

MANAGING AI-BASED SYSTEMS



Session 11: Human-AI collaboration

Managing AI-based Systems

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Institutsteil Wirtschaftsinformatik

www.ditlab.org

www.fim-rc.de

[www.wirtschaftsinformatik.fraunhofer.de](http://wirtschaftsinformatik.fraunhofer.de)

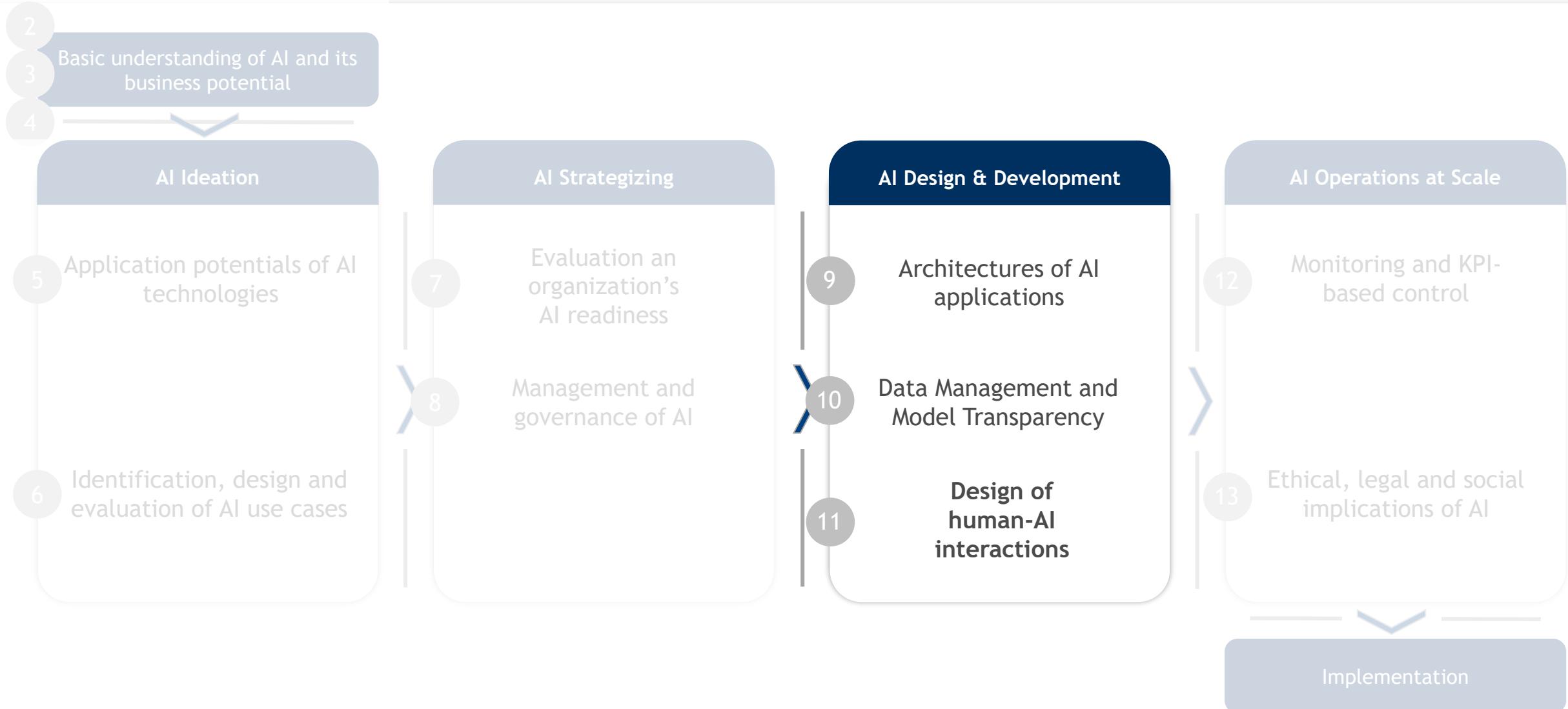
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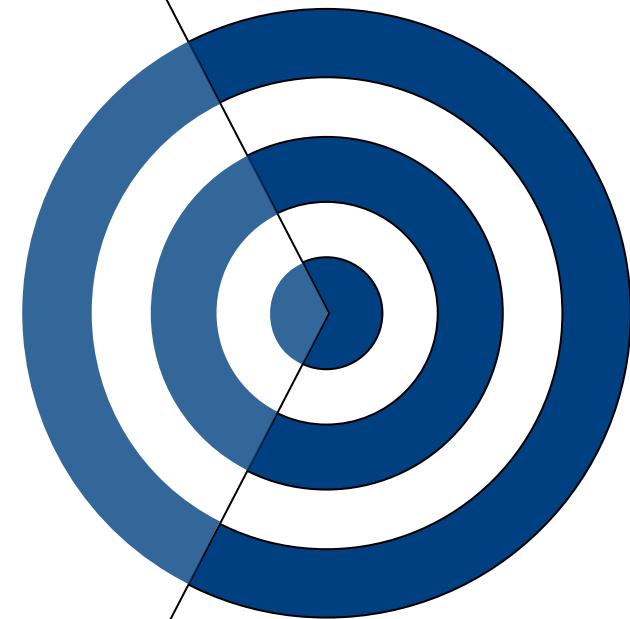
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Course navigator



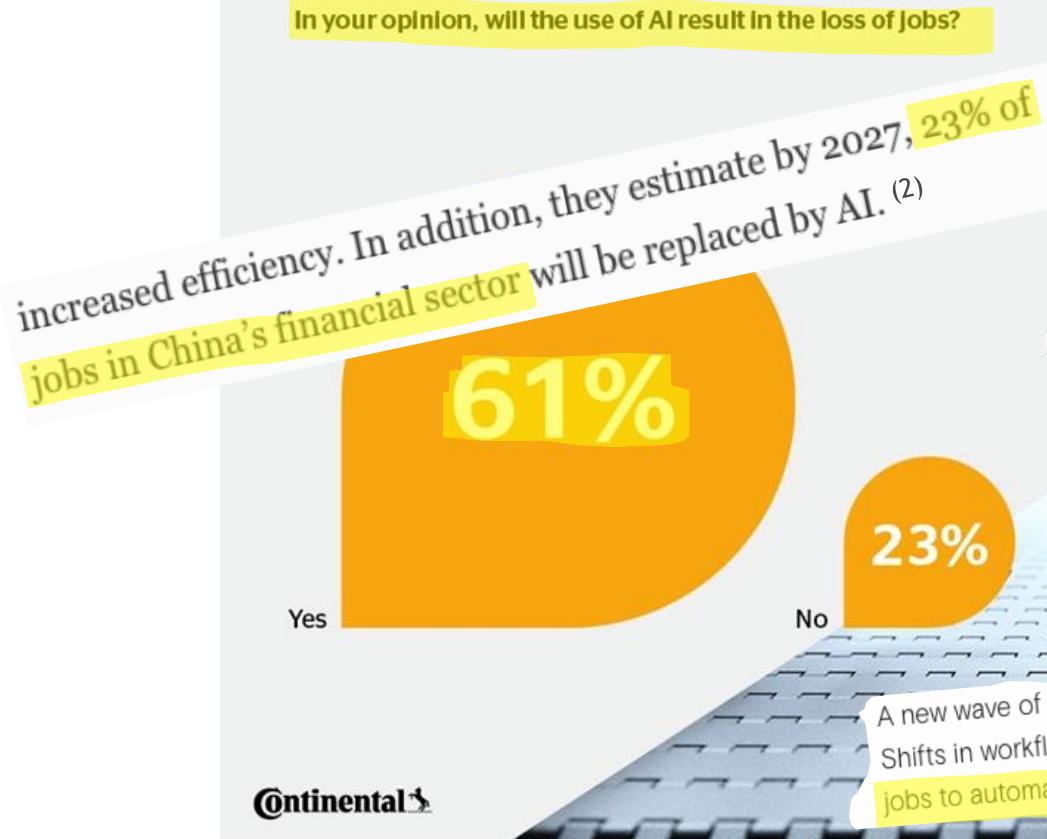
Objectives of today's lecture

1. Understand the concept of human-AI collaboration and its practical relevance
2. Comprehend the different factors enhancing acceptance of AI
3. Discover the issues arising from human-AI collaboration and possible solutions



Will AI replace humans in their jobs?

SIGNIFICANT MAJORITY EXPECTS AI TO RESULT IN JOB LOSSES



around 2053. Our updated adoption scenarios, which account for developments in generative AI, models the time spent on 2023 work activities reaching 50 percent automation between 2030 and 2060, with a midpoint of 2045—an acceleration of roughly a decade compared with the previous estimate.^[6]



A new wave of AI systems may also have a major impact on employment markets around the world. Shifts in workflows triggered by these advances could expose the equivalent of 300 million full-time jobs to automation, Briggs and Kodnani write. ⁽¹⁾

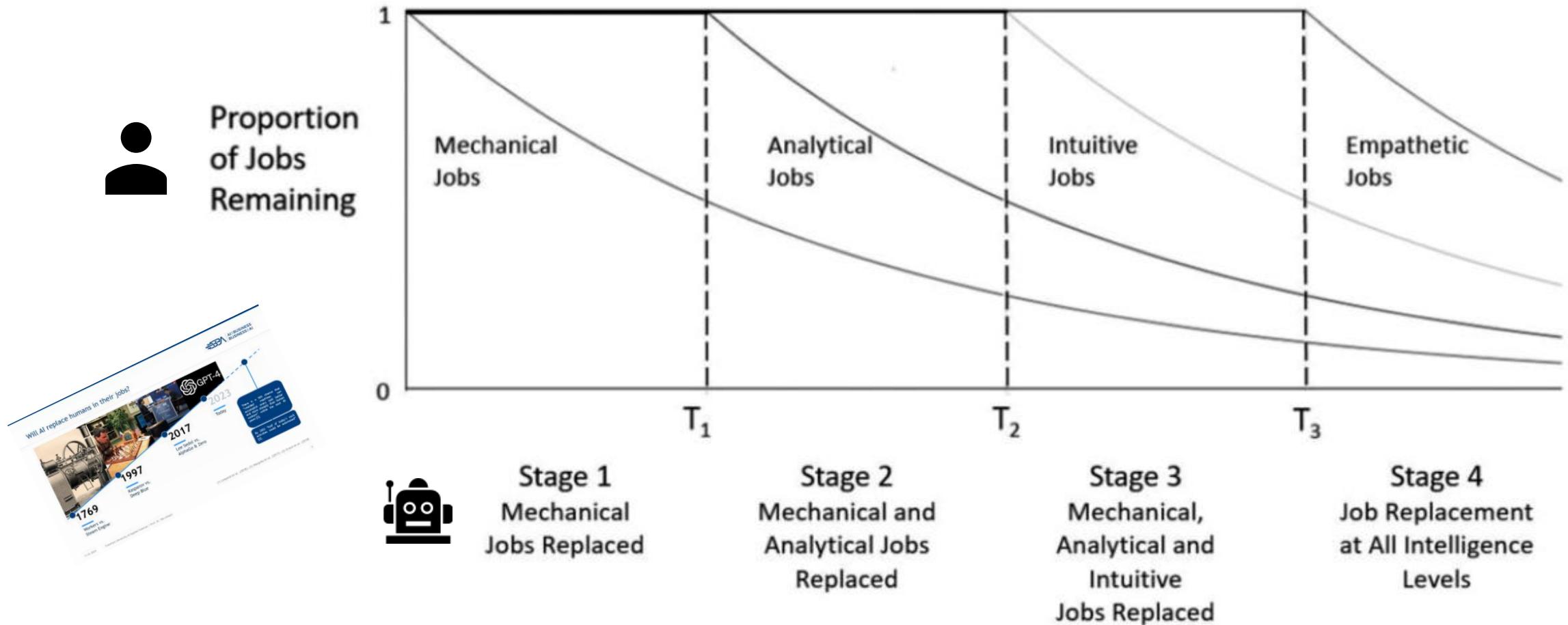
(1) Goldman Sachs (2023), (2) Forbes (2023), (3) McKinsey (2023), (4) Continental (2023)

Types of intelligence

| Mechanical | Analytical |
|--|---|
| <ul style="list-style-type: none"> Minimal degree of learning or adaption Precise, consistent, and efficient For example, self-service technologies and service robots Rely on observations to act and react repetitively | <ul style="list-style-type: none"> Skills that require limited training or education Call center agents, retail salespersons, waiters/waitress, and taxi drivers |
| Intuitive | Empathic |
| <ul style="list-style-type: none"> Learns and adapts intuitively based on understanding Artificial neural networks-based or statistical-based deep learning For example, Watson's Jeopardy, Google's DeepMind AlphaGo, and AI poker player Libratus | <ul style="list-style-type: none"> Hard thinking professionals that require creative thinking for problem-solving skills Marketing managers, management consultants, lawyers, doctors, sales managers, and senior travel agents |

Huang and Rust (2018)

Will AI replace humans in their jobs?



Huang and Rust (2018)

Wait a minute... what about emotional/ social intelligence?

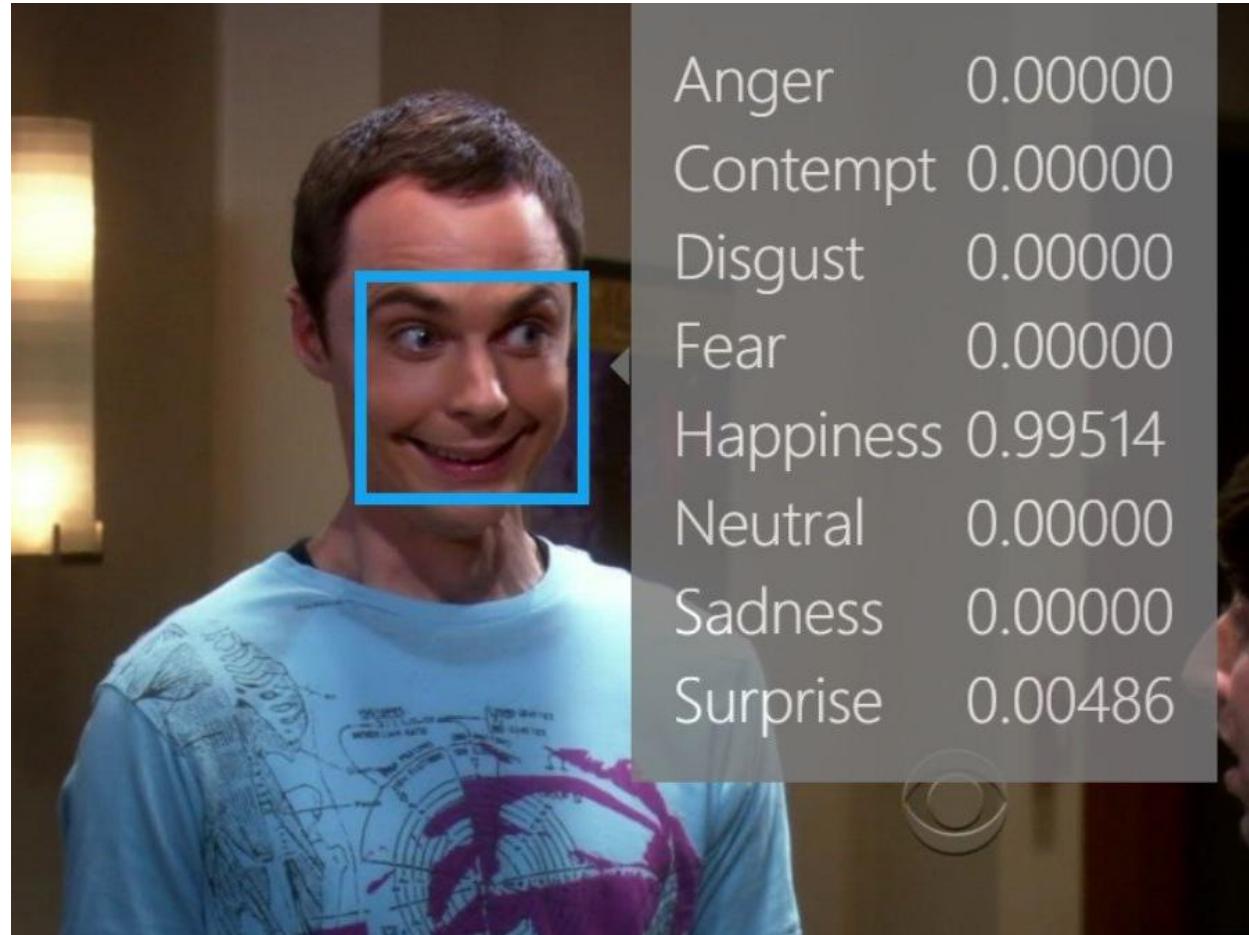
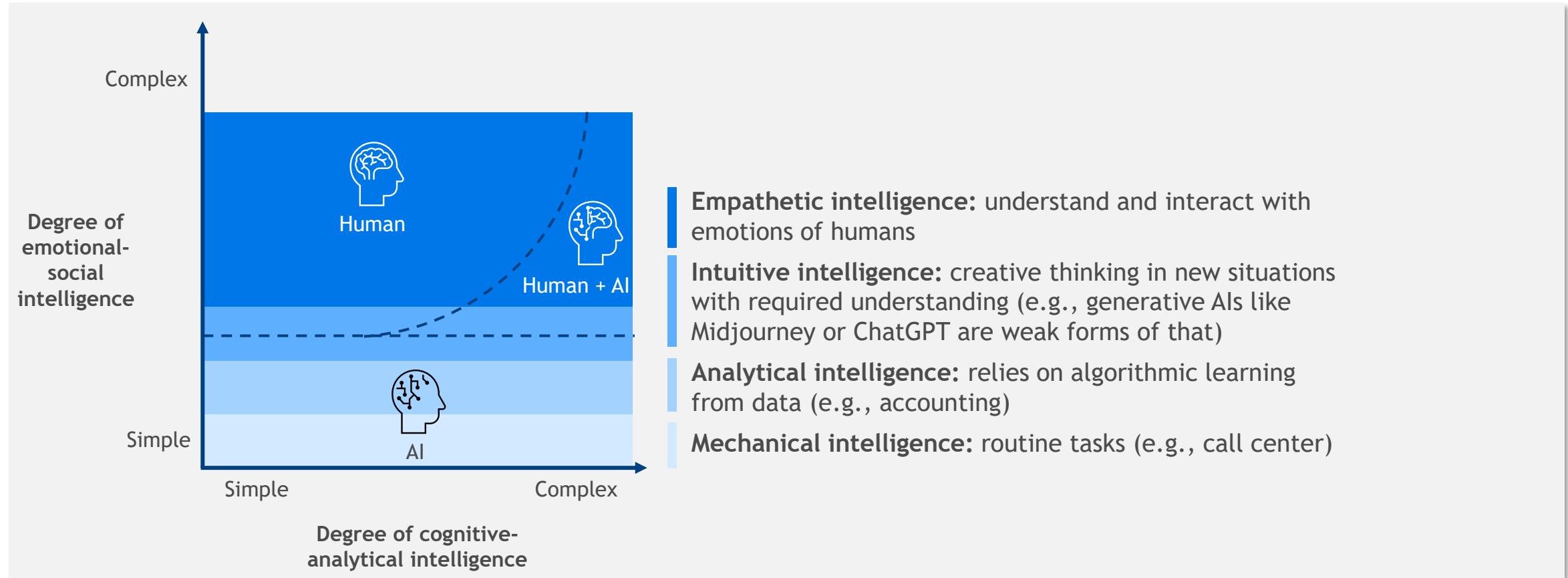


Image: knowyourmeme.com

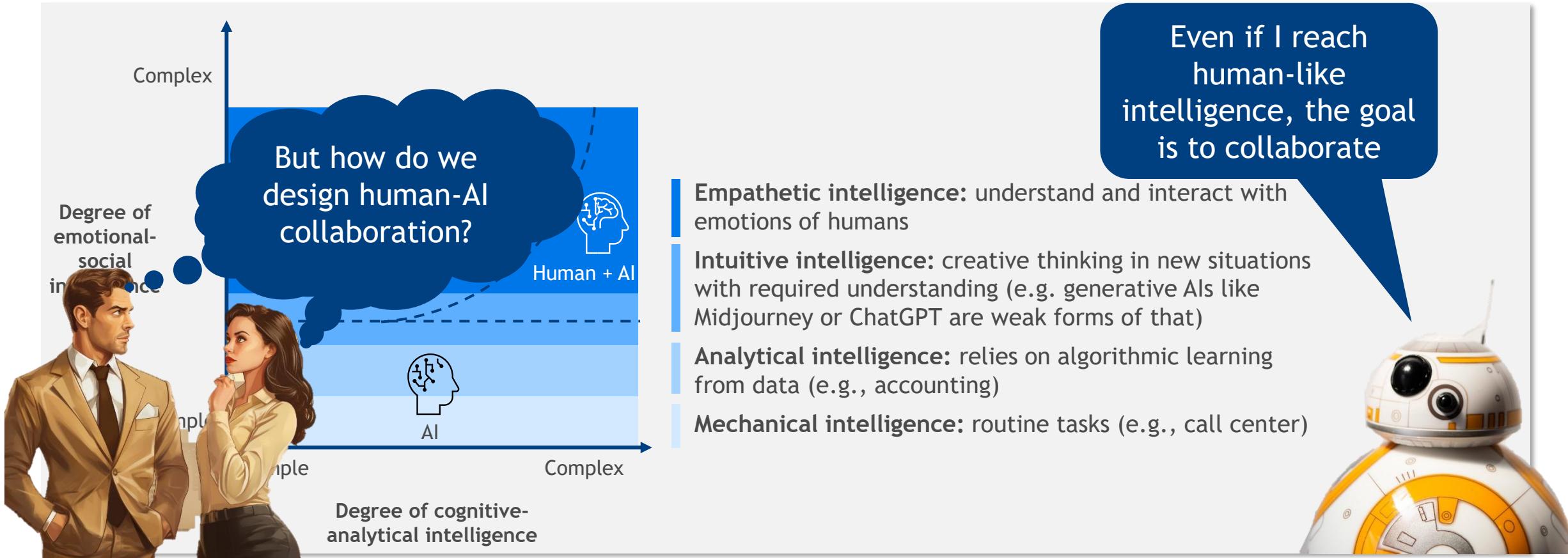
A coexistence through collaboration is more realistic



AI already has/ will probably surpass human-like intelligence in the first three levels, but it is still debatable if AI will ever achieve human-like empathetic intelligence

Wirtz et al. (2018), Huang & Rust (2018)

A coexistence through collaboration is more realistic



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Wirtz et al. (2018), Huang & Rust (2018)

The goal of HAIC is to focus on the human's benefit



Automating what humans don't want to do (e.g., transcribing interviews).



Scaling what humans practically can't do (e.g., continuous health monitoring of patients).



Performing what humans used to do at a "superhuman" level (e.g., in the future: autonomous driving)

Dimensions of HAIC

Combine complementary capabilities

Make decision models interpretable and insights explainable

Ensure legal and ethical compliance

Yeung (2020)

Agenda

01 | Acceptance driving factors of AI

02 | Algorithmic Transparency & Explainability

03 | Complementarity

04 | Fairness

05 | Delegation

06 | Risk of Human-AI Collaboration

Agenda

01 | Acceptance driving factors of AI

02 | Algorithmic Transparency & Explainability

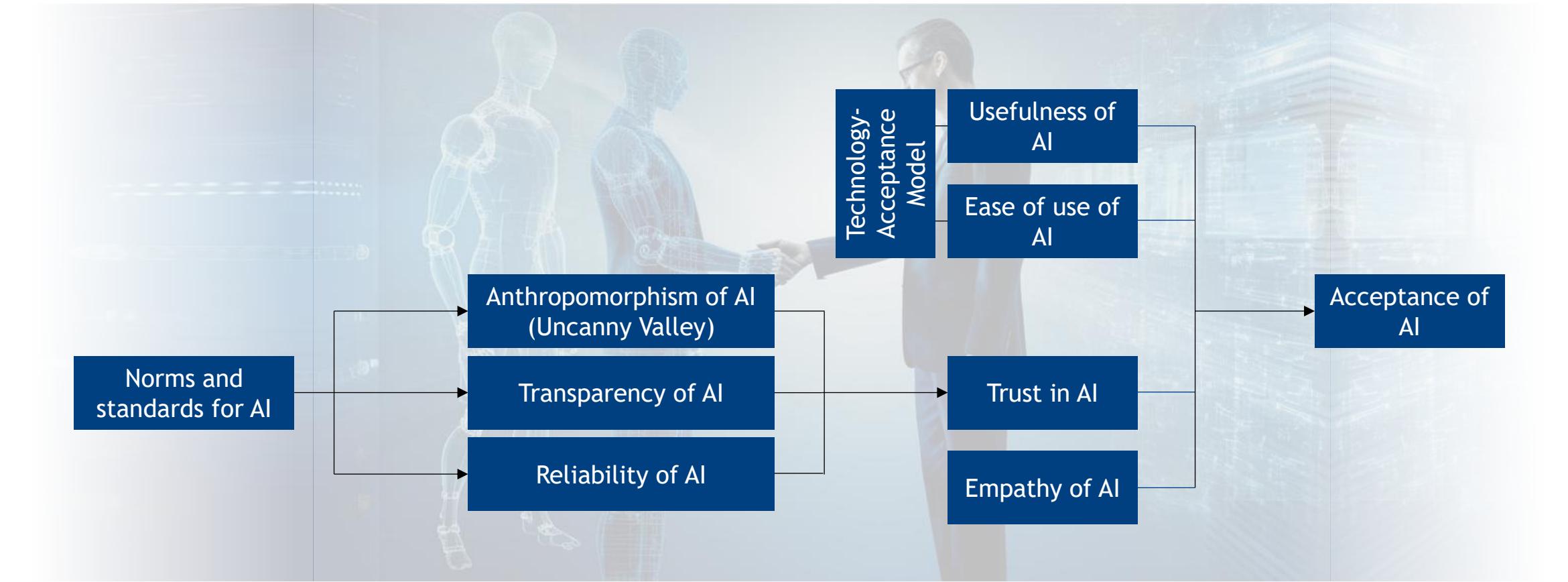
03 | Complementarity

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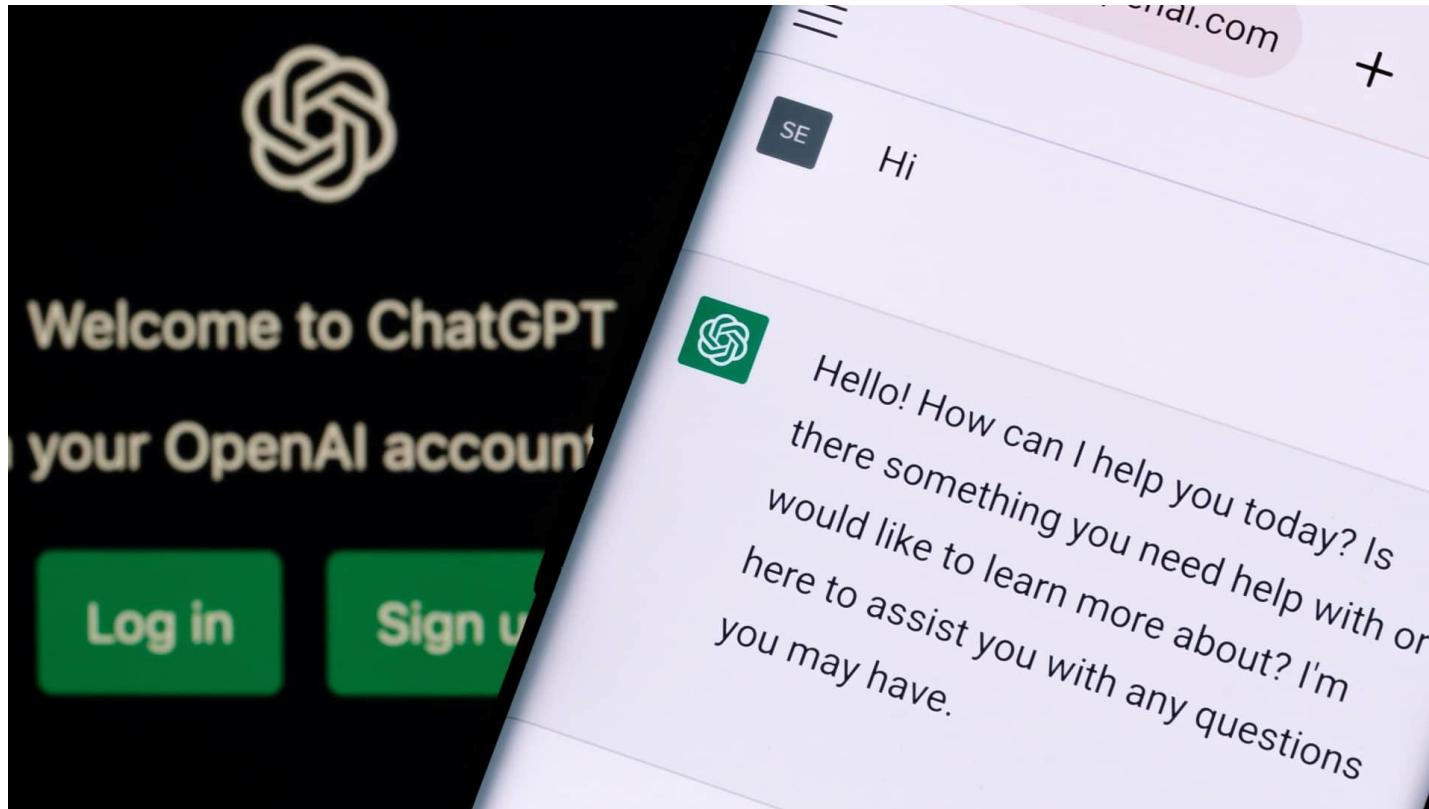
Acceptance driving factors for Human-AI Collaboration



Acceptance driving factors for AI have widely been researched and deliver a solid starting point for the design of Human-AI Collaboration

Scheuer (2020), Zhang et al. (2010), Siau & Wang (2018), Donner (2021)

Which factors do we find in current AI-systems, like ChatGPT?



<https://www.it-daily.net/it-sicherheit/cloud-security/chatgpt-ki-ist-jetzt-der-natuerlichen-ignoranz-gewachsen>

- ✓ Anthropomorphism: ChatGPT is able to chat with you like a human (passes Turing Test)
- ✓ Usefulness: If you understand for which cases ChatGPT delivers value, it can be very useful
- ✓ Ease of use: It is very easy to use in its Chat User Interface
- Transparency: Even if we somehow understand the heuristic (including temperature factor), OpenAI is not fully transparent on how it works, on which data it was trained, etc.
- Reliability: Sometimes it produces non usable output, it is even reported that the system got worse over time



In the case of ChatGPT, the most important factors for its acceptance might be its usefulness, the ease of use and its ability to write human-like.

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Algorithmic transparency

Algorithmic transparency means to disclose information about algorithms to enable monitoring, criticizing or intervening by interested parties (Diakopoulos & Koliska, 2017)



Benefits:

- People, who use, regulate or are somehow affected by AI algorithms, can understand the underlying concepts of the algorithm because of its transparency
- With that, mistakes of an algorithmic system can also be made more traceable
- The accountability of mistakes still belongs to the developer of the technology

Components of algorithmic transparency:

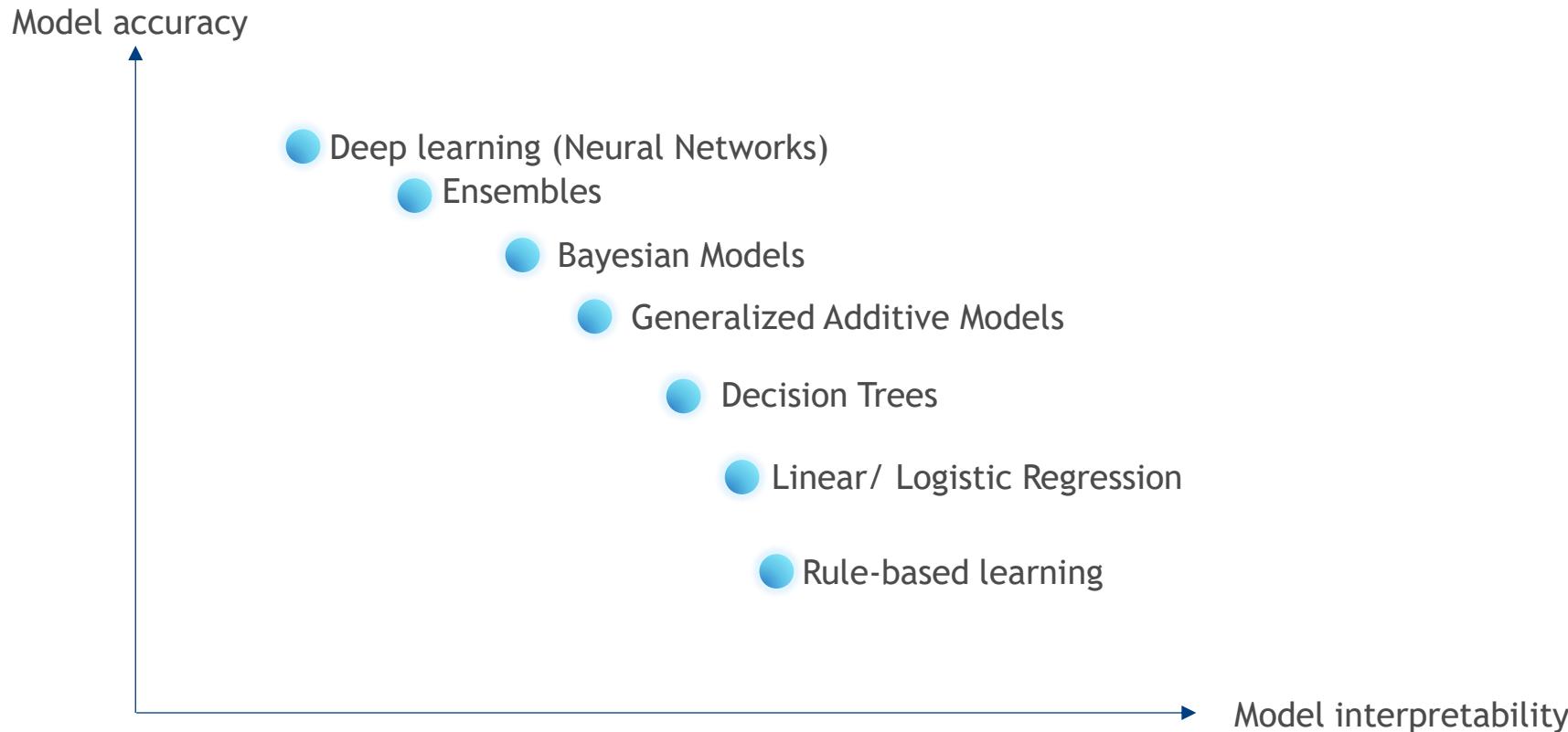
1. Human involvement (Who is accountable, goal of algorithm, who has control, ...)
2. Data (Quality of data, Data (pre)-processing, ...)
3. Model (Features and variables used, assumptions behind the model, ...)
4. Inference (Accuracy rates, biases, ...)
5. Personalization (Types of personal information used, ...)



Algorithmic transparency is an important component of Human-AI Collaboration because it sets a base for the explainability of AI

Diakopoulos & Koliska, (2017), Kossow et al. (2021)

Relationship between model interpretability and accuracy



There is a certain relationship between different models' interpretability and their accuracy, which shows why algorithmic transparency and explainability gets more important

Arrieta et al. (2020)

Why the explainability of AI matters?

Explanations of intelligent systems are important to understand

...how and why...

it arrived at a particular decision.

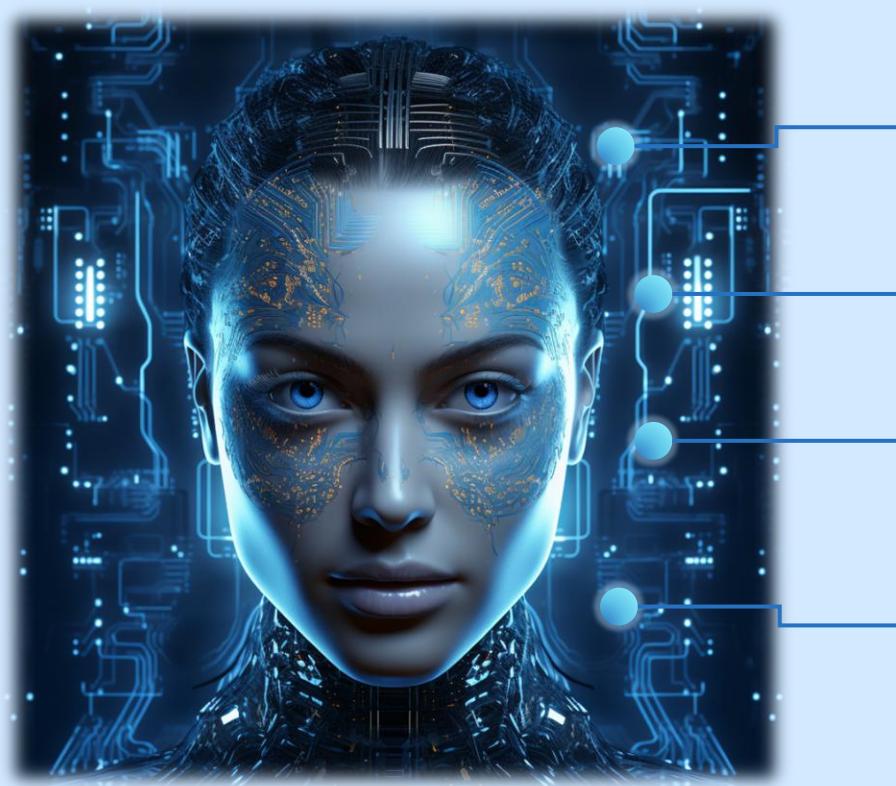
This is especially crucial in scenarios where AI makes decisions that affect people directly, like in...

Finance

Health care

Autonomous driving

Legal affairs



Benefits of AI explainability

Building trust and confidence (e.g., for decision makers)

Helping to identify bias and error (e.g., for developers)

Verifying alignment with goals and values (e.g., regulatory agencies)

Helping to understand decisions to end-users (e.g., loan applicants)



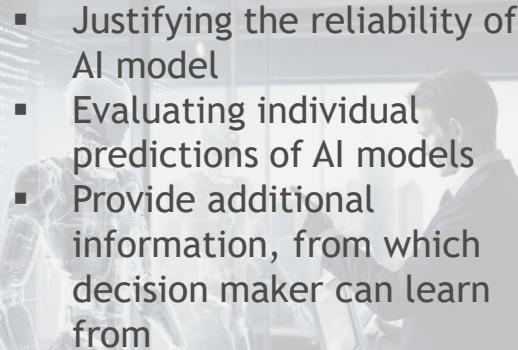
By offering explanations, the black box nature of many AI algorithms becomes more trustworthy, accountable and user-friendly

explainml-tutorial.github.io

Why different groups of people need different explanations?

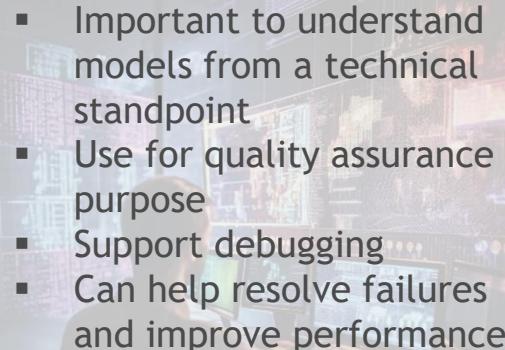


Decision-makers

- Justifying the reliability of AI model
 - Evaluating individual predictions of AI models
 - Provide additional information, from which decision maker can learn from
- 

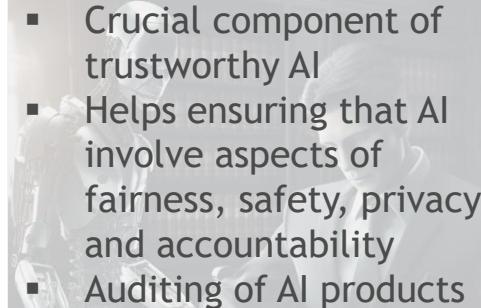


Developers

- Important to understand models from a technical standpoint
 - Use for quality assurance purpose
 - Support debugging
 - Can help resolve failures and improve performance
- 

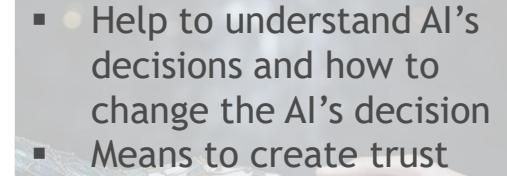


Regulators

- Crucial component of trustworthy AI
 - Helps ensuring that AI involve aspects of fairness, safety, privacy and accountability
 - Auditing of AI products
- 



End-users

- Help to understand AI's decisions and how to change the AI's decision
 - Means to create trust
- 



The explainability of AI is subjective to the stakeholder that is receiving it and thus fulfills different benefits

Tjoa & Guan (2020), Vokinger & Gasser (2021), Laato et al. (2022)

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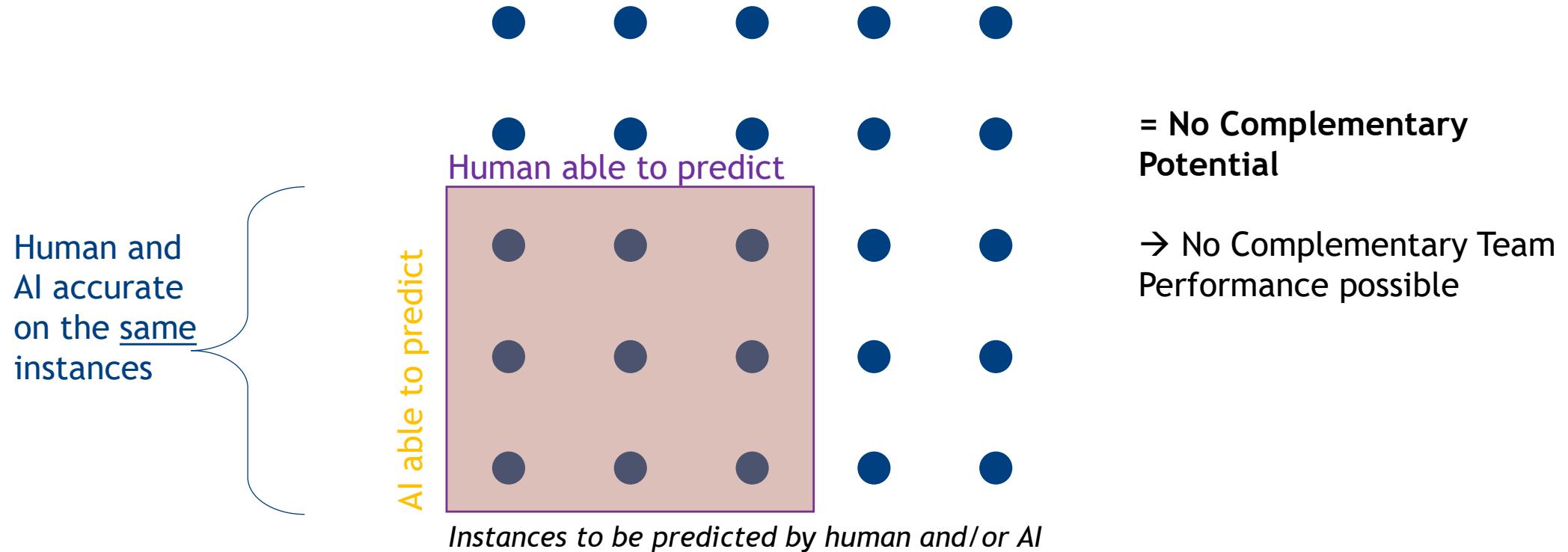
03 | Complementarity

04 | Fairness

05 | Delegation

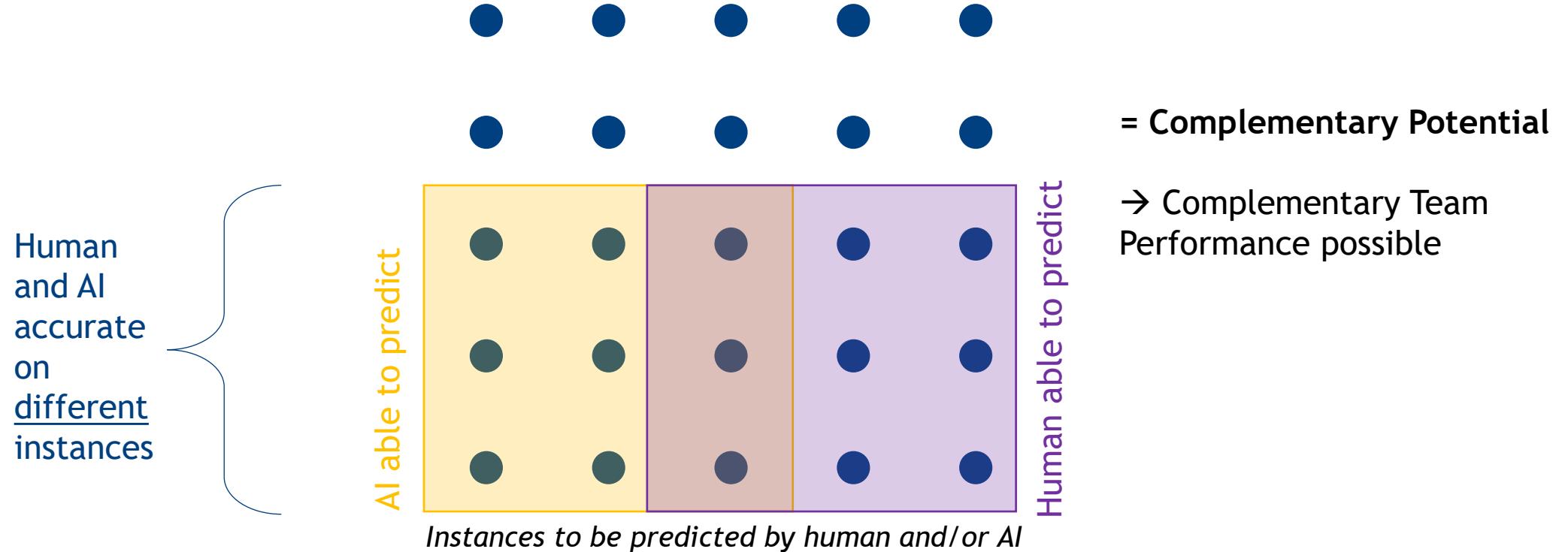
06 | Risk of Human-AI Collaboration

...as well as the distribution of the individual strengths –
the complementary potential (1/3).



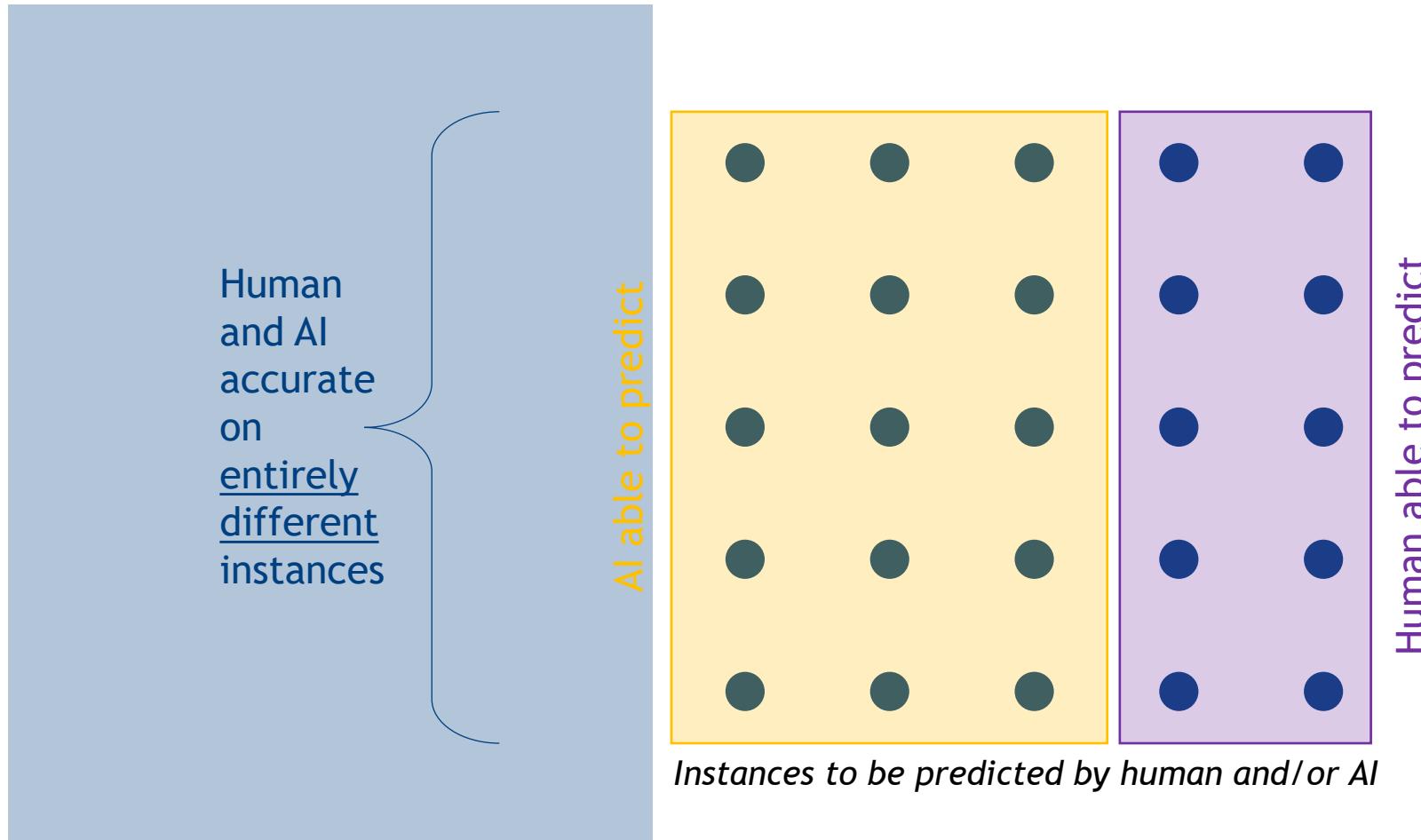
Hemmer et al. (2025), Kühl (2023)

...as well as the distribution of the individual strengths –
the complementary potential (2/3).



Hemmer et al. (2025), Kühl (2023)

...as well as the distribution of the individual strengths –
the complementary potential (3/3).



= **Maximum Complementary Potential**

→ Complementary Team Performance possible

Complementarity in prominent AI use cases

| Use case | Autonomous driving | Robo-financial - advisor | Cancer detection | Military services | Conclusion |
|------------|--|---|---|---|---|
| Task AI | <ul style="list-style-type: none"> Steering & Navigation of car according to rules, signs and environmental conditions | <ul style="list-style-type: none"> Portfolio Allocation Automated Rebalancing Risk Assessment Tax Efficiency Cost Efficiency | <ul style="list-style-type: none"> Analysis of big databases Pattern Recognition Early Detection Continuous Monitoring | <ul style="list-style-type: none"> Persistent Monitoring Terrain Mapping Early Warning Military services in dangerous areas | <p>Tasks characteristics:</p> <ul style="list-style-type: none"> Continuous Analytical task for big database Pattern Recognition Routine Dangerous |
| Task Human | <ul style="list-style-type: none"> Monitoring of AI Intervening in emergency situations Ethical decisions | <ul style="list-style-type: none"> Psychological components of investing Behavioral Coaching Personalized advice | <ul style="list-style-type: none"> Clinical Judgement Contextual Understanding Communication Ethical and cultural factors | <ul style="list-style-type: none"> Strategic decision with psychological warfare Communication and Coordination of staff and arti. units | <p>Tasks characteristics:</p> <ul style="list-style-type: none"> Monitoring AI Intervening in case of specialty Ethical, cultural and psychological topics Communicative |



Across various industries, the complementary collaboration of human and AI can lead to better overall performance

Images: Midjourney

Complementarity in cancer detection

| Use case | Autonomous driving | Robo-financial - advisor | Cancer detection | Military services | Conclusion |
|------------|---|---|--|--|---|
| Task AI | <ul style="list-style-type: none">Steering & Navigation of car according to rules, signs and environmental conditions | <ul style="list-style-type: none">Portfolio AllocationAutomated RebalancingRisk AssessmentTax EfficiencyCost Efficiency | <ul style="list-style-type: none">Analysis of big databasesPatient MonitoringMedical JudgementContextual UnderstandingCommunicationEthical and cultural factors | <ul style="list-style-type: none">Persistent MonitoringTerrain MappingEarly WarningMilitary services in dangerous areas | <p>Tasks characteristics:</p> <ul style="list-style-type: none">ContinuousAnalytical task for big databasePattern RecognitionRoutineDangerous |
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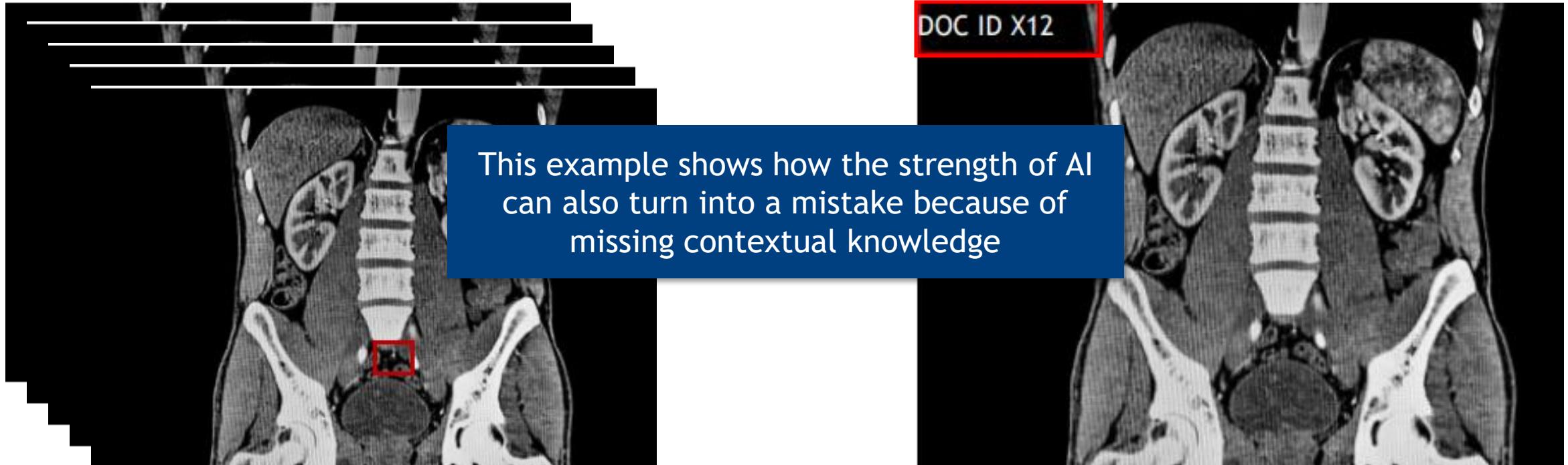
Are you sure an AI can't replace a doctor?



Across various industries, the complementary collaboration of human and AI can lead to better overall performance

Images: Midjourney

Why Human-AI Collaboration needs to be complementary

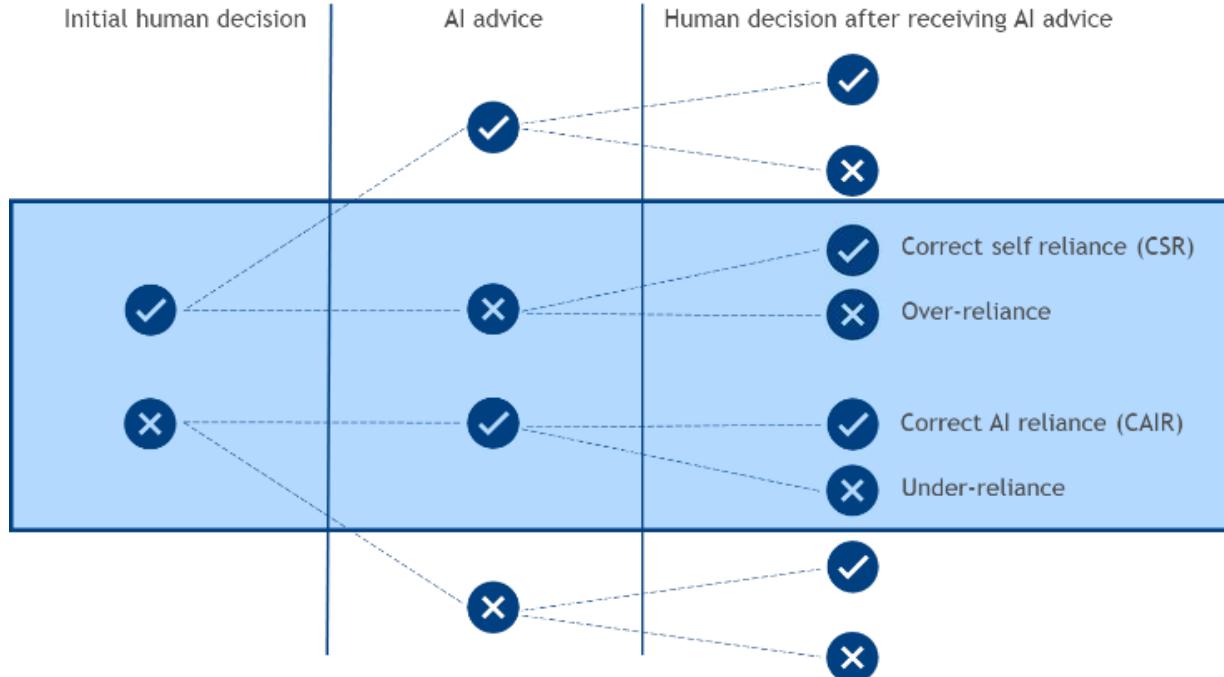


AI system finds anomaly by analyzing big data base of patients.

AI system detects picture numbering as an anomaly and reports it.

Kühl (2022)

Human-AI Collaboration strives for optimal Appropriateness of Reliance (AoR)

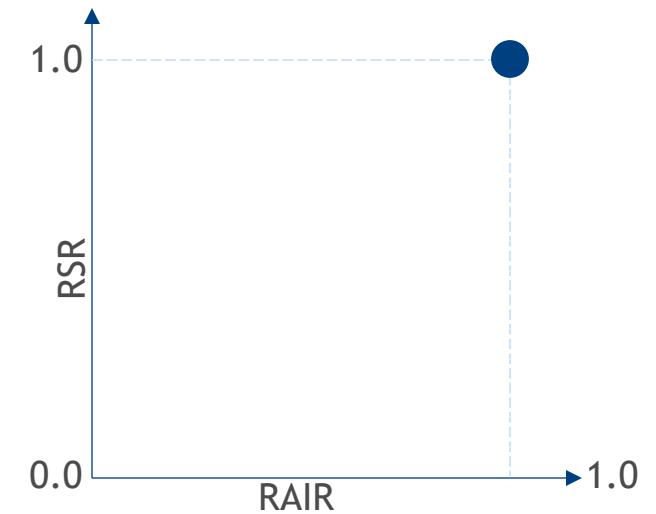


Appropriateness of Reliance (AoR) = (RSR, RAIR)

$$RAIR = \frac{\sum_{i=0}^N CAIR_i}{\sum_{i=0}^N CA_i}$$

$$RSR = \frac{\sum_{i=0}^N CSR_i}{\sum_{i=0}^N IA_i}$$

CA (Correct advice), IA (Incorrect advice)



When human and AI come to a different conclusion, over- and under-reliance are the two possible types of errors that can occur

Schemmer et al. (2023)

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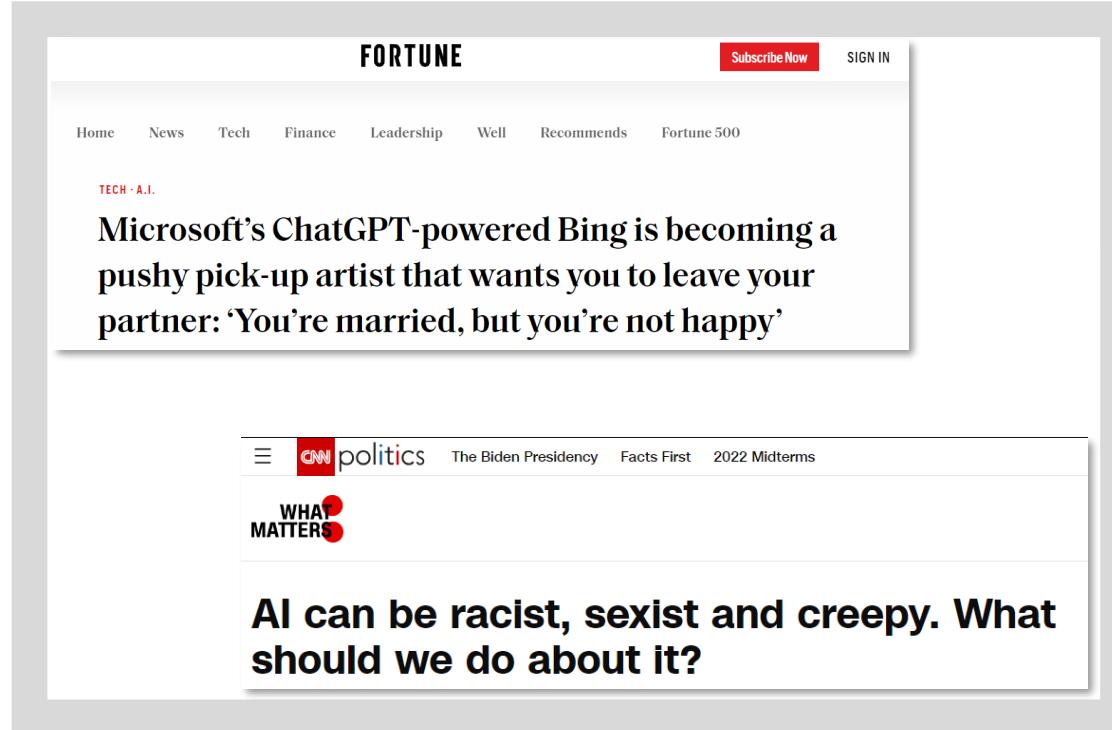
03 | Complementarity

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Some AI systems differentiate based on unjustified data



AI's task is often to find patterns and to differentiate

BUT: sometimes these differentiations are discriminations because they are based on unjustified/irrelevant information

- AI systems have no conscience and will take the “path of least resistance”

 The topic of fairness of AI based decisions also shows the relevance of complementarity to ensure that the differentiating variables are relevant and justified

Fortune (2023), CNN (2023), Ribeiro et al. (2016)

Excluding certain data does not always lead to fairness

- Some sensitive information can be reproduced from other features (e.g., gender and name, height, length of hair, etc.)
 - Excluding gender for a job application does not automatically solve the inequality issue because other features than gender could lead to the same conclusion (e.g., name)
- The decision when to in- and exclude certain sensitive information for AI based decision has to be evaluated by the society for each case

Job applicant for management position

| Surname | Last name | Age | Gender | Job last year | University | High school |
|---------|-----------|-----|--------|----------------------|------------|------------------------|
| Anna | Griffin | 34 | female | Maternity protection | Yale | Girl's school Michigan |
| Peter | O'Malley | 36 | male | AI Consultant | TUM | New jersey high school |
| Brad | Kaslik | 33 | male | CEO start-up | Cambridge | Alabama high school |



We, as an inclusive, diverse company use machine learning for the first selection of our application process but exclude gender data of our applicants to ensure equality!

The yellow highlighted cells could also lead to a similar decision to exclude the woman for the application



Omitting certain sensitive information does not automatically lead to more equality and fairness because systems can conclude similar based on other variables (redundant coding)

Ribeiro et al. (2016)

What exactly does fairness mean to you?



When is an ML algorithm fair and how can we achieve this?

Remember what we just learned about redundant encodings.

There are different approaches to achieve fairness in AI

I. Statistical parity: “Acceptance rate is equal for all sensitive groups”

- Example: 70% females and 30% males apply to university
- Statistical parity would mean that there are also 70% females and 30% males in the pool of admitted students
- I. Question to you: Does this prevent unfair outcomes?

II. Equal opportunity: “True positive rates are equal for all sensitive groups”

- Example: Out of 40 qualified female applicants, 30 were correctly accepted.
- Equal opportunity would mean that $\frac{3}{4}$ of male applicants would also have been accepted correctly
- II. Question to you: Does this prevent unfair outcomes?



Which approach do you think is fairer? (No right or wrong)

| | | Ground Truth | |
|-------------|----------|---------------------|---------------------|
| | | Positive | Negative |
| Predictions | Positive | True Positive (TP) | False Positive (FP) |
| | Negative | False Negative (FN) | True Negative (TN) |



Each approach has its own strength and weakness and is thus dependent on the case itself, which again shows the importance of Human-AI collaboration to monitor mistakes

Barocas et al. (2019), Hardt et al. (2016)

How to achieve algorithmic fairness better

a. Pre-Processing

- Edit (training) data through trying to remove underlying discrimination
- Example: Sampling of representative data with ImageNet

b. In-Processing

- Modifying algorithms to eliminate discrimination during training
- Either objective function is modified or additional constraints get introduced

c. Post-Processing

- Re-assignment of labels after training based on fairness criteria
- Mostly only the case if data and ML algorithm cannot be adapted



Even when trying to be fairer, absolute fairness is hard to achieve and likely comes with a cost in accuracy

Yang et al. (2020), Haas (2019), Rodolfa et al. (2020)

7 principles of the European Commission for trustworthy AI

| Principles | Definitions in Ethics Guideline | Implication based on lecture topics |
|---|---|---|
| 1) Human agency and oversight | Human agency and oversight: AI systems should empower human beings, allowing them to make informed decisions and fostering their fundamental rights. At the same time, proper oversight mechanisms need to be ensured, which can be achieved through human-in-the-loop, human-on-the-loop, and human-in-command approaches | European commission focuses on Human-AI collaboration |
| 2) Technical robustness and safety | Technical Robustness and safety: AI systems need to be resilient and secure. They need to be safe, ensuring a fall back plan in case something goes wrong, as well as being accurate, reliable and reproducible. That is the only way to ensure that also unintentional harm can be minimized and prevented. | Reliability and Reproducibility (connected to transparency) is important |
| 3) Privacy and data governance | Privacy and data governance: besides ensuring full respect for privacy and data protection, adequate data governance mechanisms must also be ensured, taking into account the quality and integrity of the data, and ensuring legitimised access to data. | Careful handling of sensitive data (fairness) |
| 4) Transparency | Transparency: the data, system and AI business models should be transparent. Traceability mechanisms can help achieving this. Moreover, AI systems and their decisions should be explained in a manner adapted to the stakeholder concerned. Humans need to be aware that they are interacting with an AI system, and must be informed of the system's capabilities and limitations. | Explainability and algorithmic transparency for every stakeholder |
| 5) Diversity, non-discrimination and fairness | Diversity, non-discrimination and fairness: Unfair bias must be avoided, as it could have multiple negative implications, from the marginalization of vulnerable groups, to the exacerbation of prejudice and discrimination. Fostering diversity, AI systems should be accessible to all, regardless of any disability, and involve relevant stakeholders throughout their entire life circle. | Fairness to every vulnerable group to ensure non-discrimination |
| 6) Societal and environmental well-being | Societal and environmental well-being: AI systems should benefit all human beings, including future generations. It must hence be ensured that they are sustainable and environmentally friendly. Moreover, they should take into account the environment, including other living beings, and their social and societal impact should be carefully considered. | Design of Human-AI Collaboration should be sustainable & environmentally friendly |
| 7) Accountability | Accountability: Mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes. Auditability, which enables the assessment of algorithms, data and design processes plays a key role therein, especially in critical applications. Moreover, adequate an accessible redress should be ensured. | Responsibility and accountability are crucial topics for HAIC |

<https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai>

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Different types of integration of Human and AI predictions

| | | Timing of integration | |
|------------|-------|--|---|
| | | Ex-ante (i.e., before tasks are conducted) | Ex-post (i.e., after tasks are conducted) |
| Integrator | Human | Human-led delegation | Human integration |
| | AI | AI-led delegation | AI integration |

Depending on the integrator and the timing, human and AI predictions can be integrated differently:

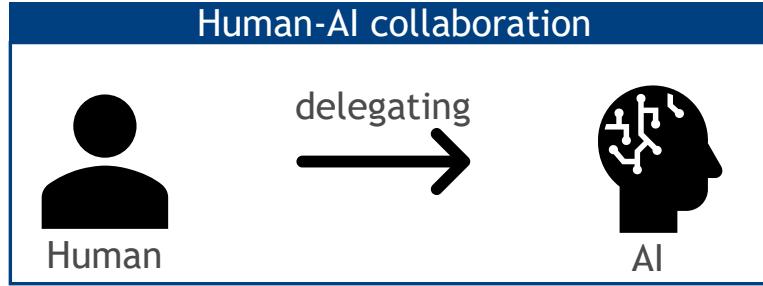
- Human-led delegation: Human delegates task to either human or an AI
- AI-led delegation: AI delegates task to either human or AI
- Human integration: Human accepts/ rejects AI advice
- AI integration: AI combines predictions of humans and AI



The delegation of tasks in Human-AI Collaboration settings can not only come from humans, but also from AI

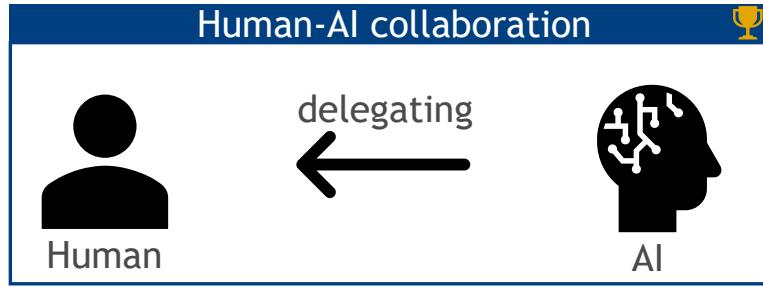
Kühl (2023), Leyer & Schneider (2019), Hemmer et al. (2022), Goodwin (2000)

Who is better at delegating - Human or AI? (in image classification)



Observations:

- Humans did not delegate well, even though they acted rationally and internally consistent and followed a clear delegation strategy
- BUT: Humans were not able to assess their own capabilities well, which then led to poor delegation decisions



Observations:

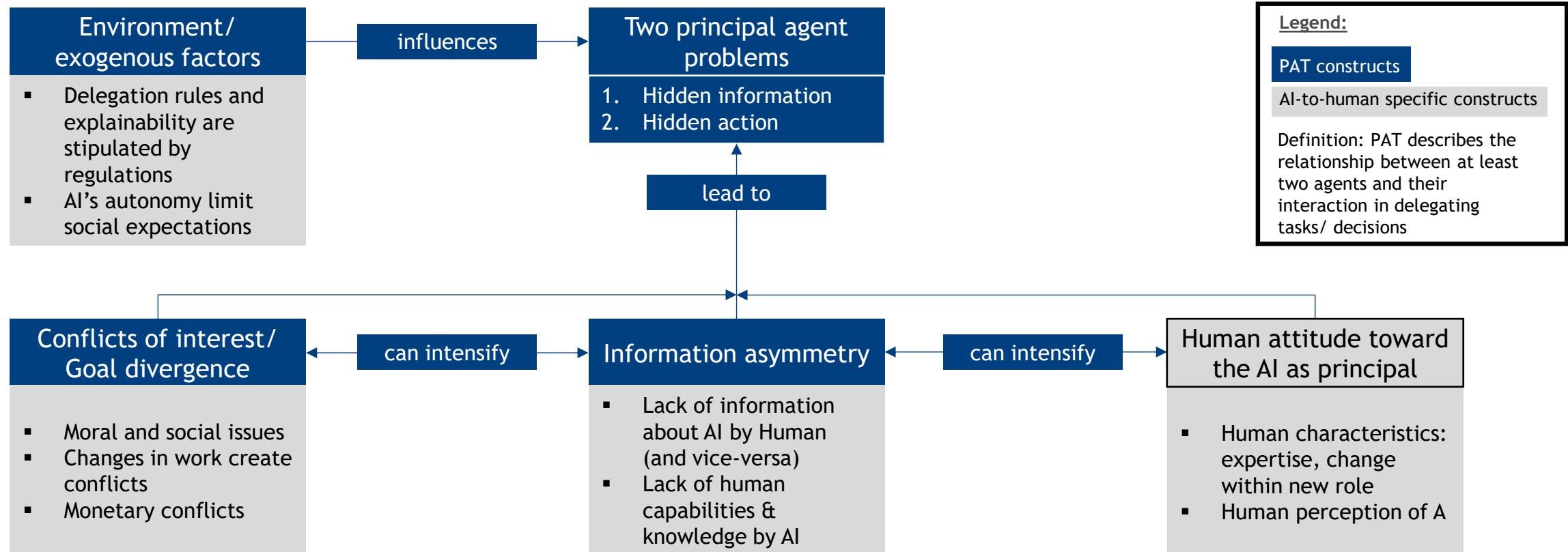
- Collaboration with delegating AI has highest performance, which makes it economically desirable
- Humans could focus on the tougher classification examples, while AI did the mundane tasks by classifying easy picture
- AI would still not be a human's boss, rather an assistant
- BUT: This comes with a loss of control since AI only asks when it needs help



Current research has figured out that for image classification Human-AI collaboration outperforms AI (only) and Human (only) at work, but only when AI is delegating tasks

Fügener et al. (2022)

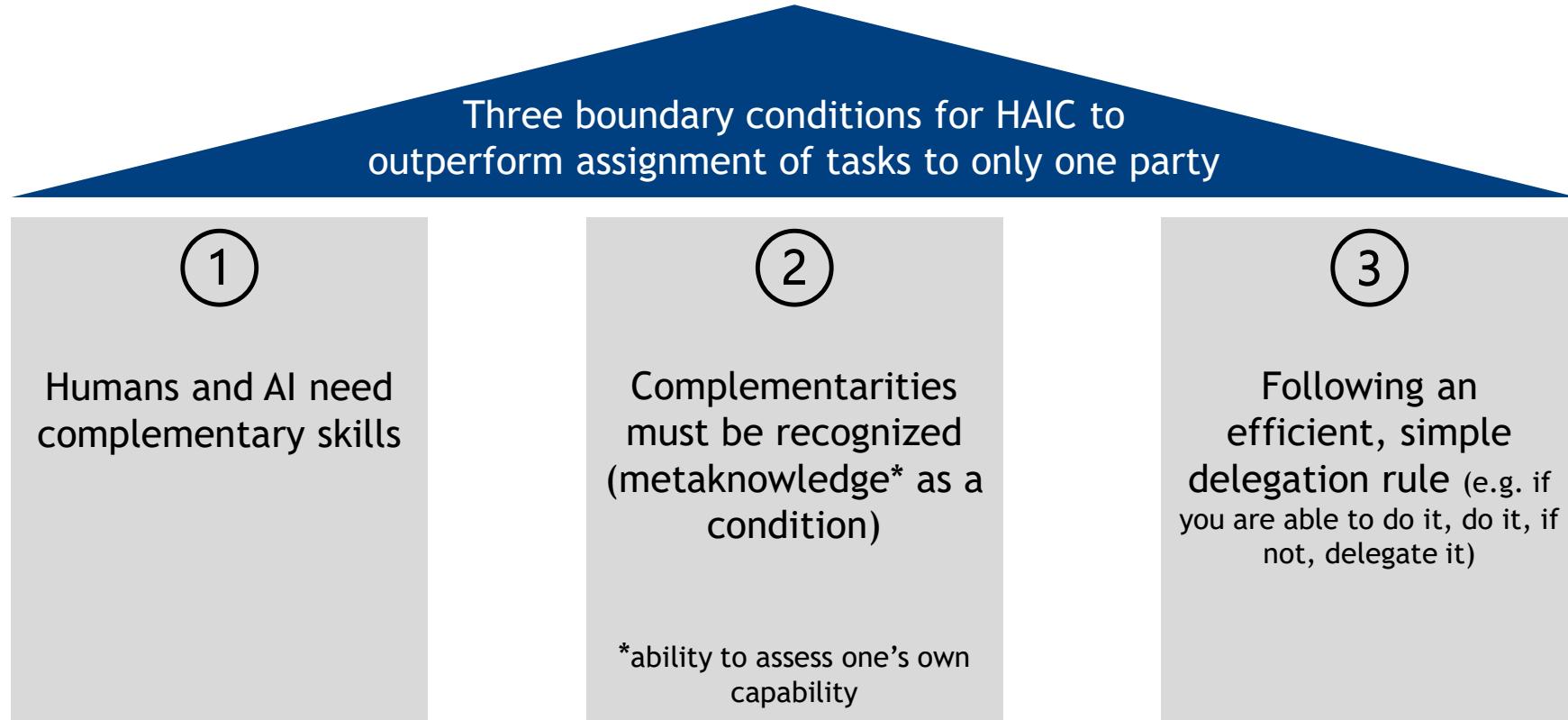
AI-led delegation from a principal-agent perspective



The principal agent theory applied to the collaboration of AI and human shows the two potential conflicts that can arise, which are hidden action and hidden information in HAIC

Guggenberger et al. (2023)

Three boundary conditions of outperforming HAIC



The three layers are important to consider for the design of Human-AI collaboration settings

Fügner et al. (2022)

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Automation bias as a risk of Human-AI Collaboration

MI I'm preparing a university lecture on "Human-AI Collaboration". Please tell me whether humans experience "automation bias". Please start with Monsier and Skitka's definition of the term.

According to Monsier and Skitka, automation bias is "the tendency for individuals to over-rely on automated systems, to the exclusion of other information or their own decision-making skills." This means that humans often have a tendency to trust the decisions and actions of AI systems without fully considering other options or using their own judgement. This can lead to problems such as over-reliance on the AI system and a lack of critical thinking on the part of the human.

Prompt was to define “automation bias” according to Mosier and Skitka (funnily with a typo)

Here is what ChatGPT did:

- ✗ Adopts typo of author (Mosier ≠ Monsier)
- ✗ Gives us a definition that sounds correct but is not from Mosier and Skitka



This example shows the importance of humans staying the last insuring instance before a decision is taken with an artificial intelligence and do not blindly trust

ChatGPT (2022)

Automation bias as a risk of Human-AI Collaboration

Skitka & Mosier: Automation Bias is “the tendency to use automated cues as a heuristic replacement for vigilant information seeking and processing”. This means that humans sometimes trust the decisions and actions of AI systems without (a) considering other options or (b) using their own judgement.

Reasons for automation bias:

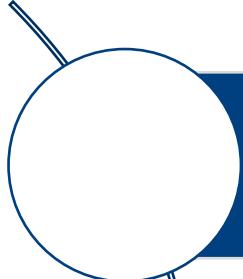
- Perceived reliability and accuracy of an “infallible” AI system
- Assumption that AI systems are unbiased and objective
- Insufficient clarity and comprehension regarding the decision-making processes of the AI system



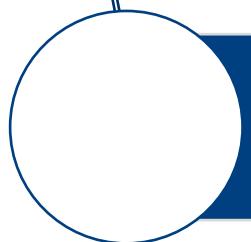
The phenomenon of automation bias can lead to overreliance on AI systems and a lacking critical thinking by humans

Mosier & Skitka (1996)

Today's lecture at a glance



We learned how algorithmic transparency, explainability and other factors influence the acceptance of AI systems by humans



We understood why omitting certain variables will not prevent AI models to come up with biased conclusions



We discovered potential issues in a human AI collaboration based on the principal agent theory

Questions, comments, observations



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