

# Leadership in the age of digital transformation:

## The emerging roles of the data scientists

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# The world today

A world of meta/post- :

- post-truth,
- post-democracy,
- post-capitalism,
- metaverse



# An era of reflection

# The world today

A world of inter- :

- interdisciplinary,
- interconnectiveness,
- intersubjectivity,



# Everything is connected

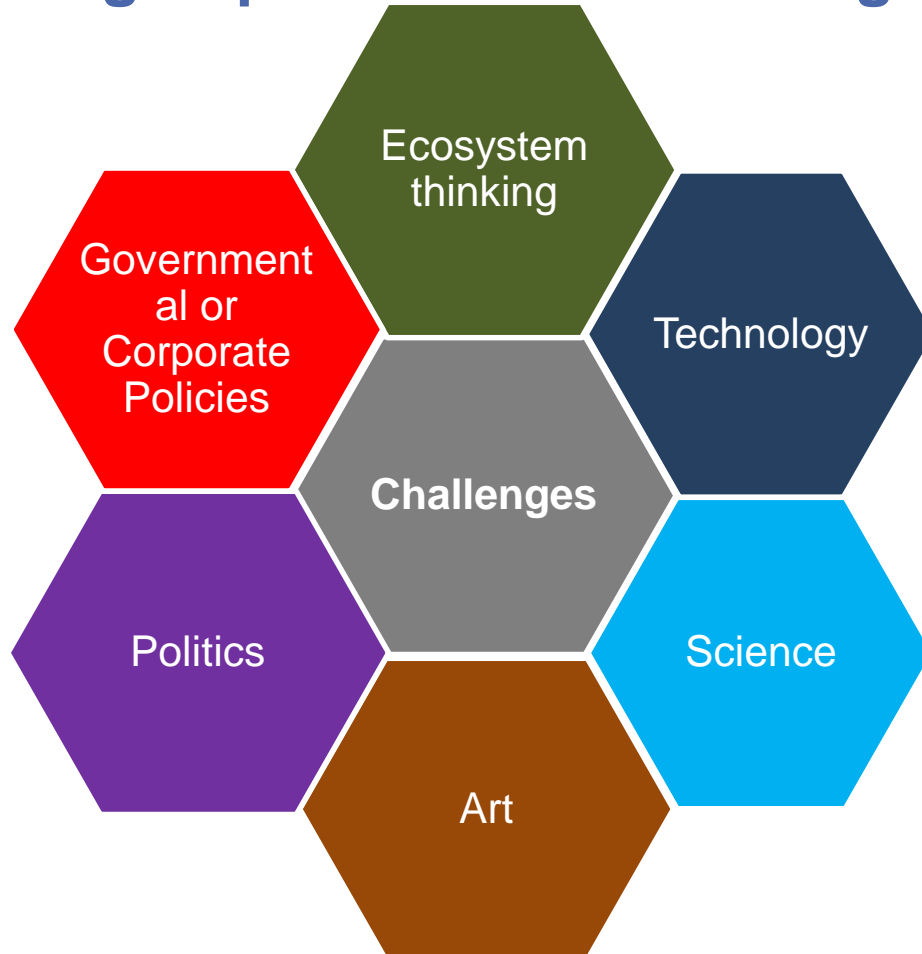
# Unprecedented challenges

- Require immediate response
- Little time to analyze and study
- No prior model with the same level of complexity.
- **No low-risk solution.**
- Leaders, aren't trained for this.
- They are trained to set a vision, build a plan, and work the plan.



## How are we coping?

# Addressing unprecedented challenges



# Revived interest in AI

Advancements in:

- computing speed
- computing storage
- Big data
- Machine Learning
- Deep learning

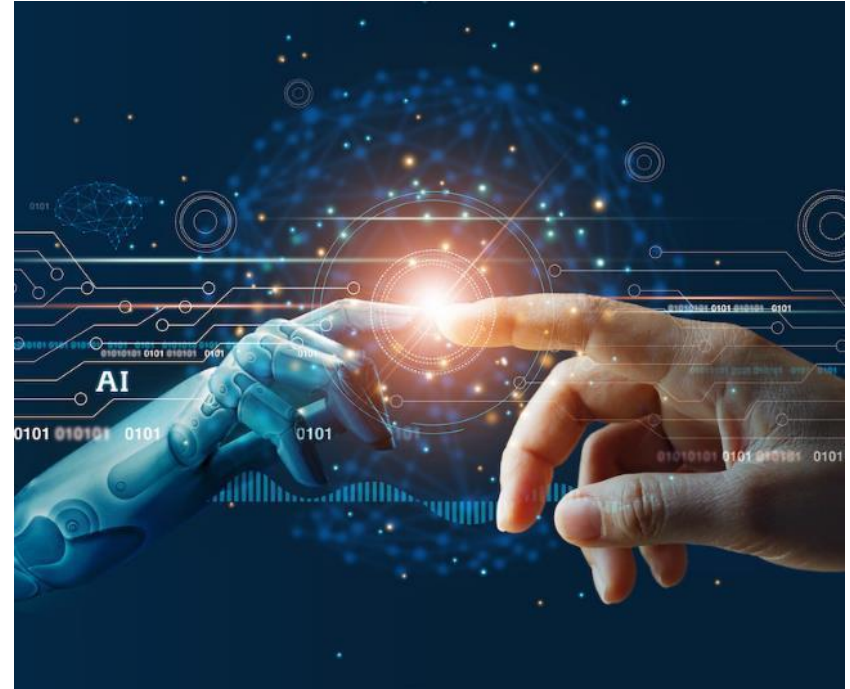


# CAN AI help?



## New emergent human-AI configurations

- Who takes care of these configurations?
- Who leads them and how leaders address technical and social aspects of change.



# CAN managers lead?

# AI investments still lack to pay off

**Despite high hopes**, AI and related business analytics technology are **just paying off for few firms**:

- Firms only seem to **realize productivity gains** from analytics investments when they...
  - have **large amounts of available data** (Tambe 2014)
  - rely on massive **information processing** (Wu et al. 2019)
  - are **active in the IT industry** (Müller et al. 2018)
- At the macro level, economists observe an **“AI productivity paradox”** (Brynjolfsson et al.; 2017)



**Scholars heavily discuss about the uses of AI technology:  
AI for automation or augmentation (support vs. replace debate)** (Raisch & Krakowski, 2020)

- “The most impressive **capabilities of AI**, particularly those based on machine learning, **have not yet diffused widely**” (Brynjolfsson et al.; 2017)
- “If I had a penny for every time that AI is mentioned as the solution to a business problem, I would be a very rich man.” (The economist, 2021)

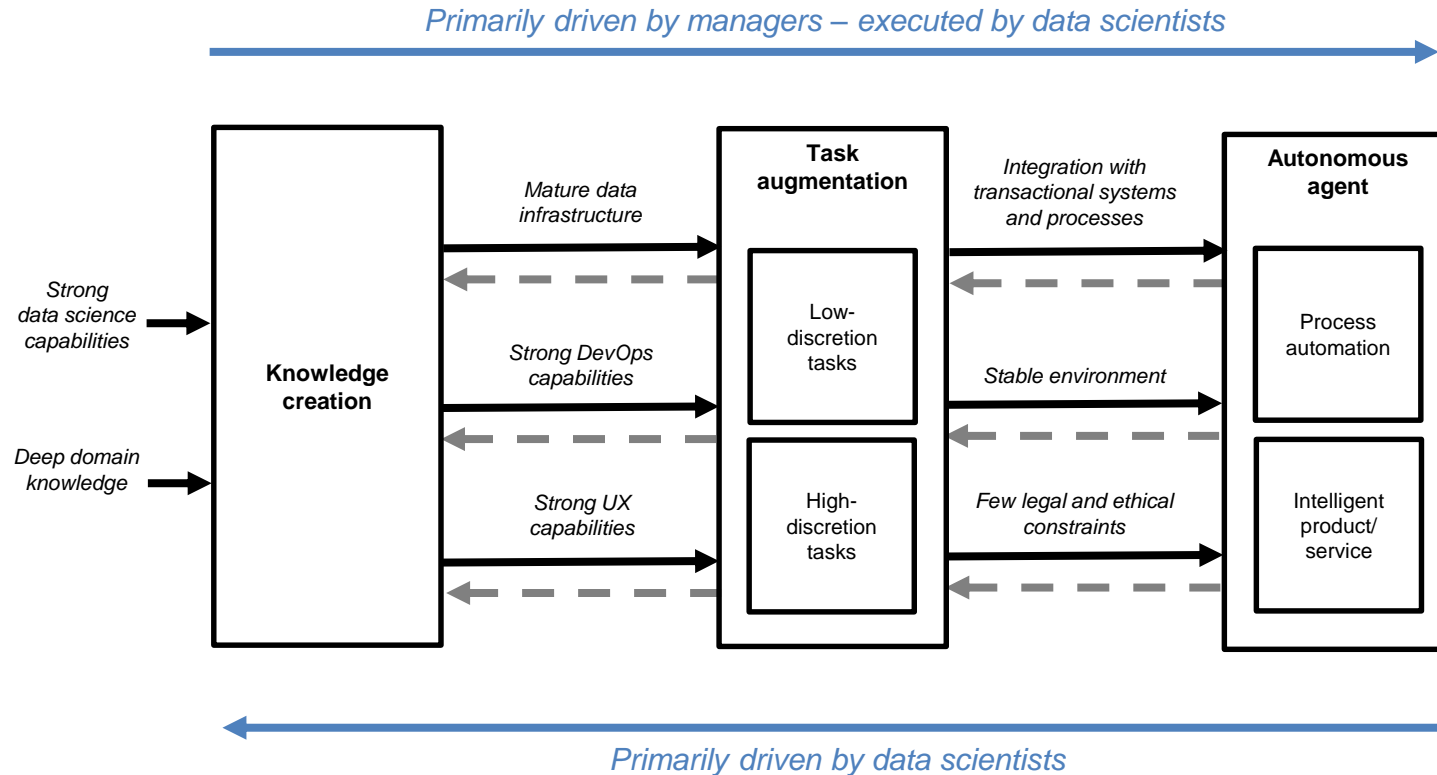
There is currently **little empirical evidence** how **AI-based information systems** can be used in organizations to create and sustain value.

*“We struggle to decide on the appropriate division of labor between the human and the machine (AI), how to share the work ... we need to understand what objectives do people seek to fulfill, what is important to them. We need to understand the task structure and sequence, the coordination challenges, the cognitive challenges, the tools that are used” (Margunn Aanestad)*

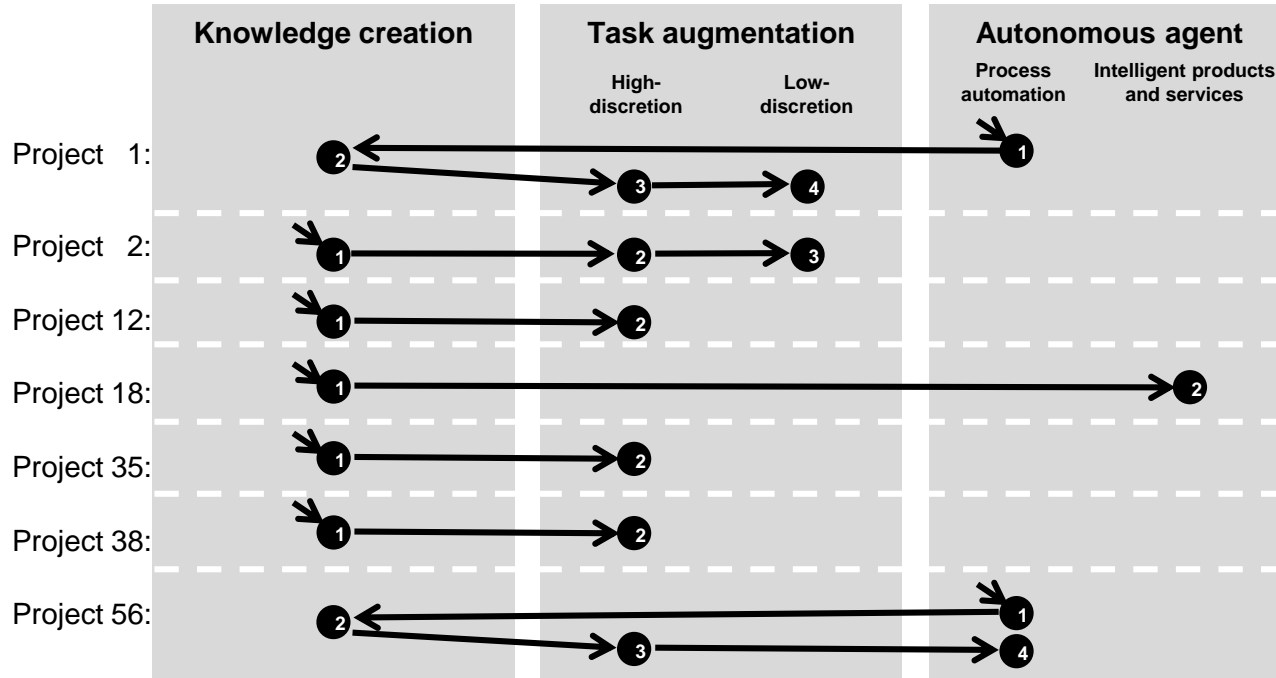
*“A lot of the practical discourse is very simplified and partly probably also the research discourse at this point in time when we talk about augmentation and automation of tasks. There is often an underlying idea that whatever the outcome is, it is stable.” (Magnus Mähring)*

# Interview study with 40 data scientists

- Interviews with 40 data scientists between 2018 and 2020 (>600 pages of interview transcript)
- Analyzed and compared 56 ML projects:
  - Identified three mechanisms of ML value creation (with 4 subtypes)
  - Explore patterns in projects of the same ML value creation mechanism
  - Conditions and reconfiguration trajectories



# Trajectories



# Data scientists as managers

- Managers “**make all key decisions about AI**” (Berente et al., 2021, p. 1434).
- However, they also face a variety of new challenges, many of which are of a technical nature (Berente et al., 2021; Davenport & Ronanki, 2018; Li et al., 2021).

*Data scientists appear to take a more prominent role as agents of change.*

Evidence from organizational field studies on human-ML configurations:

- they have “**a role that demands more responsibility and a deeper sense of accountability**” than statisticians or pure technical employees (Vaast & Pinsonneault, 2021, p. 1095),
- they switch between augmenting and altering ML models (Grønsund & Aanestad, 2020), while they decide over the inclusion and exclusion of domain experts in ML model development (van den Broek et al., 2021).
- “the role of the data scientist is to be **the value creator**—the bridge between statistician/computer engineer/etc. and key decision makers” (Vaast & Pinsonneault, 2021, p. 1095).

# Data scientists as orchestrators (leaders)

- Our interviewees repeatedly reported that managers envisioned automated processes and had high expectations with regard to productivity gains.

*“Automation is actually one of the challenges [where we have] to manage expectations, because people think much of AI—Fantastic! But it is not really like that. ... Models come with errors, you cannot do everything, and you must explain the limitations.” (P09: Automatic processing of health care policies).*

- Many interviewees reported that they need to educate business people on what problems can be solved with ML.



Our process model contributes to the current literature on designing and implementing strategies in the context of ML systems in three ways

1. linking combinations of capabilities to ML value creation mechanisms and showing that a change in these combinations (deliberate or not) triggers a change in the value creation mechanism that can be leveraged (nuance and how).
2. highlighting the emerging role of data scientists as orchestrators
3. demonstrating interaction between different value creation mechanisms, which lead to concrete orchestration paths through which organizations pursue value creation.

## Paper 2: Challenges in data science work

- C1: Inflated management expectations
- C2: Managing AI projects like traditional IT projects
- C3: Missing data in- and output links to existing systems
- C4: The Question of Why
- C5: Dynamic environments

# What is new here?

## Craftwork vs. Mechanical work



### Mastery

*Polished, refined, and difficult to obtain technical skills*

### All-roundness

*A wide variety of skills applied in the whole making process*

### Embodied expertise

*Tacit knowing, bodily and aesthetic understanding*

### Dedication

*Profound, personal commitment to work, independent of economic rewards*

### Communality

*Occupational identity and felt connection to other workers in the trade*

### Exploration

*Openness to experimentation, improvisation and experimental learning*

Skills

### Commodity

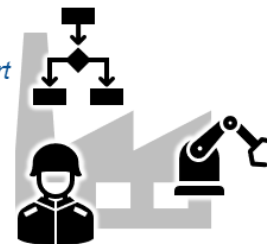
*Widely available, relatively undifferentiated, and easy to obtain technical skills*

### Specificity

*Narrow, task-specialized skills to support extreme division of labor*

### Abstract expertise

*Codifiable, formal and intellectual ways of knowing*



Attitudes

### Detachment

*Dispassionate and utilitarian involvement; efforts should lead to commensurate payment*

### Individuality

*Self-interest, competition and more transactional interactions*

### Planning

*Uncertainty reduction through structures and careful programming of activities, supported by evidence-based learning*

# Challenges as paradoxical tensions

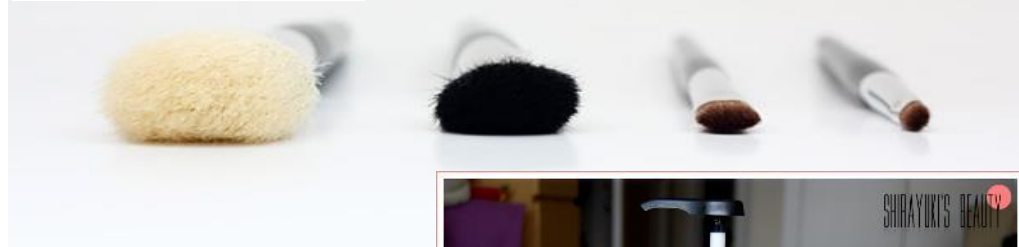
Challenge	Managements' view ( <i>Mechanical work perspective</i> )	Data Scientists' view ( <i>Craftwork perspective</i> )	Tactics to cope with the tension and ensure value creation
<b>Managing AI projects like IT projects</b>	<ul style="list-style-type: none"> <li>● Assumption that AI models consists of specific computer programs that are simply modifiable</li> <li>● Expectation that a continuous delivery of results is possible</li> </ul>	<ul style="list-style-type: none"> <li>● AI applications are learning agents, not deterministically programmed systems</li> <li>● The nature of AI projects not applicable for established agile approaches of software development</li> <li>● AI projects more like research than IT projects</li> </ul>	<ul style="list-style-type: none"> <li>● Data Scientists train managers on the job</li> <li>● Basic AI and ML courses for managers.</li> <li>● Appropriate KPIs</li> </ul>

# Paper 3: Data scientists as craftworkers

- Crafting the material



- Crafting the tools



- Crafting the products



- “Against a rising tide of automation and increasing digital complexity, we are becoming further divorced from the very thing that defines us: we are makers, crafters of things.” (Langlands, 2019, p. 22)
- “The machine is not an it to be animated, worshipped, and dominated. The machine is us, our processes, an aspect of our embodiment.” (Haraway, 1990, p. 222)

Maybe we are still crafters  
but of intelligent things

# Implications for data science programs

1. semester	2. semester	3. semester	4. semester
Innovation and Strategy in the Digital Economy (7,5 ECTS)	Data Economics (7,5 ECTS)	Electives / Internship / Exchange (30 ECTS)	Master's thesis (30 ECTS)
Datafication: Regulation, Governance, Security, Privacy and Ethics (7,5 ECTS)	Natural Language Processing and Text Analytics (7,5 ECTS)		
Foundations of Business Data Analytics: Programming and Linear Algebra (7,5 ECTS)	Predictive Analytics (7,5 ECTS)		
Visual Analytics (7,5 ECTS)	Data Mining, Machine Learning and Deep Learning (7,5 ECTS)		

# More managerial courses



- Responsible AI: what does it mean, how to build responsible AI models, who should be in charge for developing, deploying responsible AI systems and using them responsibly.
- What are appropriate methods for developing AI-based systems?
- What are the tensions that AI-based systems introduce in organizations?



# Thank you