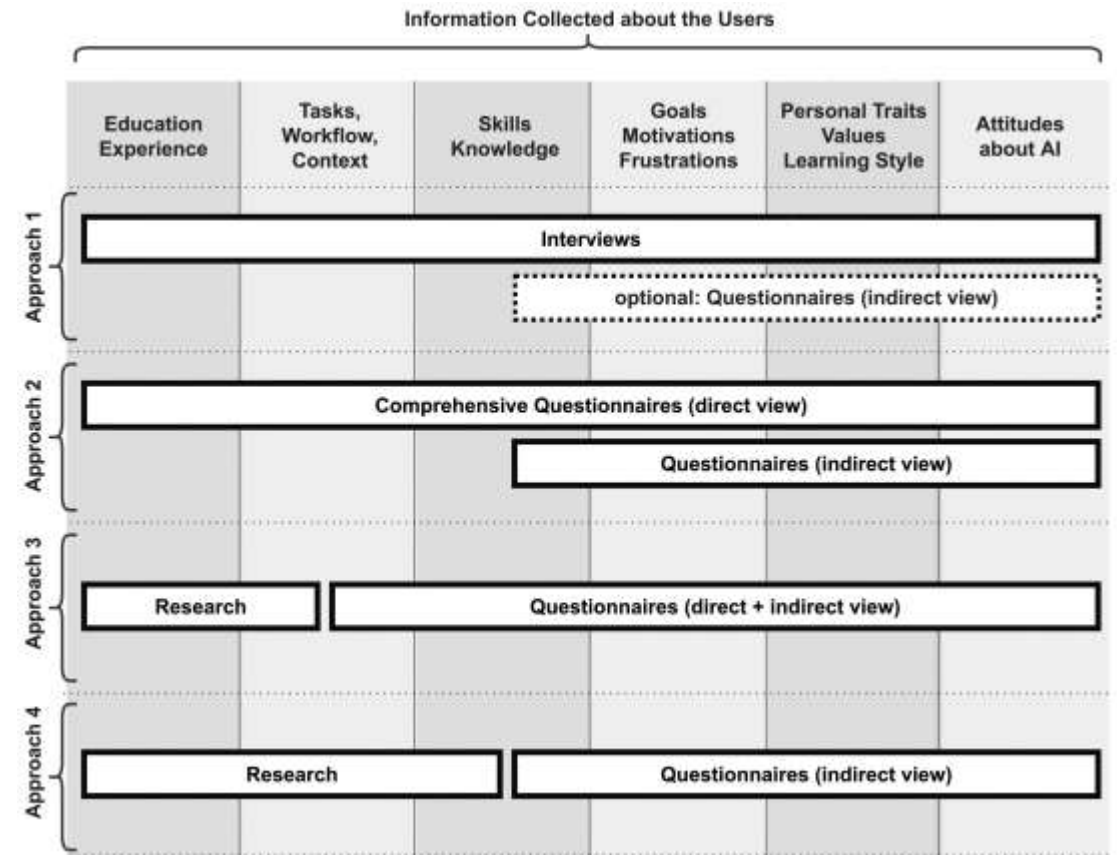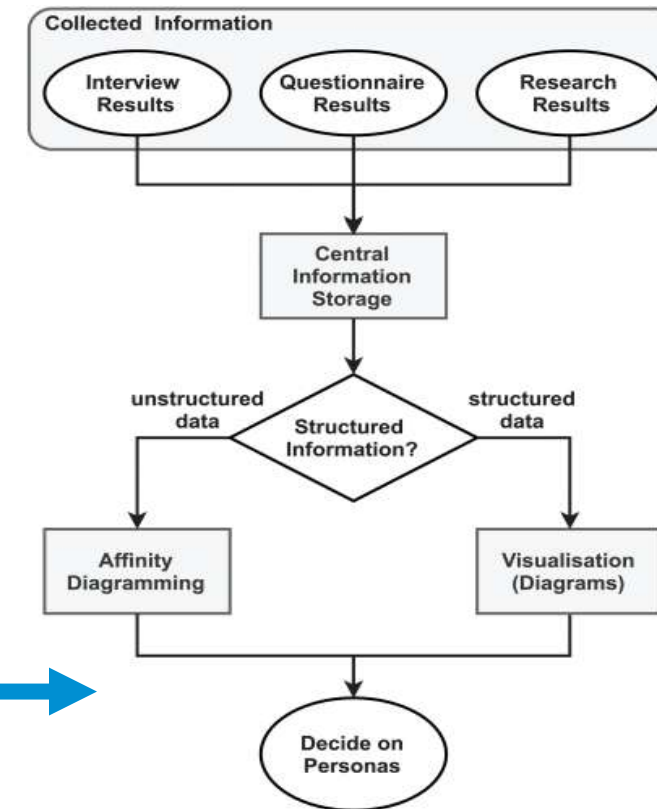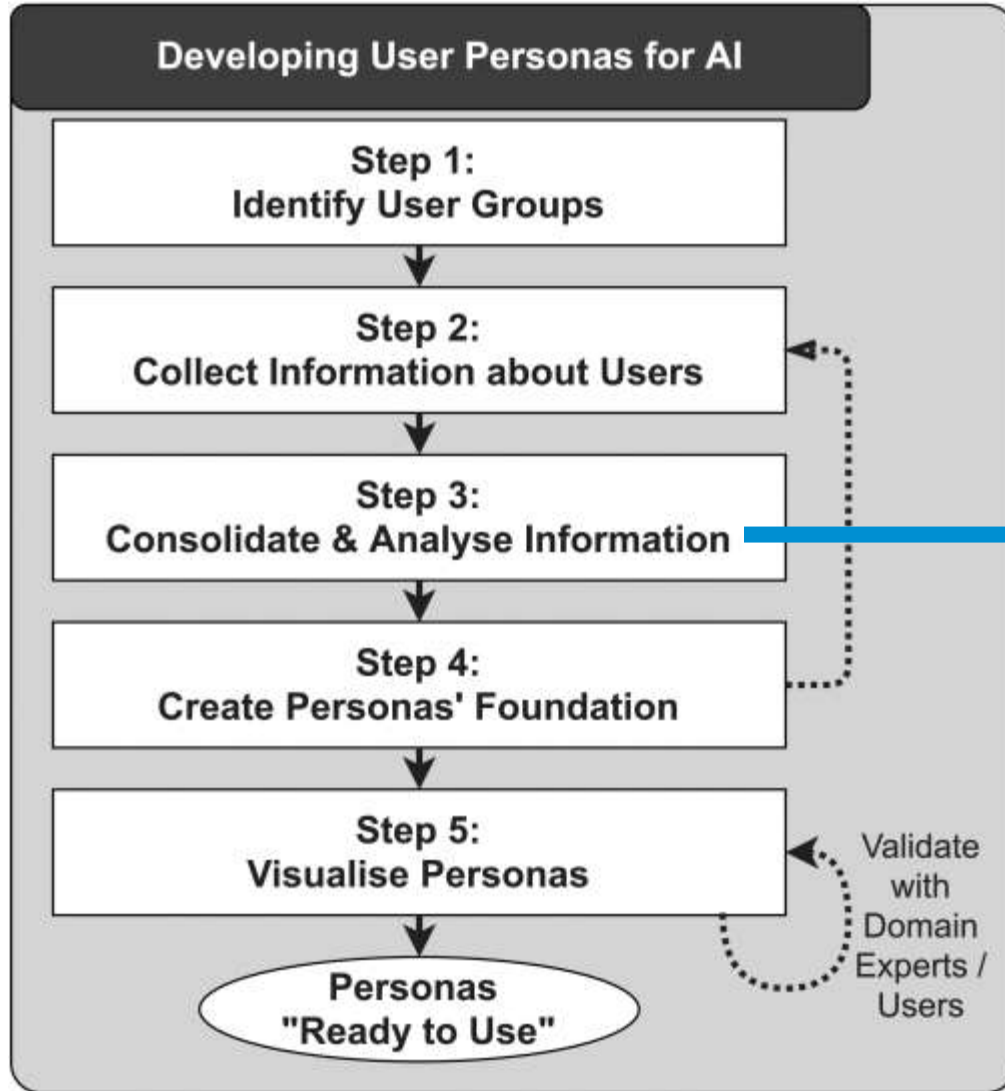
- **Goals**: short-term and long-term goals (personal/career), tasks and activities to reach them. Sources: the same used for motivation, psychographics, and skills.

- **Skills**: education, relevant skills and professional experience. Any technical skills as well as soft skills, *services/systems* *already in use*. Sources: previous studies, surveys, first-hand experience with our users, external research.

- **Psychographics**: personality types, values, opinions, beliefs, attitudes, activities, interests, lifestyles, etc. Sources: social media analytics, industry publications, blogs, academic research.

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https://www.youtube.com/watch?v=fGTNZ7YMdCk

Design Personas for AI

Developing User Personas for AI

Step 1: Identify User Groups

Step 2: Collect Information about Users

Step 3: Consolidate & Analyse Information

Step 4: Create Personas' Foundation

Step 5: Visualise Personas

Personas "Ready to Use"

Validate with Domain Experts / Users

Collected Information

Interview Results — Questionnaire Results — Research Results

Central Information Storage

Structured Information? — unstructured data / structured data

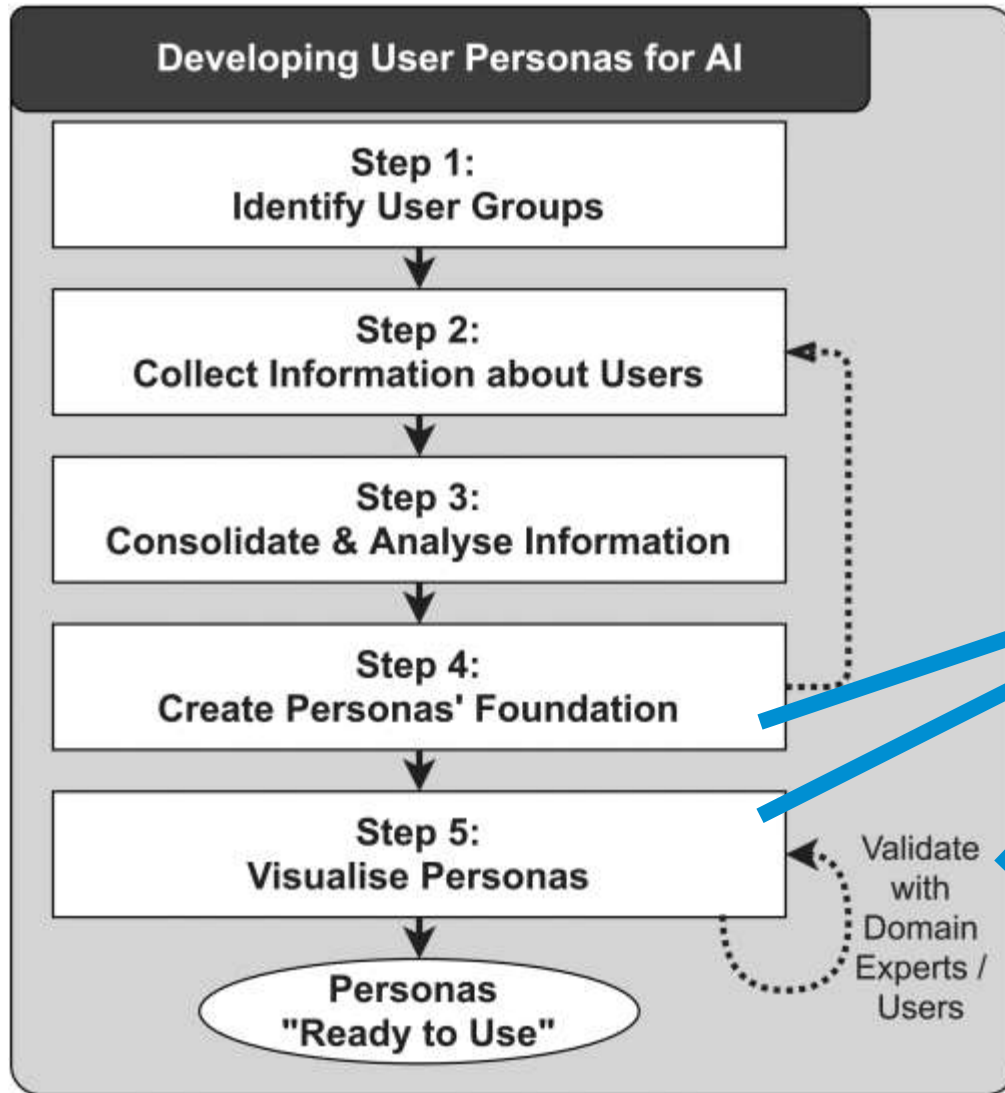Affinity Diagramming — Visualisation (Diagrams)

Decide on Personas

1. **Brief outlines** (assumptive personas or proto-personas)
2. Perform extensive data gathering and analysis
3. Validate **and refine** the personas.

Pruitt,J. & Adlin, T. The Persona Lifecycle: Keeping People in Mind Throughout Product Design . Morgan Kaufmann, 2006.

Kreitzberg, C.B., Little, A. Usability in Practice - The Power of Personas Microsoft Ignite, Volume 24 Number 04

A. Holzinger, M. Kargl, B. Kipperer, P. Regitnig, M. Plass and H. Müller, "Personas for Artificial Intelligence (AI) an Open Source Toolbox," in *IEEE Access*, vol. 10, pp. 23732-23747, 2022

Design Personas for AI

Developing User Personas for AI

- Step 1: Identify User Groups
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- Step 4: Create Personas' Foundation
- Step 5: Visualise Personas
- Personas "Ready to Use"
- Validate with Domain Experts / Users

PERSONAS

Per every personas include:
- A **photo**/portrait
- **Short bio** /demographic details
- **Mindset**: a brief description of the point of view (specific and characteristic of the person in relation to one or more aspects of the project theme
  - Role, Tasks, values
  - Work (tasks, workflows, context)
  - Education/knowledge/skills
- **Goals**, values
- Relevant **pain points and gains, motivations and barriers**
- Attitudes towards **technology/AI**

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Example

They are a sample of real users, not generic users but «archetypal», different for specific socio-demographic variables, roles, OBJECTIVES ... moving into specific **scenarios**.

**Analysis of documents
+
Interviews**

Instructions
- Length of instructions for both forms ~ 54 pages
- These hold instructions for every type of green card applicant. Intermixed so an applicant has to seek what's relevant to them

Forms
- In total the two necessary forms = 364 questions
- Many of which are situation specific or occur twice between forms
- Minimal clarification & guidance

Document Checklist
- Minimally informative with many conditional statements ("if applicable"), making many of it potentially erroneous
- Too broad - missing certain important details

Case Status
- Case status tracker shows no information about the timing of the future steps

Tools & Resources
- Available only if a user signs in/up, yet the resources are not specific to the applicant's situation, requiring sifting

"You really have to pay close attention and hunt for what details are actually relevant to you. What category do I fall in? You have to read it ten times over to figure it out and it can become overwhelming."

BIO

Sam was born in India but he's been a resident of the US for over 10 years. He originally immigrated on a student visa, then received a work-sponsored H1B visa; however, Sam's visa expires soon and he has no plans to go back to his hometown.

A few months ago, Sam married his long-time partner. The notice for his visa's expiration has catalyzed Sam's interest in applying for a family-based green card.

Sam has a couple of friends who have gone through this process before without a lawyer, so he feels confident he can do the same.

Sam and his partner are busy with work and other responsibilities, so they don't have the extra energy required to carefully discern this complex application process. In addition, since Sam's visa expires soon, it will place him out-of-status, which means he needs this process to progress smoothly.

The combination of the lack of time to get the application right and the pressure of needing it done as soon as possible has been frustrating for Sam, so he is seeking an affordable tool to help him out.

AGE	32
OCCUPATION	Data Scientist
STATUS	Married
LOCATION	Chicago, IL

GOALS
- To minimize stress during application process
- To able to continue living in the US with his spouse
- To receive approval as quickly as possible

NEEDS
- To feel in control of the outcome
- To understand the details of his application process
- To stay updated on the status of his case

FRUSTRATIONS
- Too much time spent researching legal jargon
- USCIS's use of mail for updates & communication
- Having application delayed because of insufficient supplemental documents

Example

They are
- **data-driven synthetic representation of complex knowledge**, useful for internal communication

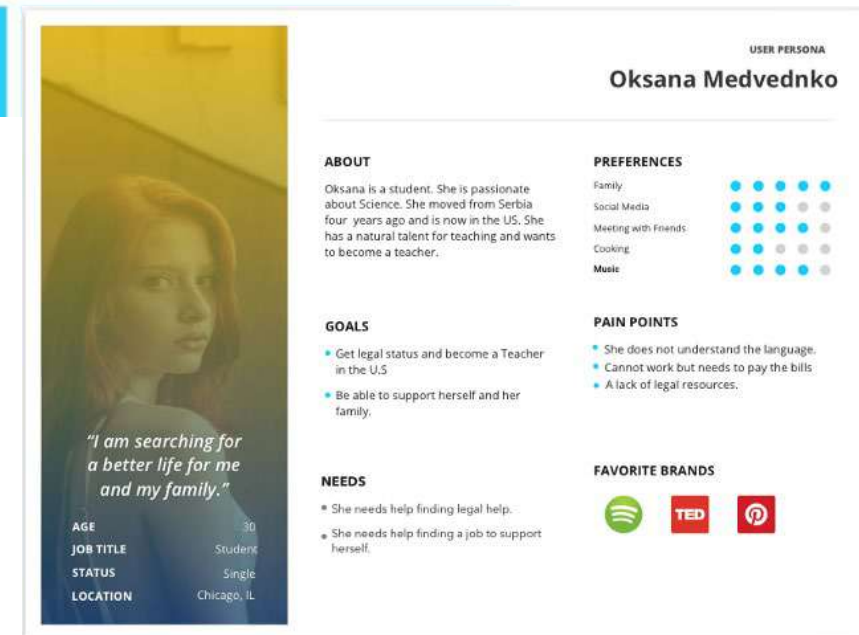- **dynamic** documents to be updated

- a **reality check tool**
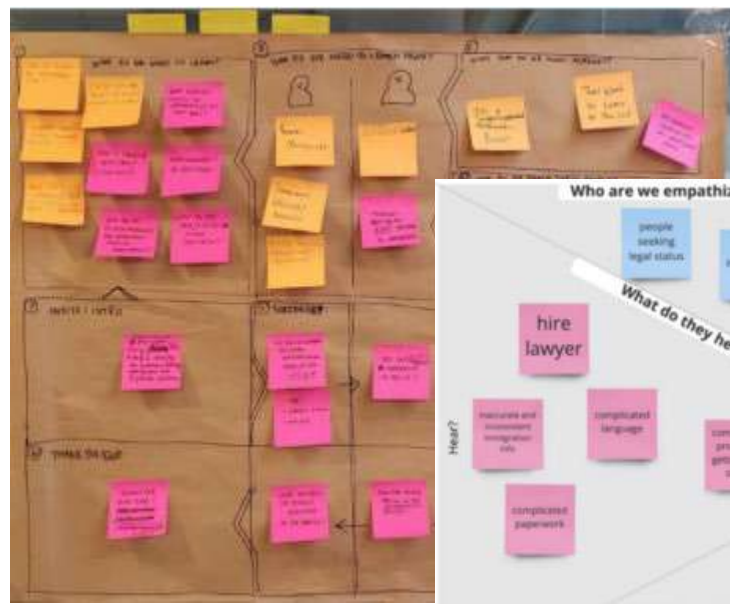
Affinity diagrams

Empathy map

Persona

Example

Bio

Julia is an artist in London. She graduated 4 years ago from art school and has been making art since joining a local studio 12 months ago.

Although she loves the people she works with, she has been giving serious thought to her future. While the studi that she works at is growing, she's worried that she wont developed a name for herself if she continues working with others. She's considering selling her art online and wants a reputable place to sell her pieces while gaining good exposure.

Marie — The artist

Looking to sell her art easily online and gain exposure as an up and coming artist.

Age: 26

Marital status: Single

Occupation: Artist/Art Buyer

Location: London, UK

Income: £32,000

Needs

- To find the right website which offers the facilties she wants.
- To find a way to fund her artworks without incurring lots of debt.

HAUS

Glöop

13% Lighting

22% Bedding
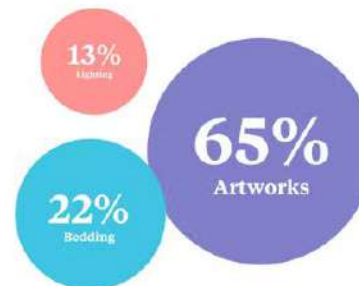
65% Artworks

The 3 most popular categories of homewares

Pain points

- Concerned that she'll need to manage mailing artworks and won't be able to afford the website fees
- Worried that she's one of many artists and wont get enough exposure
- Doesn'twant the service to take too high a percentage of her sales

Ideal experience

- Mail her pieces internationally and ensure they arrive safely
- Manage her inventory easily from her iPhone
- Make great money to sustain her passion making art

Research

2 cards, 1 document

Quotes

"It's important that I can connect with the buyers"

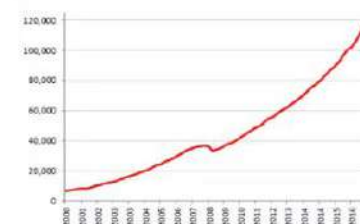"I really just need an easy way to promote my art and keep prospective buyers up to date"

"The hardest part is managing the actual transaction."

Survey results

3 words

E-Commerce Sales

120,000
100,000
80,000
60,000
40,000
20,000
0

Milanote.com

Examples

HUMAN ARCHETYPES

Tassi, R. Visual tools to design. 2016

Case study

Phase 1 (2017)

Phase 2 (2018)

Personas types

Usually, when creating a persona, **not the whole person is described**, but the focus is put only on **relevant aspects** (goals, needs, attitudes, skills…) and specific context associated with these aspects. Personas usually encompass aspects such as **context and environment**, **tasks and workflows**, **skills and knowledge, personal traits, goals, values, motivations but also frustrations**.

- **Goal-oriented personas,** distinguished from one another based on their different goals (Cooper, 1999).
- **Role-based personas**, defined by their roles, (Pruitt et al, 2000)
- **Scenario-oriented engaging personas**, based on their individual characteristics, and their goals are based on these needs and appear only in the context of a specific scenario (Nielsen).
- **Pastiche personas**, fictional portraits established on user data but entirely grounded on fictional characters from literature or film (Blythe).

To adapt the personas method to the context of HAII, additional aspects describing the user's attitude regarding AI solutions as specifically relevant for personas for AI:
- **Trust** (How much trust does the user have in the decisions/output of the AI system?)
- **Acceptance** (Does the user accept (and follow) the decision of the AI system?)
- **Assent** (Is the user willing to accept/use the support by the AI system?)
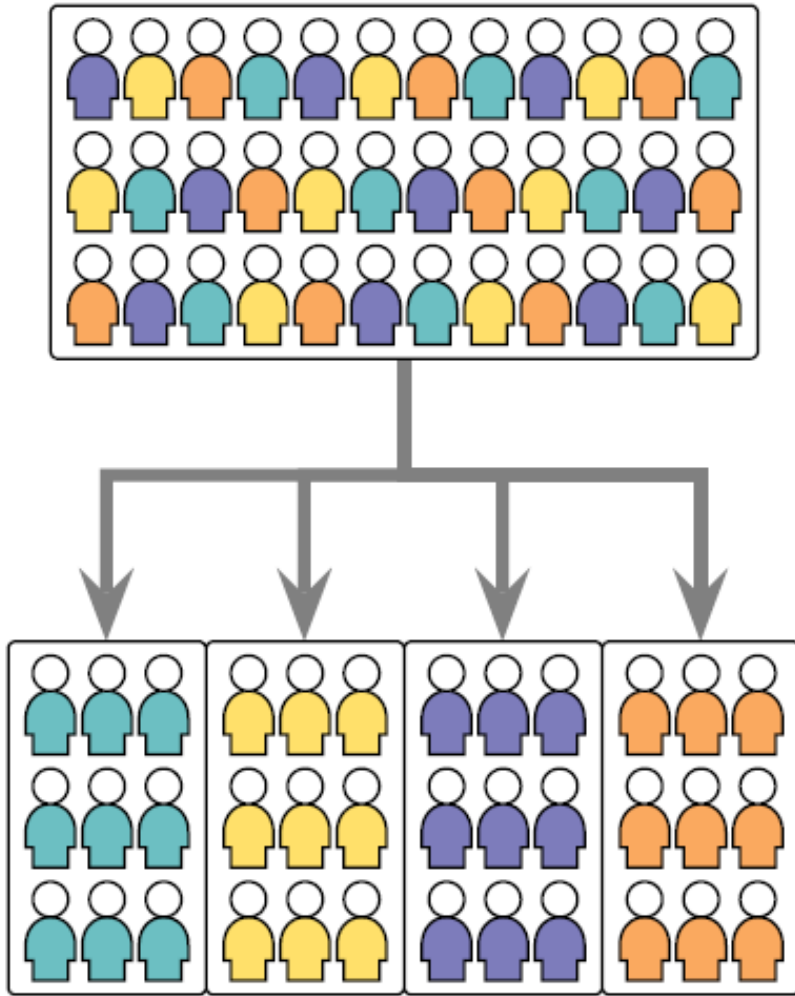
Dark personas

When designing you are completely focused on the actions
and behaviors we want to foster and support.
But there will always be someone ready to use our service in
unexpected and unwanted ways.
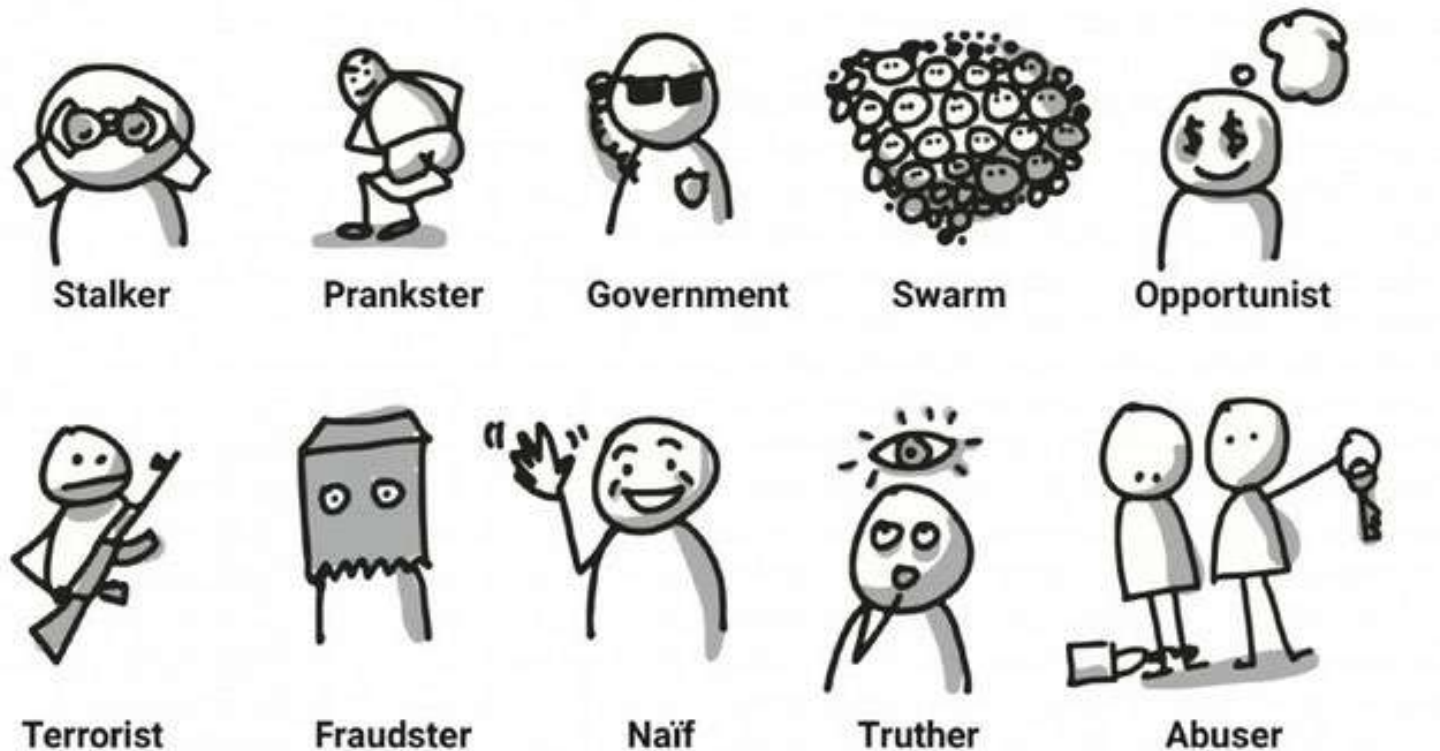
Tweet di @mollyclare

Guarantee representation and diversity

In data collection, datasets, analysis, and <u>working groups</u>.

- **Diversity:** inclusion of a wide range of perspectives, experiences, and identities (including race, gender, age, socioeconomic status, disability, culture, and more)

- **Representation**: visibility and inclusion of all groups, especially those historically marginalized. if you don't count them, they do not exist.

- **Intersectionality**: framework is used to understand how various **social identities** such as race, gender, class, sexuality, ability, and others **intersect and overlap**, creating unique experiences of oppression and privilege. It concerns both intersections of social identities and layered experiences.

Underlying definitions and categories change over time and are context-dependent.

Different context and attitudes

Aggregate multiple criteria:

Demographic criteria:
gender, age, education, marital status and family composition, income
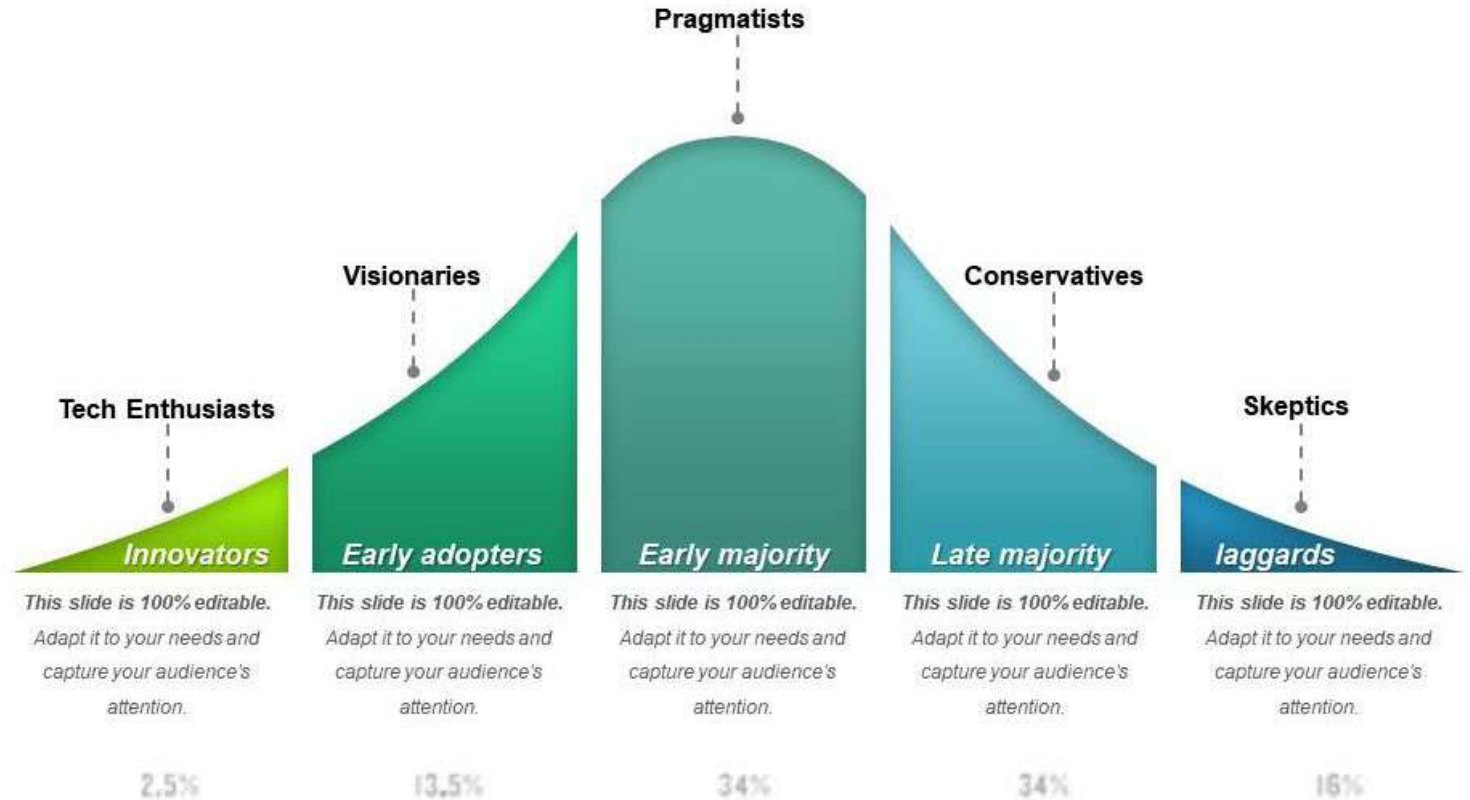
Psychographic profiles:
attitudes, opinions, perceptions

Technological profiles:
level of confidence with technologies, technological consumption

Organisational/social Roles
According to the context

Pragmatists

Visionaries

Conservatives

Tech Enthusiasts

Skeptics

Innovators
This slide is 100% editable. Adapt it to your needs and capture your audience's attention.
2.5%

Early adopters
This slide is 100% editable. Adapt it to your needs and capture your audience's attention.
13.5%

Early majority
This slide is 100% editable. Adapt it to your needs and capture your audience's attention.
34%

Late majority
This slide is 100% editable. Adapt it to your needs and capture your audience's attention.
34%

laggards
This slide is 100% editable. Adapt it to your needs and capture your audience's attention.
16%

(To mitigate our defect of knowledge bias)

Maeli, J.P. The Rogers Adoption Curve & How You Spread New Ideas Throughout Culture, Medium, 2016

The average user does not exist!

"**Where does the supposed concept of normality come from**, which defines every aspect of our lives, from the body to social status?
It is only **200 years old**.
Previously, the word 'normal' was applied only to mathematics.
Today, however, **we continuously compare ourselves to a model** of an **'average' person that... does not exist!** And above all, it is measured only based on the characteristics of a small population, the so-called **WEIRD: Western, Educated, Industrialized, Rich, Democratic, and also male and white, adds the author**."

Sarah Cheney. "Sono normale?" 2023

One size does not fit for all
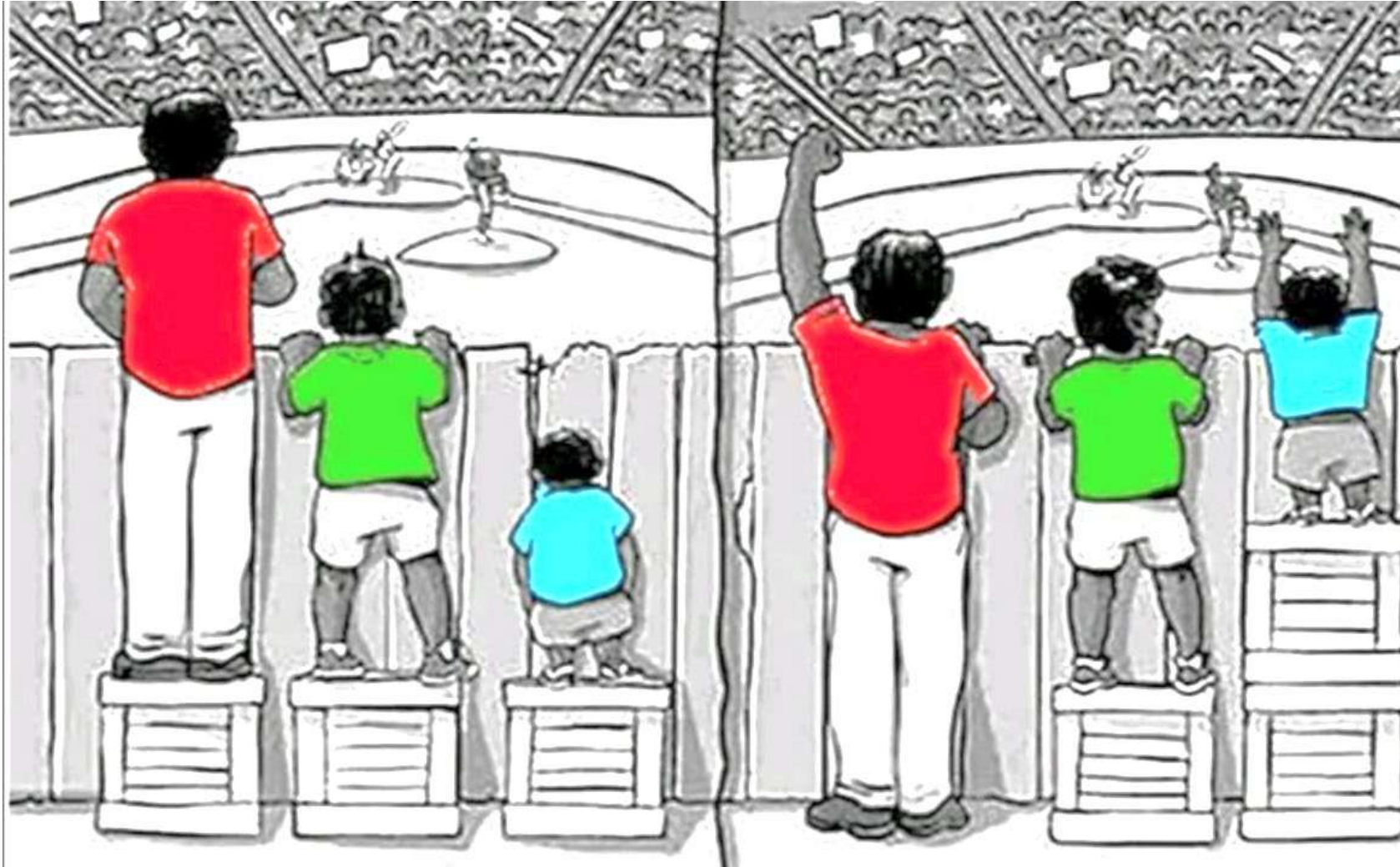
Embrace and implement diversity.

Create more personas to dig the main users considering individual and contextual variables
- Searching for more data to get deeper insights.
- Interviewing and validating personas representatives
- Searching for alternative views, diverging from your first analysis
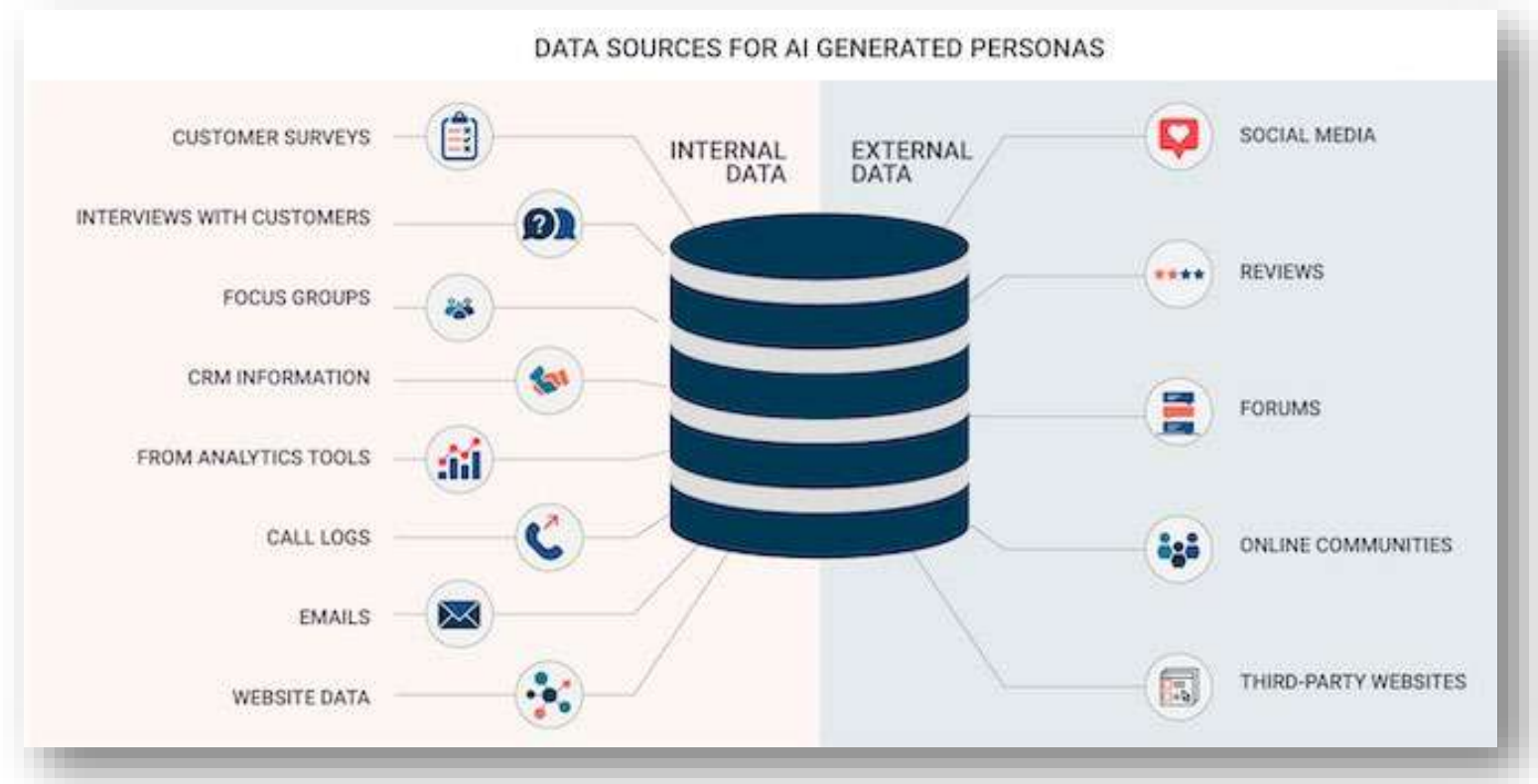- Refine the solution

AI generated personas

There is no single way of creating and using personas, neither in literature nor in practice.
Usually, with the exception of pastiche personas, **personas are based on data and information collected about real people** by using **qualitative methods** such as ethnographic interviews, open-ended survey questions, or contextual inquiries and field studies.

In the last 15 years, a collection of **large amounts of quantitative data** (for example, from web analytics, social media, online customer data, and online surveys) together with machine learning techniques led to so-called **digital data-driven personas** (mainly used in marketing and customer research).

So-called **hybrid personas** are created by utilising quantitative data from online analytics and qualitative insights.

DATA SOURCES FOR AI GENERATED PERSONAS

CUSTOMER SURVEYS
INTERVIEWS WITH CUSTOMERS
FOCUS GROUPS
CRM INFORMATION
FROM ANALYTICS TOOLS
CALL LOGS
EMAILS
WEBSITE DATA

INTERNAL DATA | EXTERNAL DATA

SOCIAL MEDIA
REVIEWS
FORUMS
ONLINE COMMUNITIES
THIRD-PARTY WEBSITES

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User personas comparison . Collection

1. Use Personas with your team members or clients to **deepen your user segments**.

2. Visually compare the user profiles created.
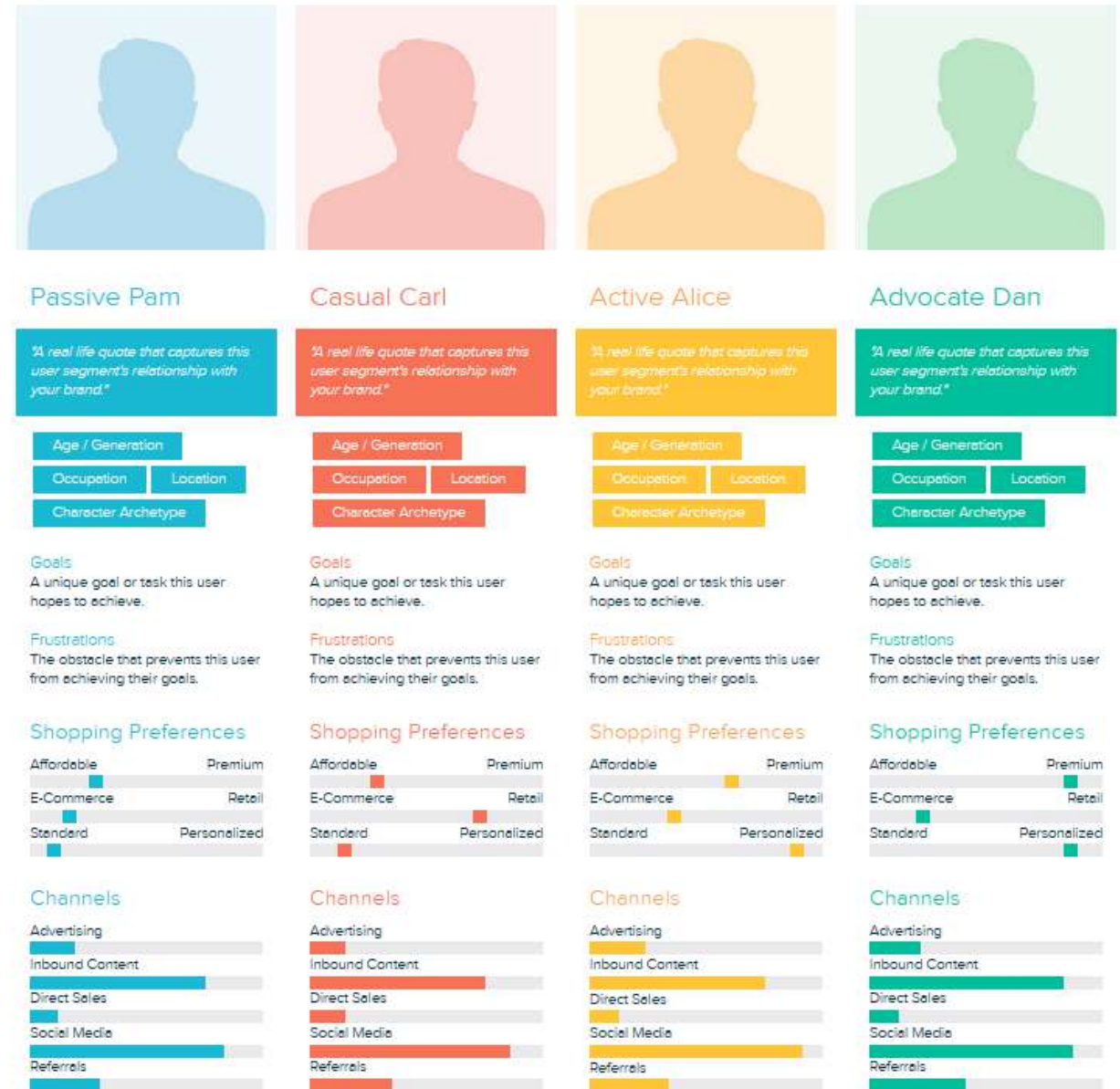
User personas comparison . Table

1. Use Personas with your team members or clients to **deepen your user segments**.

2. Condense your research and analysis to form an **executive summary,** highlighting the unique characteristics between the segments.

Build a personas
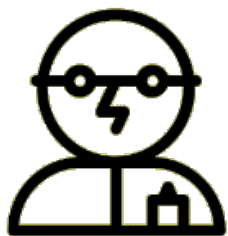
Let's design our service

1
- Which is our challenge?
- Which needs and opportunities we see?
- Who will serve?
- Who will support-it?

Context analysis and STAKEHOLDERS MAP

2
- What do your customers want to reach?
- Which data and information will be provided?
- Where do they come from?

PERSONAS

3
- How do they search for it?
- Which channels Are Important?
- Understand your users' preferences and decide how to engage with them effectively and efficiently.

CUSTOMER JOURNEY

4
- We can now define the SMART goals of the service

VALUE PROPOSITION
Smart goals
Service blueprint

Create your personas

1. Summarise the data you've collected from different sources
2. Identify the **emerging archetypes**
3. Fill in the Personas portraits (one per archetype)
4. Refine it with additional data you may collect during the process-

Focus on data →

TEMPLATE

"..." Persona

Demographics
(e.g., name, age, role, income, location)

Behaviors & Habits
(e.g., hobbies, likes, dislikes)

Pain Points & Frustrations
(e.g., what they're struggling with)

Needs & Goals
(e.g., wants, hopes)

Data can produce/use

Expected Outputs

Contacts

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