# Behind the scenes of artificial intelligence

Waardenburg, Lauren

2021

# Behind the scenes of artificial intelligence

Studying how organizations cope with machine learning in practice

Lauren Waardenburg

This book is number 70 in the ABRI dissertation series.
Alblasserdam: HAVEKA
ISBN 978–90–361–0668–9

VRIJE UNIVERSITEIT

# BEHIND THE SCENES OF ARTIFICIAL INTELLIGENCE

Studying how organizations cope with machine learning in practice

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad Doctor aan
de Vrije Universiteit Amsterdam,
op gezag van de rector magnificus
prof.dr. C.M. van Praag,
in het openbaar te verdedigen
ten overstaan van de promotiecommissie
van de School of Business and Economics
op woensdag 1 december 2021 om 15.45 uur
in een bijeenkomst van de universiteit,
De Boelelaan 1105

door

Lauren Waardenburg

geboren te Den Helder

| | |
|---|---|
| promotor: | prof.dr. M.H. Huysman |
| copromotor: | dr. A. Sergeeva |
| promotiecommissie: | prof.dr. M. de Rond<br>prof.dr. K.C. Kellogg<br>dr. E. Parmiggiani<br>dr. R. van Steden<br>prof.dr. ir. J.J. Berends |

Voor

Hoe meet je de zwaarte van een klap die nooit kwam,
zoek je de fiets waar niets mee is, die er nog staat?
De brand in een leegstaand schoolgebouw,
nooit uitgebroken, laat geen sporen na.

Hier is de eindeloze lijst van dingen die niet zijn gebeurd,
hier is de nooit betaalde prijs voor toeval, dronkenschap,
loslippigheid. Hier is het dodelijke ongeluk, de schade
die je nooit veroorzaakt hebt.

Hier klinkt de niet geslaakte kreet van twee
uit bed gebelde ouders. De stad zwermt
van ongehoord geluid. Je luistert 's nachts
naar de zachte voetstap van de dochter die
onaangetast de trap op sluipt.[1]

Ester Naomi Perquin (2018). *Lange armen: Gedichten over de politie*. Uitgeverij van Oorschot.

[1] Dit gedicht is special voor de Nederlandse Nationale Politie geschreven over de kracht van het voorspellen en daarmee voorkomen van criminaliteit.

Ahead

How do you measure the gravity of a blow that never came,
do you look for the bicycle that is not taken, that is still there?
The fire in an empty school building,
never broken out, leaves no traces.

Here's the endless list of things that didn't happen,
here is the price never paid for coincidence, drunkenness,
indiscretion. Here's the fatality, the damage
that you never caused.

Here is the unspoken cry of two
parents called out of bed. The city is swarming
of unheard-of sound. You listen at night
to the soft footstep of the daughter who
sneaks up the stairs unaffected.[2]

Ester Naomi Perquin
Dutch Poet Laureate

[2] This poem was written for the Dutch National Police about the power of predicting and preventing crime.

# Table of contents

# Preface

This dissertation is the result of my four-year Ph.D. research into how artificial intelligence (AI) is changing work and organizing. One of the key messages of this dissertation is the importance of understanding the technology we study. Before I start with the formal part of this dissertation, let me emphasize that this key message was something that I had to find out over time. To be fair, when I started the dissertation research, I knew nothing about AI (or data, or algorithms). When initially presenting my research setting of the Dutch police in academic settings, I failed many times to explain exactly *how* the system I studied was AI, or even *why* I considered it to be so. It came to a point where I decided to respond to any technology-related question with: "I'm not a computer scientist, so I don't really know."

Luckily, something clicked. The more time I spent at my field site, while at the same time starting to write some first academic drafts, the more I realized that there is no way to tell a story of AI implementation and use without fully understanding what the technology is about. So, I called one of the police data scientists and asked him everything I wanted to know about the AI system. Funny enough, him sharing technical details and me sharing experiences from the field made us realize that we should write a reflection piece on the myths of AI, which we eventually did. The point is, when I finally got into the technical details of the AI system, I could not stop anymore. I wanted to know more and more about what AI is and can do. I kept on reading and reading about the topic, which helped me to gain insights into a variety of contexts.

By then, everyone in my surroundings also knew about my near-obsession with the topic, so they started sending my mainstream articles, forwarding videos, and so on. And then another pivotal moment happened, as I was asked to co-author a managerial book on AI implementation. From then on, I could dive even deeper into the topic and write as much about AI as possible. It also gave me access to contexts other than the police, which helped me gain a broader perspective of what AI means in practice. While at first trying to get away from any technology-related question, after four years of "personal development” on the topic of AI, I ended up recording a video to explain the different types of machine learning techniques to practitioners.[3]

The pages that follow comprise the result of this journey. A journey that was fueled by much enthusiasm and love for the topic, as well as for the people I studied and who have so generously invited me into their organizational “life.” Luckily, as AI technologies continue to learn, so can I. Let this dissertation therefore not only be the end of a journey but also a “pit stop” to what is yet to come.

[3] https://youtu.be/LpLSFakNGZ8

# 1. Introduction

## Organizations and machine learning

## 1.1 A practice perspective on the influence of technology on work and organizing

From the first emergence of technology in everyday life, scholars have been fascinated by its role in and influence on human practice. For example, intrigued by the potential power of fast-moving trains, philosopher Oswald Spengler asked who amongst the present-day scholars realized that “between the space perspective of Western oil painting and the conquest of space by railroad [...] there are deep uniformities?” (Spengler, 1991 [1926], p. 7). In other words, Spengler argued that using trains that moved at high speed through terrain that one previously experienced from a horse-and-carriage changed the perception of the environment into stretched patches of color, which ultimately served as a trigger for the modernist painting style. As time progressed and technology became increasingly prevalent in everyday life, organizational scholars were surprised to see that, not only did technology influence human behavior but the same technology could be adopted in completely different ways, depending on the context (e.g., Azad & King, 2008; Barley, 1986; Boudreau & Robey, 2005; Orlikowski, 2000). This insight gave rise to what has become known as the “technology-in-practice” perspective (Orlikowski, 2000, Sergeeva et al. 2017) to understand the situated and embedded nature of technology use (Oborn, Barrett, & Davidson, 2011).

The technology-in-practice perspective finds its roots in “practice theory” (e.g., Gherardi, 2006; Feldman & Orlikowksi, 2011, Orlikowski, 2000). Practice theory builds on the fields of philosophy and sociology, with scholars such as Bourdieu, Giddens, Foucault, Garfinkel, Latour, Taylor, and Schatzki, and generally aims to understand how practices emerge and change and to uncover intended and unintended consequences of these changes (Feldman & Orlikowski, 2011). Scholars taking a practice theory approach go beyond an individual perspective to look at work practices as interdependent, mutually constitutive, and routinized types of behaviors (Bradbury & Lichtenstein, 2000; Giddens, 1984; Østerlund & Carlile, 2005; Reckwitz, 2002) through which social orders evolve and change over time (Gherardi, 2006; Reckwitz, 2002).

Scholars taking a practice-based perspective on technology consider how specific patterns of technology use emerge through an ongoing interaction between technology and its users (e.g., Barrett et al., 2012; Oborn, Barrett, & Davidson, 2011; Orlikowski, 2000; Sergeeva et al., 2017). In contrast to more deterministic approaches, the technology-in-practice perspective considers technology as “instantiated in and through the activities of human agents” (Giddens, 1984, p. 256). Zooming in on the micro-practices through which different properties of technologies become important for work and organizing, the technology-in-practice perspective has been largely influential for organizational and information systems scholars (e.g., Azad & King, 2008; Boudreau & Robey, 2005; Hevner et al., 2004; Jasperson, Carter, & Zmud, 2005; Leonardi, Treem, & Jackson, 2010; Mazmanian, 2013; Mazmanian, Orlikowski, & Yates, 2013; Orlikowski & Scott, 2014; Sein et al., 2011). For example, Azad and King (2008) studied how a pharmacy dispensing system was used in practice by a group of pharmacists and how they, in their interactions with the technology, eventually developed workarounds that allowed them to let go of the system altogether.

By looking at the meaning of specific technological features in particular contexts, scholars taking a technology-in-practice perspective how uncovered, for example, how collective patterns of technology use emerge and stabilize, or how unexpected patterns of technology use emerge (Azad & King 2008; Burton-Jones & Gallivan 2007; Leonardi 2013; Oborn et al. 2011; Orlikowski 2000; Schultze & Orlikowski 2004; Stein et al. 2015; Vaast & Walsham 2005). As technologies evolve and contexts change, the technology-in-practice is as relevant today as it was when it first emerged. This becomes especially clear when we consider recent technological developments such as large-scale digitization and datafication that have stirred great debate about the potentially extensive consequences of “artificial intelligence” (AI). Although existing research now suggests that work and organizing are bound to be altered by the introduction of AI systems (e.g., Faraj, Pachidi, & Sayegh, 2018; Kellogg, Valentine, & Christin, 2020), they are still a “new but poorly understood phenomenon” (Von Krogh, 2018, p. 408) both regarding their unique features and their meaning, as well as their consequences in practice. It is thus time to take a deep dive into the implementation of AI systems in organizations or, in other words, to take a technology-in-practice perspective and look "behind the scenes of AI."

## 1.2 A brief history of AI

In 1950, Alan Turing asked the infamous question: "Can machines think?" (Turing, 1950, p. 433) and with that, a new era was born in which computer scientists tried to create technologies that could think for themselves. Not only would such technologies have the potential to shape existing world views, but they would also independently generate insights that no human had ever done before or could potentially ever do (Wooldridge, 2020). In short, computer scientists' quest for *artificial intelligence* had started. Today, AI refers to a field in computer science that is concerned with creating systems that can accomplish tasks that normally require human intelligence (Nilsson, 1971; Pesapane, Codari, & Sardanelli, 2018). These tasks can include, for example, facial or voice recognition and generating decisions or predictions. As mentioned above, AI has been in development since the 1950s. Across the 70 years to now, it has seen many milestones, but computer scientists also encountered several periods in which its development came to a halt, which are also known as "AI winters" (Cariani, 2010; Wooldridge, 2020). Because the field of AI has been in development for such a long time and has encountered victories as well as bottlenecks, the definition has altered and different techniques have been used over time. For example, in the 1990s it was common to refer to AI when talking about expert systems; i.e., systems for which computer scientists had to extract the expert rules from human experts and manually code these rules into logical sequences (e.g., Forsythe, 1993). Now, about 20 years onwards, researchers agree that the ability to learn distinguishes AI from other "intelligent technologies" (Bailey & Barley, 2020; Faraj et al., 2018).[4]

The 1950s are considered the birth period of AI, with mathematician, philosopher, and inventor Alan Turing as its founding father (who is also known for his skills at deciphering

[4] Parts of paragraphs 1.2 and 1.3 are based on chapters of my book: Waardenburg, L., Huysman, M., & Agterberg, M. (2021). *Managing AI wisely: From development to organizational change in practice.* Edward Elgar Publishing. These paragraphs have been fully rewritten to fit the aims and style of this dissertation.

the encrypted messages of the German forces in World War II). Turing believed that human decision-making is based on specific, explicit factors, which could be extracted so that a machine should be able to learn these factors too. Building on this belief, he created the "Turing test" – which, due to the movie that has been made about his life, is widely known as the "imitation game" – through which one should be able to determine whether a machine is intelligent or not. The test consists of three players: one, two, and three. Let us say that player one is the interrogator, who asks direct questions to players two and three, while one of these players is actually a machine. Communicating via text messages, the interrogator has to distinguish the machine from the human in these messages. If the interrogator fails to make the distinction, Turing argued, the machine can be considered "intelligent" (Turing, 1950).

The Turing test was mainly adopted for chatbots, but the biggest problem with the test was humans themselves, as it turned out that people are quite lenient when it comes to written text and consider something to be "intelligent" rather quickly. For example, "Eliza,"[5] the first talking bot ever, simulated a psychologist who responded to written chat messages. All her answers were pre-programmed, which meant that if you kept chatting with her long enough, she would start repeating herself. Eliza was considered a great achievement, people even willingly shared secrets with her, but was she really intelligent? After Eliza, a number of pre-programmed bots followed. Chatbot Parry performed the role of a patient with schizophrenia[6] and chatbot Catherine was a very pleasant conversation partner, as long as you only talked about Bill Clinton. The first chatbot to really pass the Turing test was Ukrainian-speaking "Eugene Goostman."[7] Though developed in 2001, it took 13 years for the bot to convince a significant part of a jury that Eugene was a "real" Ukrainian boy (Shah et al., 2016). Interestingly, the human jury attributed his stiff way of talking and his grammatical errors to the culture and language barrier, rather than to the possibility of Eugene being a machine (Waardenburg, Huysman, & Agterberg, 2021).

[5] Developed by Joseph Weizenbaum at the MIT AI Laboratory in 1966.
[6] Psychiatrist Kenneth Colby wrote its script.
[7] Built in 2001 by Vladimir Veselov and Eugene Demchenko.

A major change in the performance of AI systems occurred in the late 1980s when computer scientists discovered the possibilities of machine learning. Machine learning became a research area in the field of AI, in which computer scientists aim to construct algorithms – i.e., a sequence of coded instructions which are aimed to solve a computational problem – that can autonomously improve through experience and therefore have the capacity to learn (Tegmark, 2017; Wooldridge, 2020). In 1988, using machine learning resulted in the first self-driving car "ALVINN" (Autonomous Land Vehicle In a Neural Network). In the years that followed, machine learning has become increasingly central in our understanding of AI.

Using machine learning gave rise to what is now called "affective computing" (Picard, 1995), in which a computer learns to recognize, understand, and simulate human emotions. Most generally known, though, is the application of machine learning in the field of Natural Language Processing (NLP). When in 2011 IBM's Watson defeated its human opponents in the American television show "Jeopardy!" there seemed to be no turning back from AI systems becoming increasingly "intelligent." In this game show, one needs to give the right question to a given answer. To be able to do this, and win the show, Watson was given a huge amount of "reading material," namely 200 million pages of text which included all of Wikipedia and the World Book Encyclopedia (Best, 2013). During the game, Watson's algorithms searched for a number of questions for each answer, assigned a score to each of the options, and the question with the highest score won. And so did Watson.

Another AI achievement came with Google DeepMind's "AlphaGo" in 2014. The game Go is one of the most complex board games in the world, which therefore seemed to be an excellent opportunity to test the possibilities of machine learning. At the start of the game, one can choose between 361 moves (compared to 20 moves in chess). After the first move, there are 129 960 new options. After two moves, this becomes about 17 billion, and so on (Susskind, 2020; Wooldridge, 2020). For the AI system to learn to play Go, it used 30 million previous Go games and played against itself until it could predict a good move. In 2016, the AI system defeated human world champion Lee Sedol.

Since 2011, AI systems are no longer only the research domain of computer scientists to see what such systems can potentially do. Instead, they are increasingly implemented in everyday life. Voice assistants such as Sire, Google Now, and Cortana are increasingly used on smartphones, which can adapt to new situations remarkably quickly. The potential market value and practical applications of AI systems have also been noticed by organizations, where the impact of AI is also increasing. For example, machine learning is now not only important for self-driving cars, but also for analyzing medical scans (Kim et al., 2021). However, before turning to the increased prevalence of AI systems as an organizational phenomenon, I first explore more technical details about the most common techniques used for machine learning today.

## 1.3 Techniques used for machine learning

In machine learning, learning algorithms are developed that can improve through experience (Tegmark, 2017; Wooldridge, 2020). Using large amounts of data and advanced computational and statistical methods, learning algorithms can autonomously generate decisions, classifications, or predictions (Faraj et al., 2018) that can potentially go beyond what is possible for humans alone (Leavitt et al., 2020; Tshitoyan et al., 2019). For example, AI systems can detect tumors that are sometimes invisible to the human eye (Aerts, 2018; Beck et al., 2011; Kim, Rezazade Mehrizi, & Huysman, 2020), they can predict where and when a crime is most likely to occur (Brayne, 2020; Waardenburg, Sergeeva, & Huysman, 2018), or they can dig through lengthy legal documents and find the right information only seconds after asking for it (Zhang et al., 2020). Generally, there are three different machine learning techniques that can be used for training learning algorithms today: supervised learning, unsupervised learning, and reinforcement learning.

### 1.3.1 Supervised learning

The term “supervised learning” refers to the nature of the data sets used. In the case of supervised learning, each data point in the data set needs to be labeled, meaning that it should be indicated what each data point entails. For example, data point X should be labeled as Y, so that the supervised learning algorithm can learn to categorize all X as Y (Yeung et al., 2017). Suppose that data point X is an image of a fork, then this data point should be labeled (Y) "fork." By feeding the learning algorithm with a data set containing as many labeled images of forks as possible, it can learn to distinguish forks from other objects.

Because the data set used for supervised learning always contains the intended result (in this case, an image is either a fork or not), with this technique you can always compare the predictions with reality, which also makes it possible to calculate the accuracy of the model. For this purpose, in the case of supervised learning, the original data set is usually split into 80 percent training data (for the algorithm to learn) and 20 percent test data (to calculate the accuracy and quality of the learning algorithm). The most common methods used for constructing supervised learning algorithms are regression and classification. Regression is used when a value or number needs to be predicted, classification when the outcome should be a group or category. Rule-based classification is not part of supervised learning, as explicating rules does not involve any further "learning."

The first learning algorithms used in AI systems were based on supervised learning, in which the algorithms were trained to learn a mapping between given characteristics and a known outcome. To this day, the majority of AI systems being developed still work based on supervised learning. A well-known example is Facebook's friend-tagging in photos. In this case, we provide the characteristics and the labels used in the data set ourselves, by uploading photos and tagging our friends. Using all of this data to learn from, Facebook's friend-tagging algorithm now autonomously offers suggestions regarding who is present in our photos.

### 1.3.2 Unsupervised learning

In the case of unsupervised learning, the data set does not contain labels, but the algorithm autonomously sorts data on the basis of underlying patterns through clustering, dimensionality reduction, or association. In clustering, the learning algorithm sorts data based on common characteristics. For example, the algorithm clusters objects with three teeth as "forks" and objects with a smooth blade as "knives." As objects with three teeth have more in common with other objects with three teeth than with smooth-bladed objects, the learning algorithm autonomously clusters objects with similar characteristics together. Dimensionality reduction is about lowering the number of properties in a data set. For example, by sorting "brown-black coat," "triangular ears," "long nose," and "long tail" into the category "shepherd," four traits present in a data set are reduced to one. Association is used to relate different data points together, which is mainly used in transaction data. A common example is a recommendation system.

Unsupervised learning algorithms thus try to find hidden underlying structures in data sets and use these structures for sorting out data points. Because unsupervised learning requires an even larger amount of data than what is necessary for supervised learning, and because there is no way to measure its reliability, it is more difficult to apply this technique in practice and it is thus not yet as widely used. Currently, the main examples of unsupervised learning are recommendation systems used in online shops and on social media.

### 1.3.3 Reinforcement learning

Reinforcement learning is yet another technique that is unique in its use of "reward" and "punishment" or, in computer science terms, using "delayed consequences" and "exploration." Delayed consequences mean that the ramifications of separate actions are not immediately marked as right or wrong. Instead, they are assessed after a series of actions that together led to a successful or unsuccessful outcome. This way, a reinforcement learning algorithm learns to recognize not only the correct single action but also the correct patterns of multiple actions.

Exploration means that, in the case of reinforcement learning, the learning process should resemble how a child achieves new skills. A reinforcement learning algorithm therefore is only fed with a large data set, through which the algorithm has to find out for itself which outcome is right and which one is wrong. An example of this is how a reinforcement learning algorithm taught itself to play the Atari game "Pong" where one needs to destroy a brick wall with a ball and a bat. As the system was not taught anything by its developers, the learning algorithm first had to find out what the ball and the bat were for and initially made many mistakes. Yet, over time, the algorithm improved and eventually found unique ways to remove as many bricks as possible with a single hit (Wooldridge, 2020).

The advantage of reinforcement learning over the other two machine learning methods is that it does not only learn the things that humans already demonstrated or prepared, as is most specifically the case in supervised learning. As such, reinforcement learning algorithms are promised to ultimately learn to perform certain tasks better than humans, which holds great promise for the future of AI. However, mainly due to the high margin of error at the start of its learning process, reinforcement learning algorithms are currently rarely used.

### 1.3.4 Generalization, optimization, and datafication

While the techniques, objectives, and tasks for which learning algorithms are developed can thus vary greatly, they all coincide around the overarching machine learning aims of generalization and optimization (e.g., Thomas et al., 2020). Because it is impossible to capture all cases or examples of a specific topic for an algorithm to learn from, generalization is the objective to solve new problems based on generic information. Optimization is the aim to make AI systems perform tasks to the highest standards possible, thereby making the best decisions or predictions with the (generic) information available. Together, generalization and optimization form a *Perpetuum mobile* when it comes to data collection and use; the more data is available, the better a learning algorithm will be at generalizing and the more optimal the decisions or predictions will be. As such, datafication – the constant tracking, monitoring, and registering of behavior (Newell & Marabelli, 2015) – has become the core practice associated with the development and use of AI systems (Brynjolfsson & McAfee, 2014; Davenport & Harris, 2017; Zuboff, 2019).

## 1.4 AI as an emerging organizational phenomenon

In recent years, we have seen large-scale digitization and datafication of organizational processes (e.g., Faraj et al., 2018; Günther et al., 2017; Hartmann & Henkel, 2020; O'neil, 2016; Von Krogh, 2018). It therefore comes as no surprise that AI systems are now increasingly developed for, and implemented in organizations. For organizations, it is specifically interesting to deploy AI systems, as the decisions and predictions – or "machine learning knowledge" – that are generated through learning algorithms are promised to be more objective, efficient, and new (Van den Broek et al., 2021). Compared to human experts, the data that is used for training learning algorithms is supposed to be 'raw' and to represent reality in a more holistic and objective manner (Anderson, 2008; Agrawal et al., 2018; Cukier & Mayer-Schönberger, 2013; Jones, 2019; Kitchin, 2014; Siegel, 2016). AI systems can go through extremely vast amounts of data in an unprecedented manner, which arguably makes them more efficient (Domingos, 2015; Schildt, 2017). And since learning algorithms can autonomously generate connections between data points using advanced computational techniques, machine learning knowledge is argued to be new, or different from human expertise (Beck et al., 2011; Bonde Thylstrup, Flyverbom, & Helles, 2019; Henriksen & Bechmann, 2020; Leavitt et al., 2020). Because of the promised objectivity, efficiency, and novelty of machine learning knowledge, organizations increasingly adopt AI systems expecting a variety of opportunities not only in terms of productivity, and cost reduction (Newell & Marabelli, 2015), but also in terms of consistent decision-making and the ability to overcome many of the human limitations in knowledge work (Agarwal & Dhar, 2014; Agrawal et al., 2018; Barrett & Oborn, 2013; Davenport & Kirby, 2016; Domingos, 2015; Feigenbaum & McCorduck, 1984; Lebovitz, Levina, & Lifshitz-Assaf, 2021; Mitchell, Michalski, & Carbonell, 1986; Van den Broek et al., 2021; Zarsky, 2016).

Several studies that adopted this perspective on the use of AI systems for acquiring new knowledge have indicated its potential for radically transforming work processes by visualizing and predicting specific patterns (e.g., Brynjolfsson & McAfee, 2014; Cantwell

Smith, 2019; Davenport, 2018; Shestakofsky, 2017). For example, some researchers argue that by using AI systems, underlying assumptions about work that impact the performance of an organization can be brought to the fore, which can benefit the objectivity of organizational processes (e.g., Nikolaidis & Shah, 2012; Sachon & Boquet, 2017; Shah et al., 2011). These studies highlight the opportunities for organizations to deploy AI systems for knowledge acquisition and learning (Balasubramanian et al., 2020). Yet, not everyone agrees with this perspective, as an increasing number of organizational and information systems scholars voice critiques regarding the possible consequences of machine learning knowledge for work and organizing (e.g., Faraj et al., 2018; Kellogg, Valentine, & Christin, 2020).

As discussed above, using AI systems to generate new machine learning knowledge requires large amounts of data. Accordingly, deploying AI systems leads to the need and legitimacy to increasingly turn work processes and activities into numbers (e.g., Pachidi et al., 2020). While this can lead to better insights into who or what is of value to organizations, it also puts workers under increased organizational control (e.g., Ananny, 2016; boyd & Crawford, 2012; Kellogg et al., 2020; Orlikowski & Scott, 2016). An example of the disrupted balance between professional freedom and organizational control can be found at Amazon, where employees were assessed by how much time they spent between finding a package in the warehouse and shipping it, which limited their freedom of movement to such an extent that some employees were afraid to take bathroom breaks. Scholars point out that not maintaining a balance between professional freedom and organizational control can lead to workarounds in such a way that the collected data does not even reflect reality anymore (Christin, 2020; Pachidi et al., 2020). Think, for example, of journalists tactically uploading "quick-and-dirty" articles to enhance their publication score (Christin, 2020) or sales employees registering what they think management expects from them regarding sales numbers (Cunha & Carugati, 2018).

Other studies emphasize the decisions that need to be made for data collection and how they determine what ultimately ends up in data sets used for training learning algorithms (e.g., Barocas & Selbst, 2016; Gitelman, 2013; Pine & Liboiron, 2015). For example, if data is collected using the existing work protocols, it will not become visible whether this protocol works or not or how often employees deviate from it. Pine and Liboiron (2015) studied how, in a medical setting, such a protocol does not represent reality, as medical personnel often perform treatment activities in a different order than how they are reported in the data system. Not only do data sets therefore lack a lot of the contextual knowledge that is embedded in work practices, but it is also even argued that the need to follow rigid systems when performing reporting work can affect the creativity and flexibility of teams (Pine & Mazmanian, 2017).

Also, not everyone agrees with the objectivity perspective on machine learning knowledge (e.g., Christin & Brayne, 2020; Elish & boyd, 2018; O'Neil, 2016). Increasingly, researchers emphasize that learning algorithms are not objective entities, but that computer scientists encode them with certain views, opinions, and habits (Faraj et al., 2018; Introna, 2016; Waardenburg et al., 2021). As a result, a learning algorithm can, for example, take on a political orientation that impacts decision-making processes in organizations (Introna & Nissenbaum, 2000). This becomes even more problematic as AI systems are becoming increasingly opaque or "black-boxed" (Ajunwa, 2020; Burrell, 2016; Faraj et al., 2018, Pasquale, 2015), meaning that people are often not aware of how learning algorithms arrive at insights. As AI systems are able to autonomously create connections between a large number of data points, it means that even if full disclosure would be given about the data set used to train the learning algorithm, still it would be difficult if not impossible to find out how machine learning knowledge was generated (Mittelstadt et al., 2016).

As such, scholars now emphasize that by deploying AI systems to potentially generate more objective, efficient, and even new knowledge, organizations may run the risk of missing out on precisely those outliers and contextual details that are necessary to innovate or even survive as an organization (Pachidi & Huysman, 2016). Machine learning knowledge is said to provide a "narrow" perspective (Wooldridge, 2020) in which unexpected success, alternative perspectives, and groundbreaking insights are no longer possible. To go beyond such a narrow perspective, Pachidi and Huysman (2016, p. 9) argue that: "In order to innovate and to survive in highly volatile environments, organizations also need to apply 'technologies of foolishness' (March, 1988), being open to new alternatives by employing playfulness, trial and error, and improvisation. Acting irrationally can sometimes lead to great outcomes for the organization. The organization needs to have some Don Quixote's, the people who seem crazy by deviating from the expected behavior and remaining open to unexpected consequences (March & Weill, 2009) … Not only should organizations reduce their high expectations regarding what [AI systems] bring to organizational intelligence, it would be smart to include technologies of foolishness when engaging in learning." In line with this, organizational and information systems scholars have started calling for the need to combine machine learning knowledge with human expertise, thereby creating new types of "hybrid intelligence" (e.g., Ebel et al., 2021; Graef et al., 2020; Mirbabaie, Stieglitz, & Frick, 2021).

## 1.5 Towards "hybrid intelligence"?

Recent studies have referred to, for example, "metahuman systems" (Lyytinen, Nickerson, & King, 2020), "human-machine collaboration" (Graef et al., 2020), "mutual learning" (Van den Broek et al., 2021), "digital/human work configurations" (Baptista et al., 2020), and "human-in-the-loop" (Grønsund & Aanestad, 2020) to describe the coming together of machine learning knowledge and human expertise. The idea of hybrid intelligence resides in the field of simulation and modeling, where humans traditionally provided feedback on the performance of models with the aim to improve them (Grønsund & Aanestad, 2020; Sheridan, 1995). With the emergence of AI systems in organizations, the understanding of hybrid intelligence changed slightly to include the interaction between humans and learning algorithms to create knowledge that cannot be produced by technology or humans alone (e.g., Ebel et al., 2021; Gal, Jensen, & Stein, 2020; Glaser, Pollock, & D'Adderio, 2020; Graef et al., 2020; Mirbabaie et al., 2021). While this seems like an interesting way to find the "best of both worlds," looking closely at the nature of human knowledge versus machine learning knowledge brings to the fore that combining these two might lead to new organizational challenges, which as of yet have been largely left unaddressed.

Organizational research commonly includes three premises about human knowledge: (1) human knowledge is socially and materially constructed, (2) human knowledge is situated, and (3) human knowledge is relational, i.e., it is shaped by the need to communicate knowledge across boundaries. The sociomaterial perspective on knowledge production implies how "the social and material are inherently inseparable" (Orlikowski & Scott, 2008, p. 456). Human and material agents are viewed as intertwined and brought about through their relations towards each other (Introna, 2011; Orlikowski, 2010). Knowledge is therefore socially and materially produced in practice (Orlikowski & Scott, 2008). For example, Scott and Orlikowski (2014) studied how hotel evaluations were produced in practice by comparing the AA's traditional accreditation scheme with the online hotel evaluation algorithm "TripAdvisor." Their analysis showed how meaning and matter are intertwined in the production of knowledge about hotels, as the anonymity produced through the use of TripAdvisor afforded the customers a voice to share their experiences. Human knowledge is also situated, in that it is shaped by occupational structures and expertise, with their own standards of excellence, social relations, and identities (e.g., Anthony, 2018; Van Maanen & Barley, 1984). Finally, human knowledge is relational, as achieving interdependent knowledge-related tasks depends on integrating expertise across organizational boundaries (e.g., Barbour, Treem, & Kolar, 2017; Barley, 2015; Brown & Duguid, 2001; Faraj & Sproull, 2000; Faraj & Xiao, 2006).

In contrast, as discussed above, machine learning knowledge is produced by learning algorithms that autonomously generate connections between a large number of data points. To understand how machine learning knowledge differs from human reasoning, Burrell (2016, p. 9) provides a useful example of a spam filter: "Humans likely recognize and evaluate spam according to genre: the phishing scam, the Nigerian 419 email, the Viagra sales pitch. By contrast, the 'bag of words' approach [i.e., machine learning] breaks down texts into atomistic collections of units, words whose ordering is irrelevant." While humans thus interpret emails through a sociomaterial, situated, and relational perspective to assess if it is spam or not, learning algorithms use words that are disconnected from their context (e.g., click, dollar, price) to determine whether an email is spam based on the aggregate of the weights of all the words together (Burrell, 2016).

With its focus on hybrid intelligence and combining the two types of knowledge, organizational and information systems scholars increasingly argue that, beyond automation, AI systems can actually augment existing work practices (e.g., Davenport & Kirby, 2016; Raisch & Krakowski, 2020). Augmentation is said to work two ways, as when organizational actors collaborate closely with learning algorithms, they can complement machine learning knowledge with unique human capabilities – such as intuition, emotions, and common-sense reasoning – while AI systems can also complement these actors' domain knowledge by offering previously unknown insights (Daugherty & Wilson, 2018; Raisch & Krakowski, 2020). Interestingly, those studies arguing for the potential of machine learning knowledge to enhance existing work through hybrid forms of intelligence seem to overlook the fundamental difference between the procedures used for developing machine learning knowledge and how human knowledge is produced. However, this inherent difference creates a knowledge boundary (Carlile, 2004), which makes it challenging to find common ground for sharing and collectively producing knowledge in the first place. Even though the expectations about the possibilities for machine learning for organizing are high, organizations thus face new yet unknown challenges when implementing machine learning knowledge. Therefore, the overarching research question of this dissertation is: *How do organizations cope with the production and use of machine learning in practice?* By taking a holistic and practice-based perspective on the implementation of machine learning in organizations, I address recent calls for research that unpacks the unique nature of AI systems and how this prompts organizational change (Bailey & Barley, 2019; Christin & Brayne, 2020; Faraj et al., 2018; Glaser et al., 2020; Huysman, 2020; Kellogg et al., 2020; Raisch & Krakowski, 2020; Von Krogh 2018).

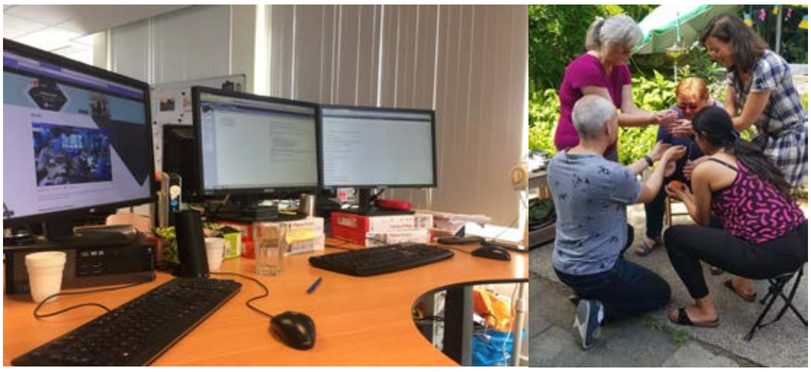
## 1.6 Using ethnography to study AI at work

For the longest time, AI was a topic to be studied in computer science or operations research and humans were the focus of organization and management studies (Rahwan et al., 2019; Raisch & Krakowski, 2020; Simon, 1987). This is in line with a broader divide in organizational literature between either a focus on technology development and or understanding organizational change (Faraj & Pachidi, 2021; Leonardi & Barley, 2010). In this dissertation, I have intended to bridge the divide between technology and organizing by taking a long-term, “deep dive” into one organization to understand every facet of the technology, as well as the organization. Being convinced that “it takes richness to grasp richness” (Weick, 2007, p. 16), my ethnographic research approach could be called “slow research,” taking time to gain a lived experience not only of organizational life but also of the role of technology in it.

### 1.6.1 Behind the scenes of predictive policing at the Dutch National Police

For this dissertation, I performed three years of ethnographic work at the Dutch National Police to understand the influence of an AI system to predict where and when crimes were most likely to occur on police work and organizing. From my first interactions in 2016 with the data scientist who was the main developer of the “Crime Anticipation System” (CAS), I was fascinated by the police’s intention to predict crime and its potential consequences for police work and organizing. However, gaining full-time, unrestricted access to join police officers in the street turned out to be challenging, so I decided to first start my observations inside the police station, at the intelligence department of a large Dutch city (see Figure 1.1).

**Figure 1.1 At the intelligence department**



***(Left: daily view - Right: joining a team building exercise)***

I selected the intelligence department because I was told that the so-called "intelligence officers" working there were the only ones who directly interacted with the machine learning knowledge generated by the AI system. I was intrigued by this role and decided that this could be an interesting group to study. I could not have made a better decision, as the intelligence officers turned out to play a key role in the use of crime predictions by the police. In the end, I stayed at the intelligence department for about two years, closely following how their work and status changed over time in relation to the AI system. I saw how they continued to struggle with understanding the machine learning knowledge generated by the AI system, which became a core theme in Study 2 in this dissertation, which is dedicated to the intelligence officers' work as "algorithmic brokers." Joining the intelligence department for such a long time allowed me to gain a full "lived experience" of intelligence work, with its associated struggles but also its unique group dynamics. Being part of a police department for such a long time also gave me the opportunity to gain a deep understanding of the daily organizing of the police, with all its associated abbreviations and unique features (I will never forget the first time I joined a meeting with police officers coming in armed). At the same time, my time at the intelligence department gave me the opportunity to continue my interactions with the data scientists, through which I learned about the details of the AI system itself.

During the two years with the intelligence officers, I also managed to negotiate access to about a year of unrestricted, full-time participant observations with police officers at the emergency response department of the same police station (see Figure 1.2). This gave me a unique experience of what it means to be a police officer, especially in a time when data and AI systems are becoming increasingly important. Quickly nicknaming me "the professor," the police officers took me in as one of their colleagues, often giving me tasks such as guarding roadblocks after accidents or logging police activities. During my time at the emergency response department, I have seen more than one normally experiences in a lifetime, I have laughed and cried and everything in-between, but I have also been utterly bored at the extreme amount of time that police officers have to spend behind their computer to make the data that can be used to further develop AI systems. Experiencing this unexpected yet extreme difference between the often adrenaline-filled street work and the long and tiresome hours behind the computer triggered me to explore the role of data work in police officers' daily situated work, which I describe in Study 1 of this dissertation.

**Figure 1.2 At the emergency response department**

### 1.6.2 Why ethnography as a method to study AI at work is important

Ethnography is a particularly useful method for bridging the gap between technology development and organizational change that is currently still prevalent in organizational literature. Being present in the field for an extended period of time, in my case years, allows researchers to uncover the longitudinal process of development and change, both on the side of the technology as well as on the side of the organization. As AI systems are currently in the spotlight, many organizations appear to engage with this technology in one way or another. Yet, not much is known about the organizational processes and practices required to make AI systems work in practice. Uncovering these practices is even further complicated by the fact that AI systems depend on large amounts of data, often from a variety of sources, and use complex computational methods to arrive at insights, which makes these learning algorithms opaque or "black-boxed." Understanding AI systems and their consequences for work and organizing therefore requires long-term embedded research.

Entering an organization to look "behind the scenes" of these AI systems and into the social and material work practices involved in making AI work allows researchers to uncover alternative views and unexpected consequences. Moreover, by being fully embedded in an organization, researchers can gain a holistic perspective on the various actors involved in the development, implementation, and use of AI. This also helps researchers to develop deep knowledge about the various angles from which AI systems can be approached (for example, in my case, the data scientists had a fundamentally different idea of crime than the police officers). Understanding these different angles can also help to understand the epistemic differences or "clashes" (Pachidi et al., 2021) that emerge when technologies such as AI systems are implemented in organizations.

### 1.6.3 Why ethnography as a method to study AI at work is challenging

While I argue that ethnography is an extremely important method for studying AI at work, it also comes with its challenges. Using ethnographic methods to understand technology and work requires one to not only be fully embedded in the work domain of technology users but to also unpack in detail the features of the technology studied. This means that, as a researcher, you need to understand multiple worlds; you need to develop knowledge about statistics and data science and about the user domain. As these topics are already challenging on their own, performing ethnography of technology at work requires an extreme engagement and enthusiasm of the researcher to uncover as many technology-related and work-related details as possible. Yet, uncovering such details leads to a challenge on its own, as this is not always appreciated by organizations. As developing and using machine learning knowledge by means of AI systems is still a sensitive topic, not every organization is willing to open its doors to a researcher to uncover what happens behind the scenes of AI at work. A deep ethnography of AI at work therefore depends on the stamina of the researcher, as well as the openness of the organization.

## 1.7 Dissertation outline

To answer my overarching research question "How do organizations cope with the production and use of machine learning in practice?" I performed three studies with specific sub-research questions. These studies are presented in Chapters 2, 3, and 4. In Chapter 5, I take a holistic perspective on the insights derived from the three studies and discuss the theoretical and practical implications and directions for future research. Table 1.1 provides the outline of this dissertation and the outlets in which each study has been peer-reviewed and presented.

### 1.7.1 Chapter 2: The burden of data production

***Understanding the influence of data work on existing work practices.*** This study is based on the final part of my ethnographic research at the Dutch police, as described above. Even though this is the last part of my empirical work, the topic I studied relates to the core feature of AI systems: data. As the making of data becomes increasingly important in organizations for developing and training AI systems, I ask what happens when workers are facing the need to embed such "data work" practices in their existing, situated work. By comparing the police officers' experience of data work and the characteristics of their situated work, three data work tensions emerge. Interestingly, in this study I show that police officers cope with these tensions by anticipating the data work and adopting three strategies in their situated work: avoiding work, deviating from protocol, and capturing experiences. While these strategies helped the police officers to alleviate the burden of data production they experienced on a daily basis; they had a large influence on how police officers performed their situated work. As a consequence, what and how crimes were reported and data was produced was significantly influenced by their coping strategies.

**Table 1.1 Outline of the dissertation**

| Chapter | Purpose | Related output | Co-authors |
|---|---|---|---|
| 1. Introduction: Organizations and machine learning knowledge | Setting the scene of the dissertation. Introducing the problem. Discussing the research approach and outline of the dissertation | Parts of the introduction have been re-written based on my co-authored managerial book:<br>Waardenburg, L., Huysman, M., & Agterberg, M. (2021). *Managing AI wisely: From development to organizational change in practice.* Edward Elgar Publishing. | - |
| 2. The burden of data production | Empirical study to examine how, as AI systems call for increased amounts of data, workers incorporate such data making work in their daily practices and with what consequences for their situated work. | Chapter 2 has been peer-reviewed at:<br>- 37th EGOS Colloquium (2021)<br>- 12th Process Symposium (2021)<br>- In preparation for submission to MIS Quarterly | Anastasia Sergeeva Marleen Huysman |
| 3. In the land of the blind, the one-eyed man is king | Empirical study to examine how a group of "algorithmic brokers" translates machine learning knowledge and copes with the opaque nature of learning algorithms in practice. | Chapter 3 is currently under review (3rd round) at *Organization Science.*<br>Chapter 3 has been peer-reviewed and presented at:<br>- 80th Annual Meeting of the Academy of Management (2020)<br>- 79th Annual Meeting of the Academy of Management (2019)<br>- Digiera19, Organizing in the Era of Digital Technology (2019)<br>- Working Conference on the Interaction of Information Systems and the Organization,<br>part of the International Conference on Information Systems (2018)<br>- 34th EGOS Colloquium (2018) | Anastasia Sergeeva Marleen Huysman |
| 4. Organizing for AI at work | Review study enriched with empirical illustrations that examines how organizations "cross the implementation line" between technology development and use in the case of AI implementation. | Chapter 4 is currently under review (1st round) at *Information and Organization*<br>Chapter 4 is an academic re-interpretation of the co-authored managerial book: Waardenburg, L., Huysman, M., & Agterberg, M. (2021). *Managing AI wisely: From development to organizational change in practice.* Edward Elgar Publishing. | Marleen Huysman |
| 5. Discussion: The road ahead when studying AI at work | Summarizing the findings and discussing the final conclusions. Presenting the limitations of the dissertation and reflecting on the research methods. Discussing the practical implications | - | - |

### 1.7.2 Chapter 3: In the land of the blind, the one-eyed man is king

***Understanding how machine learning knowledge is translated in practice.*** The second study presented in this dissertation builds on my two years of fieldwork at the intelligence department. In this study, I unpack two more features of AI systems: their opaque nature and the ability to produce new knowledge. With this study, I offer one of the first empirical accounts of algorithmic knowledge brokers and ask how such brokers can translate machine learning knowledge when they cannot understand how the knowledge is generated. In this study, I find that as these knowledge brokers try to understand machine learning knowledge to translate it to the user domain, they enact different translation practices over time and perform increasingly influential brokerage roles, i.e., messenger, interpreter, and curator. At the end, when the brokers come to the conclusion that they can never understand how machine learning knowledge is generated, they act like "kings in the land of the blind" and substitute the algorithmic predictions with their own judgments.

### 1.7.3 Chapter 4: Organizing for AI at work

***Understanding the organizing efforts of implementing AI.*** In the third study of this dissertation, I build on the three unique features of AI systems that I unpacked in the first two studies, i.e., their dependence on large amounts of data, their ability to self-learn which limits their explainability, and the capability to generate alternative, pattern-based insights. I use unique insights from five different cases across different industries to ask how the "implementation line" can be crossed in the case of AI, in which technology development and organizational deployment are often worlds apart. I identify three different AI implementation practices – i.e., organizing for data, organizing for explainability, and organizing for new insights. I return to the notion of "hybrid intelligence" by showing how, through these implementation practices, developers and organizational actors are required to engage in continuous and reflective "collaborative learning" and elaborate on the socio-technical consequences for AI development and organizing.

## 1.8 Contributions of this dissertation

This dissertation as a whole contributes to the discussion on the production and use of knowledge that has been core to the field of organization theory for decades. By taking a practice perspective, I unpack how new, machine-based knowledge is developed, implemented, and used in practice and with what consequences for work and organizing. Moreover, by including and theorizing the specific features of AI systems and their relation to organizing, this dissertation responds to the call to bridge the divide between technology development and organizational change that has traditionally informed organizational scholarship (Faraj & Pachidi, 2021; Leonardi & Barley, 2010). Also, this dissertation links to the field of information systems by going beyond the “AI hype” to unpack the challenges that emerge when organizing for machine learning knowledge in practice (e.g., Brynjolfsson & McAfee, 2014; Cantwell Smith, 2019; Davenport, 2018; Shestakofsky, 2017).

In addition to the overall theoretical contributions of this dissertation, each study also contributes to specific theoretical debates. Chapter 2 contributes to current debates on data production (e.g., Cunha & Cargugati, 2018; Pine & Bossen, 2020; Sachs, 2020) by arguing that the need to perform data work can fundamentally alter other, more situated work. Chapter 3 contributes to perspectives on the translation of knowledge (e.g., Carlile, 2004; Røvik, 2016) by emphasizing the importance of understanding how knowledge is produced to perform translation work. Also, Chapter 3 adds to our current understanding of knowledge brokers (e.g., Barley, 1996; Brown & Duguid, 1998) by showing that, in contrast to what is commonly assumed, their work can be highly influential and consequential. Chapter 4 contributes to the literature on the relationship between technology and organizing (e.g., Faraj & Pachidi, 2021; Leonardi, 2009; Zammuto et al., 2007) by taking a holistic perspective on AI system implementation. Also, Chapter 4 includes a plea for organizational and information systems scholars to take an embedded, long-term approach to study technology and organizing.

Finally, this dissertation also has practical implications. I urge managers to let go of the "AI hype" and instead consider AI implementation as effortful, skillful, and requiring long-term involvement. As this dissertation emphasizes, AI systems cannot be bought "off the shelf" but require careful, tailored development and deep organizational involvement. AI systems can therefore not be considered as a quick and easy solution to large amounts of data, nor as crystal balls that will magically lead organizations to new insights. Instead, long-term and direct involvement will provide managers with behind-the-scenes knowledge about the skills and efforts required for successfully producing and using machine learning knowledge.

## References


Aerts, H. J. (2018). Data science in radiology: A path forward. *Clinical Cancer Research, 24*(3), 532–534.

Agarwal, R., & Dhar, V. (2014). Big data, data science, and analytics: The opportunity and challenge for IS research. *Information Systems Research, 25*(3), 443–448.

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence.* Harvard Business Press.

Ajunwa, I. (2020). The "black box" at work. *Big Data & Society, 7*(2), 1–6.

Ananny, M. (2016). Toward an ethics of algorithms: Convening, observation, probability, and timeliness. *Science, Technology & Human Values, 41*(1), 93–117.

Anderson, C. (2008). The end of theory: The data deluge makes the scientific method obsolete, *Wired Magazine, 16*(7).

Anthony, C. (2018). To question or accept? How status differences influence responses to new epistemic technologies in knowledge work. *Academy of Management Review, 43*(4), 661–679.

Azad, B., & King, N. (2008). Enacting computer workaround practices within a medication dispensing system. *European Journal of Information Systems, 17*(3), 264-278.

Bader, V., & Kaiser, S. (2019). Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence. *Organization, 26*(5), 655–672.

Bailey, D. E., & Barley, S. R. (2020). Beyond design and use: How scholars should study intelligent technologies. *Information and Organization, 30*(2). doi:10.1016/j.infoandorg.2019.100286

Balasubramanian, N., Ye, Y., & Xu, M. (2020). Substituting human decision-making with machine learning: Implications for organizational learning. *Academy of Management Review.* doi:10.5465/amr.2019.0470

Baptista, J., Stein, M.-K., Klein, S., Watson-Manheim, M. B., & Lee, J. (2020). Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations. *The Journal of Strategic Information Systems, 29*(2). doi:10.1016/j.jsis.2020.101618

Barbour, J. B., Treem, J. W., & Kolar, B. (2017). Analytics and expert collaboration: How individuals navigate relationships when working with organizational data. *Human Relations, 71*(2), 256–284.

Barley, S. R. (1986). Technology as an occasion for structuring: Evidence from observations of CT scanners and the social order of radiology departments. *Administrative Science Quarterly, 31*(1), 78–108.

Barley, W. C. (2015). Anticipatory work: How the need to represent knowledge across boundaries shapes work practices within them. *Organization Science, 26*(6), 1612–1628.

Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review, 104*, 671–732.

Barrett, M., & Oborn, E. (2013). Envisioning E-HRM and strategic HR: Taking seri- ously identity, innovation practice, and service. *Journal of Strategic Information Systems, 22*(3), 252–256.

Barrett, M., Oborn, E., Orlikowski, W. J., & Yates, J. (2012). Reconfiguring boundary relations: Robotic innovations in pharmacy work. *Organization Science, 23*(5), 1448–1466.

Beck, A. H., Sangoi, A. R., Leung, S., Marinelli, R. J., Nielsen, T. O., Van De Vijver, M. J., ... & Koller, D. (2011). Systematic analysis of breast cancer morphology uncovers stromal features associated with survival. *Science Translational Medicine, 3*(108), 108ra113-108ra113.

Best, J. (2013). *IBM Watson: The inside story of how the Jeopardy-winning super-computer was born, and what it wants to do next.* Via: https://www.techrepublic.com/ article/ibm-watson-the-inside-story-of-how-the-jeopardy-winning-supercomputer -was-born-and-what-it-wants-to-do-next/.

Bonde Thylstrup, N., Flyverbom, M., and Helles, R. (2019) Datafied knowledge production: Introduction to the special theme. *Big Data & Society, 6*(2), 1–5.

Boudreau, M. C., & Robey, D. (2005). Enacting integrated information technology: A human agency perspective. *Organization Science, 16*(1), 3–18.

boyd, d., & Crawford, K. (2012). Critical questions for Big Data. *Information, Communication & Society, 15*(5), 662–679.

Bradbury, H., & Lichtenstein, B. M. B. (2000). Relationality in organizational research: Exploring the space between. *Organization Science, 11*(5), 551–564.

Brayne, S. (2020). *Predict and surveil: Data, discretion, and the future of policing.* Oxford: Oxford University Press.

Brown, J. S., & Duguid, P. (1998). Organizing knowledge. *California Management Review, 40*(3), 90–111.

Brown, J. S., & Duguid, P. (2001) Knowledge and Organization: A Social-Practice Perspective. *Organization Science, 12*(1), 198–213.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* New York: W.W. Norton & Company.

Burrell, J. (2016). How the machine ‘thinks’: Understanding opacity in machine learning algorithms. *Big Data & Society, 3*(1). doi:10.1177/2053951715622512

Burton-Jones, A., & Gallivan, M. J. (2007). Toward a deeper understanding of system usage in organizations: A multilevel perspective. *MIS Quarterly, 31*(4), 657–679.

Cantwell Smith, B. (2019). *The promise of artificial intelligence: Reckoning and judgment.* Cambridge, MA: The MIT Press.

Cariani, P. (2010). On the importance of being emergent. *Constructivist Foundations, 5*, 86–91.

Carlile, P. R. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization Science, 15*(5), 555–568.

Christin, A. (2020). *Metrics at work: Journalism and the contested meaning of algorithms.* Princeton, NJ: Princeton University Press.

Christin, A., & Brayne, S. (2020). Technologies of crime prediction: The reception of algorithms in policing and criminal courts. *Social Problems*. doi:10.1093/socpro/spaa004

Cukier, K., & Mayer-Schönberger, V. (2013). The rise of big data: How it's changing the way we think about the world. *Foreign Affairs, 92*(3), 28–40.

Cunha, J., & Carugati, A. (2018). Transfiguration work and the system of transfiguration: How employees represent and misrepresent their work. *MIS Quarterly, 42*(3), 873–894.

Daugherty, P. R., & Wilson, H. J. (2018). *Human+ machine: Reimagining work in the age of AI.* Cambridge, MA: Harvard Business Press.

Davenport, T. (2018). *The AI advantage: How to put the artificial intelligence revolution to work.* Cambridge, MA: MIT Press.

Davenport, T., & Harris, J. (2017). *Competing on analytics: Updated, with a new introduction: The new science of winning.* Harvard Business Press.

Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines.* New York, NY: Harper Business.

Domingos, P. (2015). *The master algorithm: How the quest for the ultimate learning machine will remake our world.* Basic Books.

Ebel, P., Söllner, M., Leimeister, J. M., Crowston, K., & de Vreede, G.-J. (2021). Hybrid intelligence in business networks. *Electronic Markets.* doi:10.1007/s12525-021-00481-4

Elish, M.C., & boyd, d. (2018). Situating methods in the magic of Big Data and AI. *Communication Monographs, 85*(1), 57–80.

Faraj, S., & Pachidi, S. (2021). Beyond Uberization: The co-constitution of technology and organizing. *Organization Theory, 2*(1). doi:10.1177/2631787721995205

Faraj, S., & Sproull, L. (2000). Coordinating expertise in software development teams. *Management Science, 46*(12), 1554–1568.

Faraj, S., & Xiao, Y. (2006). Coordination in fast-response organizations. *Management Science, 52*(8), 1155–1169.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62-70.

Feigenbaum, E. A., & McCorduck, P. (1984). *The Fifth Generation.* London: Pan Books London.

Feldman, M. S., & Orlikowski, W. J. (2011). Theorizing practice and practicing theory. *Organization Science, 22*(5), 1240–1253.

Forsythe, D. E. (1993). Engineering knowledge: The construction of knowledge in artificial intelligence. *Social Studies of Science, 23*(3), 445–477.

Gal, U., Jensen, T. B., & Stein, M.-K. (2020). Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. *Information and Organization, 30*(2). doi:10.1016/j.infoandorg.2020.100301

Gherardi, S. (2006). *Organizational knowledge: The texture of workplace learning.* Oxford: Blackwell.

Giddens, A. (1984). *The constitution of society*. Cambridge, UK: Polity Press.

Gitelman, L. (2013). *Raw data is an oxymoron.* Cambridge, MA: MIT press.

Glaser, V. L., Pollock, N., & D'Adderio, L. (2020). The biography of an algorithm: Performing algorithmic technologies in organizations. *Organization Theory, 2*(2). doi:10.1177/26317877211004609

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660.

Graef, R., Klier, M., Kluge, K., & Zolitschka, J. F. (2020). Human-machine collaboration in online customer service – a long-term feedback-based approach. *Electronic Markets.* doi:10.1007/s12525-020-00420-9

Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *The Journal of Strategic Information Systems, 29*(2). doi:10.1016/j.jsis.2020.101614

Günther, W. A., Mehrizi, M. H. R., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems, 26*(3), 191-209.

Hartmann, P., & Henkel, J. (2020). The rise of corporate science in AI: Data as a strategic resource. *Academy of Management Discoveries.* doi:10.5465/amd.2019.0043

Henriksen, A., & Bechmann, A. (2020). Building truths in AI: Making predictive algorithms doable in healthcare. *Information, Communication & Society*, *3*(6), 802–816.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly, 28*(1), 75–105.

Introna, L. D. (2011). The enframing of code agency, originality and the plagiarist. *Theory, Culture & Society, 28*(6), 113–141.

Introna, L. D. (2016). Algorithms, governance, and governmentality: On governing academic writing. *Science, Technology & Human Values, 41*(1), 17–49.

Introna, L. D., & Nissenbaum, H. (2000). Shaping the Web: Why the politics of search engines matters. *Information Society, 16*(3), 169–185.

Jasperson, J., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly, 29*(3), 525–557.

Jones, M. (2019). What we talk about when we talk about (big) data. *The Journal of Strategic Information Systems, 28*(1), 3–16.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.

Kitchin, R. (2014). Big Data, new epistemologies and paradigm shifts. *Big Data & Society, 1*(1), 1–12.

Leavitt, K., Schrabram, K., Hariharan, P., & Barnes, C. M. (2020). Ghost in the machine: On organizational theory in the age of machine learning. *Academy of Management Review.*

Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2021). Is AI ground truth really "true"? The dangers of training and evaluating AI tools based on experts' know-what. *MIS Quarterly, Forthcoming.*

Leonardi, P. M. (2009). Crossing the implementation line: The mutual constitution of technology and organizing across development and use activities. *Communication Theory, 19*(3), 278–310.

Leonardi, P. M. (2013). When does technology use enable network change in organizations? A comparative study of feature use and shared affordances. *MIS Quarterly, 37*(3), 749–775.

Leonardi, P. M., & Barley, S. R. (2010). What's under construction here? Social action, materiality, and power in constructivist studies of technology and organizing. *Academy of Management Annals, 4*(1), 1–51.

Leonardi, P. M., Treem, J. W., & Jackson, M. H. (2010). The connectivity paradox: Using technology to both decrease and increase perceptions of distance in distributed work arrangements. *Journal of Applied Communication Research, 38*(1), 85–105.

March, J. G. (1988). Technology of foolishness. In *Decisions and organizations*, J.G. March (ed.), Oxford: Blackwell, pp. 253–265.

March, J. G., & Weil, T. (2009). *On leadership*. Hoboken, NJ: John Wiley & Sons.

Mazmanian, M. (2013). Avoiding the trap of constant connectivity: When congruent frames allow for heterogeneous practices. *Academy of Management Journal, 56*(5), 1225–1250.

Mazmanian, M., Orlikowski, W. J., & Yates, J. (2013). The autonomy paradox: The implications of mobile email devices for knowledge professionals. *Organization Science, 24*(5), 1337–1357.

Mirbabaie, M., Stieglitz, S., & Frick, N. R. J. (2021). Hybrid intelligence in hospitals: Towards a research agenda for collaboration. *Electronic Markets.* doi:10.1007/s12525-021-00457-4

Mitchell, R., Michalski, J., & Carbonell, T. (1986). *Machine learning: An artificial intelligence approach.* Los Altos, CA: Morgan Kaufmann.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society, 3*(2), 1–21.

Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'. *Journal of Strategic Information Systems, 24*(1), 3–14.

Newell, A., & Simon, H. (1956). The logic theory machine - A complex information processing system. *IRE Transactions on Information Theory, 2*, 61–79.

Newell, A., Shaw, J. C., & Simon, H. A. (1959). Report on a general problem solving program. *International Conference on Information Processing*, (pp. 256–264). Santa Monica, CA: Rand Corporation.

Nilsson. N. (1971). *Problem-solving methods in artificial intelligence.* New York: McGraw-Hill.

Nikolaidis, S., & Shah, J. (2012). Human–robot teaming using shared mental models. *ACM/IEEE HRI.*

Oborn, E., Barrett, M., & Davidson, E. (2011). Unity in diversity: Electronic patient record use in multidisciplinary practice. *Information Systems Research, 22*(3), 547–564.

O'neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy.* Crown.

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization science, 11*(4), 404–428. Orlikowski, W. J. (2010). The sociomateriality of organizational life: Considering technology in management research. *Cambridge Journal of Economics, 34*(1), 125–141.

Orlikowski, W.J., & Scott, S.V. (2008). Sociomateriality: Challenging the separation of technology, work and organization. *Academy of Management Annals, 2*(1), 433–474.

Orlikowski, W. J., & Scott, S. V. (2014). What happens when evaluation goes online? Exploring apparatuses of valuation in the travel sector. *Organization Science, 25*(3), 868–891.

Orlikowski, W. J., & Scott, S. V. (2016). *Digital work: A research agenda. A research agenda for management and organization studies.* Cheltenham, UK and Northampton, MA, USA: Edward Elgar Publishing.

Østerlund, C., & Carlile, P. (2005). Relations in practice: Sorting through practice theories on knowledge sharing in complex organizations. *The Information Society, 21*(2), 91–107.

Pachidi, S., Berends, H., Faraj, S., & Huysman, M. (2020). Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organization Science.* doi:10.1287/orsc.2020.1377

Pachidi, S., & Huysman, M. (2016). *Organizational intelligence in the digital age: Analytics and the cycle of choice.* Routledge Companions in Business, Management, and Accounting. London, UK and New York, USA: Routledge.

Pasquale, F. (2015). *The black box society.* Cambridge, MA: Harvard University Press.

Pesapane, F., Codari, M., & Sardanelli, F. (2018). Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine. *European Radiology Experimental, 2*(1), 1–10.

Picard, R.W. (1995). *Affective computing.* MIT Media Laboratory Perceptual Computing Section Technical Report No. 321, Cambridge, MA, 2139.

Pine, K. H., & Bossen, C. (2020). Good organizational reasons for better medical records: The data work of clinical documentation integrity specialists. *Big Data & Society, 7*(2). doi:10.1177/2053951720965616

Pine, K. H., & Liboiron, M. (2015). The politics of measurement and action. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems.*

Pine, K. H., & Mazmanian, M. (2017). Artful and contorted coordinating: The ramifications of imposing formal logics of task jurisdiction on situated practice. *Academy of Management Journal, 60*(2), 720–742.

Pomerleau, D. (1989). ALVINN: An Autonomous Land Vehicle in a Neural Network. *Advances in Neural Information Processing Systems*, 305–313.

Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., Crandall, J. W., Christakis, N. A., Couzin, I. D., Jackson, M. O., Jennings, N. R., Kamar, E., Kloumann, I. M., Larochelle, H., Lazer, D., McElreath, R., Mislove, A., Parkes, D. C., Pentland, A. "Sandy," Roberts, M. E., Shariff, A., Tenenbaum, J. B., & Wellman, M. (2019). Machine behaviour. *Nature, 568*, 477–486.

Raisch, S., & Krakowski, S. (2020). Artificial intelligence and management: The automation- augmentation paradox. *Academy of Management Annals.* doi:10.5465/2018.0072

Reckwitz, A. (2002). Toward a theory of social practices: A development in culturalist theorizing. *European Journal of Social Theory, 5*(2), 243–263.

Røvik, K. A. (2016). Knowledge transfer as translation: Review and elements of an instrumental theory. *International Journal of Management Reviews, 18*(3), 290–310.

Sachon, M., & Boquet, I. (2017). *KUKA: Planning for the Future of Automation.* IESE Business School Case: Universidad de Navarra.

Sachs, S. E. (2020). The algorithm at work? Explanation and repair in the enactment of similarity in art data. *Information, Communication & Society, 23*(11), 1689–1705.

Schildt, H. (2017). Big data and organizational design – the brave new world of algorithmic management and computer augmented transparency. *Innovation, 19*(1), 23–30.

Schultze, U., & Orlikowski, W. J. (2004). A practice perspective on technology-mediated network relations: The use of internet-based self-serve technologies. *Information Systems Research, 15*(1), 87–106.

Scott, S.V., & Orlikowski, W. J. (2014). Entanglements in practice: Performing anonymity through social media. *MIS Quarterly, 38*(3), 873–893.

Sein, M. K., Henfridsson, O., Purao, S., Rossi, M., & Lindgren, R. (2011). Action design research. *MIS Quarterly, 35*(1), 37–56.

Sergeeva, A., Huysman, M., Soekijad, M., & van den Hooff, B. (2017). Through the eyes of others: How onlookers shape the use of technology at work. *MIS Quarterly, 41*(4), 1153–1178.

Shah, H., Warwick, K., Vallverdú, J., & Wu, D. (2016). Can machines talk? Comparison of Eliza with modern dialogue systems. *Computers in Human Behavior, 58*, 278–295.

Shah, J., Wiken, J., Williams, B., & Breazeal, C. (2011). Improved human–robot team performance using chaski, a human-inspired plan execution system. In *Proceedings of the 6th International Conference on Human–Robot Interaction.*

Sheridan, T. B. (1995). Human centered automation: oxymoron or common sense?. In *1995 IEEE International Conference on Systems, Man and Cybernetics. Intelligent Systems for the 21st Century*, vol. 1, pp. 823–828. IEEE.

Shestakofsky, B. (2017). Working Algorithms: Software Automation and the Future of Work. *Work and Occupations, 44*(4), 376-423.

Siegel, E. (2013). *Predictive analytics: The power to predict who will click, buy, lie, or die.* New Jersey: John Wiley & Sons.

Simon, H. A. (1987). Two heads are better than one: The collaboration between AI and OR. *Interfaces, 17*, 8–15.

Spengler, O. (1991 [1926]). *The decline of the West.* Oxford University Press, USA.

Stein, M. K., Newell, S., Wagner, E., & Galliers, R. D. (2015). Coping with information technology: Mixed emotions, vacillation and nonconforming use patterns. *MIS Quarterly, 39*(2), 367–392.

Stilgoe, J. (2018). Machine learning, social learning and the governance of self-driving cars. *Social Studies of Science, 48*(1), 25–56.

Susskind, D. (2020). *A world without work: Technology, automation, and how we should respond.* London: Allen Lane.

Tegmark, M. (2017). *Life 3.0: Being human in the age of artificial intelligence.* Knopf.

Thomas, V., Pedregosa, F., Merriënboer, B., Manzagol, P. A., Bengio, Y., & Le Roux, N. (2020). On the interplay between noise and curvature and its effect on optimization and generalization. In *International Conference on Artificial Intelligence and Statistics* (pp. 3503–3513). PMLR.

Tshitoyan, V., Dagdelen, J., Weston, L., Dunn, A., Rong, Z., Kononova, O., ... Jain, A. (2019). Unsupervised word embeddings capture latent knowledge from materials science literature. *Nature, 571*(7763), 95–98.

Turing, A. M., 1950, Computing machinery and intelligence, *Mind, 59*, 433–460.

Vaast, E., & Walsham, G. (2005). Representations and actions: The transformation of work practices with IT use. *Information & Organization, 15*(1), 65–89.

Van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. *MIS Quarterly, Forthcoming.*

Van Maanen, J., & Barley, S.R. (1984). Occupational communities: Culture and control in organizations. In B. Staw, L.L. Cummings (Eds) *Research in Organizational Behaviour* (pp. 287–365). Greenwich: JAI Press.

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries, 4*(4), 404-409. doi:10.5465/amd.2018.0084

Waardenburg, L., Huysman, M., & Agterberg, M. (2021). *Managing AI wisely: From development to organizational change in practice.* Edward Elgar Publishing.

Waardenburg, L., Sergeeva, A., & Huysman, M. (2018). Hotspots and blind Spots. In *Working Conference on Information Systems and Organizations* (pp. 96–109). Springer, Cham.

Weick, K. E. (2007). The generative properties of richness. *Academy of Management Journal, 50*(1), 14-19.

Wooldridge, M. (2020). *The road to conscious machines: The story of AI.* Penguin UK.

Yeung, S., Ramanathan, V., Russakovsky, O., Shen, L., Mori, G., & Fei-Fei, L. (2017). Learning to learn from noisy web videos. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 5154–5162).

Zammuto, R. F., Griffith, T. L., Majchrzak, A., Dougherty, D. J., & Faraj, S. (2007). Information technology and the changing fabric of organization. *Organization Science, 18*(5), 749–762.

Zarsky, T. (2016). The trouble with algorithmic decisions: An analytic road map to examine efficiency and fairness in automated and opaque decision making. *Science, Technology & Human Values, 41*(1), 118–132.

Zhang, Z., Nandhakumar, J., Hummel, J. T., & Waardenburg, L. (2020). Addressing the key challenges of developing machine learning AI systems for knowledge-intensive work. *MIS Quarterly Executive, 19*(4), 221–238.

# 2. The burden of data production

## How anticipating data work shapes police practices

# Abstract

Organizational research on data production often aims to unpack the nature and meaning of data and the work practices through which it is made. Yet, not much is known about how the growing need to produce data influences the performance of other, more situated work. Our three-year ethnographic study of the Dutch police unravels this issue and shows that police officers adopt three strategies to cope with anticipated data work in their situated practices: avoiding work, deviating from protocol, and capturing experiences. These strategies helped police officers to alleviate the burden of data production, but also influenced how they performed their situated work and what and how crimes were reported, which contrasted the aims of data-driven police work. Our findings have implications for existing research on data production and for studies on anticipatory work by arguing that data construction starts at the situated practices and by showing how anticipating the work needed to produce data influences how both situated and data work are performed.

**Keywords:** data work, data production, anticipation, anticipatory work, representation work

## 2.1 Introduction

> “[B]efore you arrive at the scene, you are actually already dealing with the call and writing your report in your head.” (Interview with police officer Misha)

Everyday work life is becoming more and more datafied. Given the growing importance and influence of data in organizations, information systems and organizational scholars increasingly focus their attention towards its consequences for work and organizing by, for example, questioning the nature and meaning of data (e.g., boyd & Crawford, 2012; Kitchin & Lauriault, 2014) and studying how it is produced (e.g., Pachidi, Berends, Faraj, & Huysman, 2020; Pine & Bossen, 2020; Sachs, 2020). Studies on data production reside in different fields but generally come to the same conclusion: data is socially and politically constructed (e.g., Pine & Liboiron, 2015). For example, Latour and Woolgar (2013 (1979)) unraveled how scientists transformed the ‘messy’ process of doing science into an orderly representation of seemingly objective and indisputable scientific facts.

One of the most recent subfields in the literature on data construction is focused on “data work,” i.e., the specific practices workers engage in to produce data (e.g., Bossen et al., 2016; Cunha & Cargugati, 2018; Gray & Suri, 2019; Kellogg, Valentine, & Christin, 2020; Kittur et al., 2013; Pine & Bossen, 2020; Sachs, 2020; Truelove, 2019). For example, Pine (2019) examined the decisions and efforts that “medical records coders” and “birth certificate clerks” put into creating administrative medical data. These studies have provided very important first steps to understand the work practices that are involved in making data. However, because they have mostly been motivated to unpack the construction of data and how this leads to misrepresentation and misalignments with ‘reality,’ how the growing need to produce data influences the performance of more situated work is not yet fully understood. This becomes especially interesting when workers produce data about their own activities, such as sales employees reporting their sales performance, doctors and nurses keeping electronic health records, or police officers reporting their responses to crime events. In the case of such self-reporting, workers are not only producers, but also subjects of data, which leads to a direct connection between data work and the performance of situated practices. To better understand this relationship, we ask: *How do workers cope with data work in their situated practices?*

To answer this question, we build on three years of fieldwork at the Dutch police, specifically using insights from eight months of full-time research at the police emergency department of a large Dutch city (between September 2018 and April 2019). The first author spent over 100 shifts (day, evening, and night) following how police officers went about their work. By studying the performance of situated work and data work, we found that, instead of 'misrepresenting' their situated activities in their reports, police officers adjusted their situated work to fit the practice of data work. We explain this outcome by unpacking how the police officers coped with the tensions they experienced between data work and their situated performances. On a daily basis, they experienced the practice of data work as bodily constrained, materially rigid, and ethereal, while they experienced their situated work as deeply embodied, contextual, and lived. To cope with these tensions, the police officers enacted three coping strategies in their situated work: avoiding work, deviating from protocol, and capturing experiences. By using these coping strategies, they adjusted the situated activities that they subsequently had to record and thereby aligned their situated work to reflect the practice of data work. As such, they *ex-ante* enacted data work in their situated practices

Our findings offer contributions to existing research on data production, and specifically data work (Bossen et al., 2016; Cunha & Carugati, 2018; Pachidi et al., 2020; Pine & Bossen, 2020; Pine & Liboiron, 2015; Truelove, 2019), and for studies on anticipation and anticipatory work (Barley, 2015; Bucher, Schou, & Waldkirch, 2020; Flyverbom & Garsten, 2021). We emphasize that, in contrast to how data work has previously been understood, constructing data is not a separate activity but is inherently entwined with situated work. In addition, we argue that, while current research considers anticipation as building upon data, our findings show the importance of anticipation for the construction of data. We argue that data work practices go beyond 'impression management' and call for the importance of including situated work to understand the practice of data work.

## 2.2 Research on data work

Data is generally considered as "information that can be used for reference, analysis, calculation, and computer operations" (Christin, 2020, p. 1116). Given the widespread development of digital information systems, collecting, storing, and analyzing data has become possible for many organizations. As a consequence, data is now central to producing knowledge, conducting business, and enacting governance (Kitchin & Lauriault, 2014). With this growing pervasiveness of datafication, scholars increasingly focus their attention on data and its consequences for work and organizing (e.g., Bietz & Lee, 2009; Borgman, 2015; Brayne, 2017; Newell & Marabelli, 2015; Stein et al., 2018). Studies taking on this topic show that using data can fundamentally alter situated work practices and that people adjust their behavior when they are the 'subjects' of datafication (Brayne, 2017; Christin, 2020). For example, Christin (2020) described how, when using data about the popularity of articles, journalists adjust their work and become more similar to each other because they focus on pursuing the same topics and headlines and use a similar writing style that attracts the highest number of readers.

The rapid rise of data use in organizations also led scholars to critically reflect on the nature and meaning of data. These studies build on the foundations of critical accounting studies, which focus on understanding and questioning the nature of accounts or representations as a means for recording and managing activities (e.g., Bevan & Hood, 2006; Hull, 2012; Power, 2021; Quatrone, 2015; Roberts, 1991; Van Maanen & Pentland, 1994). For example, Roberts (2009) criticized the ideal of transparency in financial institutions and explained how the nature of accounts is influenced by individual choices (e.g., trying to appear perfect), as well as social norms and environmental characteristics (e.g., expectations to be met). Adopting this perspective, critical data scholars argue that data is not raw, unbiased, and objective, but instilled with decisions, judgments, and values dictating what should be taken into account and what not (e.g., boyd & Crawford, 2012; Christin, 2020; Gitelman, 2013; Pine & Liboiron, 2015; Slota, Hoffman, Ribes, & Bowker, 2020). For example, Kitchin and Lauriault (2014) argued that data is socially constructed by an assemblage of social and material actors directly or indirectly involved in the data production process.

Digging deeper into the social construction of data, recent studies started to unpack the work practices involved in constructing and producing data (Bossen et al., 2016; Cunha & Carugati, 2018; Pachidi et al., 2020; Pine & Bossen, 2020; Pine & Liboiron, 2015; Truelove, 2019). Commonly referred to as "data work," these studies highlight its "effortful, skillful, and resource-intensive" nature (Pine & Bossen, 2020, p. 4). For example, Slota et al. (2020) studied how data scientists generated datasets and emphasized that data is never 'out there' for data scientists to use, but has to be actively 'sought out' or 'prospected' by them. Cunha and Carugati (2018) asked what happens when sales employees are responsible for data production by reporting their own work. They found that, instead of having the data reflect their sales work, these employees engaged in 'transfiguration work' to adjust sales data to meet managerial demands. Besides, some studies have found new occupations to emerge and adopt the specific skills for doing data work (Gray & Suri, 2019; Kellogg et al., 2020; Kittur et al., 2013; Pine, 2019; Pine & Bossen, 2020; Sachs, 2020). For example, Gray and Suri (2019) described how "ghost workers" emerged as a new occupation because of the need to review and categorize data to be used in the learning algorithms of companies such as Uber.

Studies on data work have been highly insightful for understanding how new work practices emerge when workers are confronted with data-making requirements. Yet, to show the consequential nature of such practices, these scholars have mostly been motivated to unpack how data work can lead to misalignment between data and 'reality' (Cunha & Carugati, 2018; Pachidi et al., 2020; Pine & Liboiron, 2015). For example, to return to Cunha and Carugati (2018), their study points to the discrepancy that emerges when workers adjust the data to fit managerial needs while continuing to perform their established, situated work. While these studies have helped us understand that data work is a sociomaterial practice yielding flawed representations of work, we have so far left out what happens to the situated work practices that are being represented. Adopting a practice theory perspective, we argue that when workers are required to produce data about their own activities (e.g., sales employees reporting their sales numbers, doctors keeping electronic health records about treatments, or police officers reporting crime events), maintaining such a strict divide between data work and situated practices is problematic. In fact, in our setting, we saw that data work requires physical, emotional, and cognitive efforts that may be in conflict with the situated work that is represented by data work. Coping with these misalignments or tensions may have significant consequences, not only for what is represented but also for how situated work is performed. However, this has not yet been a topic of research. We therefore ask: *How do workers cope with data work in their situated practices?*

## 2.3 Anticipating data work

The concept of anticipation is helpful to better understand the potentially problematic relationship between data work and situated practices. Anticipation is commonly understood as "foreseeing, foreshadowing, or forecasting future events" (Flyverbom & Garsten, 2021, p. 2). Recently, Flyverbom and Garsten (2021) have conceptualized anticipation as a way of producing knowledge about the future, which has effects on organizing. Other scholars have also emphasized this "performative" nature of anticipation (Barley, 2015; Loxley, 2007) and focused on how the future could have an active influence on the present (Slaughter, 1993). For example, Barley (2015) studied how weather scientists adjusted their work practices in anticipation of the kind of knowledge that weather forecasters would need from them. As such, the weather scientists changed their work and the knowledge they produced. Recent developments in digital technologies, and specifically datafication, have triggered renewed scholarly interest in anticipation (Bucher et al., 2020; Flyverbom & Garsten, 2021). Some scholars argue that data sources promise to generate more objective and new perspectives on the future (Engle Merry 2011; Muller, 2019), while others take a more critical perspective and claim that data creates the future (boyd & Crawford, 2012; O'Neil, 2016). Interestingly, scholars interested in the relationship between data and anticipation take data as a source for producing knowledge about the future, but leave out the potential role of anticipation for performing data work itself.

To fully grasp the performative nature of anticipation in data work, we adopt a practice theory perspective. Practice theory originates from scholars in the field of philosophy and sociology – such as Bourdieu, Giddens, Foucault, Garfinkel, Latour, Taylor, and Schatzki – and is mainly concerned with understanding how practices emerge and change, and their intended and unintended consequences (Feldman & Orlikowski, 2011). Core to practice theory is a focus that goes beyond the individual towards work practices, which are considered routinized types of behaviors that are interdependent and mutually constitutive (Bradbury & Lichtenstein, 2000; Giddens, 1984; Østerlund & Carlile, 2005; Reckwitz, 2002). In other words, "social orders (structures, institutions, routines, etc.) cannot be conceived without understanding the role of agency in producing them, and similarly, agency cannot be understood "simply" as human action, but rather must be understood as always already reconfigured by structural conditions" (Feldman & Orlikowski, 2011, p. 1242). Practice theory therefore implies that social orders are never static or established, but evolve and change over time (Gherardi, 2006; Reckwitz, 2002).

Practice theory has been increasingly adopted by information systems scholars to understand how technology and work are mutually constitutive and with what consequences for organizations (Oborn, Barrett, & Davidson, 2011). Especially the technology-in-practice perspective as defined by Orlikowski (2000) – which emphasizes that social structures, such as rules, are not embedded in technology but instantiated by the activities of people engaging with it – has been largely influential in the information systems field (e.g., Azad & King, 2008; Hevner, March, Park, & Ram, 2004; Jasperson, Carter, & Zmud, 2005; Sein et al., 2011; Sergeeva, Huysman, Soekijad, & Van den Hooff, 2017). For example, Sergeeva et al. (2017) used the technology-in-practice perspective to study the use of mobile technology in operating rooms and showed how so-called 'onlookers' play an important role in how collective patterns of technology use are structured.

Recently, scholars have argued that most IS research using a practice lens to study technology adopted only a partial definition of practice theory, which is mainly focused on the role of human and material agency (e.g., Hindmarsh, Hyland, & Banerjee, 2014; Oborn et al., 2011; Sergeeva, Faraj, & Huysman, 2020; Vertesi, 2012). These studies emphasize the need for a more holistic perspective on technology in practice, in which technology is embedded and interrelated with core elements of a practice that are often overlooked, such as bodily strains and emotions (Oborn et al., 2011), and which can have a formative effect on how a technology is perceived and used. In other words, recent calls for a more holistic perspective on technology in practice leave room to explore the so-called 'lived experience' of technology use, in which we not only look at the direct relationship between human action and technology, but include more of how technology is experienced in everyday organizational life. Below, we analyze how police officers experienced the use of an information system to perform data work as in conflict with their everyday situated work and how they coped with this tension by adjusting their situated practices to the anticipated data work.

## 2.4 Methods

### 2.4.1 Data-driven police work

Being accountable for their actions and decisions in the field is one of the key elements of police work. This is specifically prevalent in the administrative work of officers after an encounter or incident took place. This 'administrative burden' has been part of police work for decades (Van Maanen, 1980; Van Maanen & Pentland, 1994). Yet, crime reporting has become a specifically labor-intensive and pervasive part of police work in the last two decades, given the increasing incorporation of data-driven decision-making into law enforcement practices (Brayne, 2017). One of the main reasons for law enforcement to embrace data-driven technologies is said to be the implicit assumption that the "rapid and efficient flow of information (by technological means) would in itself empower policing" (Manning, 2001, p. 84). For example, it could allow the police to gather intelligence through data and visualize patterns of criminality that might otherwise remain hidden from view (Ferguson, 2019).

In the Netherlands, so-called "data-driven policing" was nationally introduced in 2008 and implemented across all levels of the organization. The implementation of this strategic change was the key moment for the increasing importance and formalization of crime reporting. Organizational changes included a focus on improving reporting skills of police officers by adding this in the initial police training, a formal differentiation between strategic and operational information, making operational information available in real-time to police officers, and establishing formal procedures for analyzing data points which otherwise remained unutilized. In the years after 2008, the police paid increasing attention to developing and implementing technologies that would facilitate and support data-driven activities. For example, they merged all local police data into one nationally organized database and digitalized the format of police reports, which allowed for the quick and easy sharing and retrieval of police data (e.g., police reports, information about known suspects across the country). They also hired data scientists for developing systems to analyze data (e.g., a learning algorithm for predicting crime). On a departmental level, all police officers were equipped with secured smartphones that allowed them to retrieve and share information while working 'on the beat.'

A focal consequence of data-driven policing for officers working at the emergency response department was that crime reporting (i.e., data work) became more embedded in the responsibilities of police officers. When asked about how activities of crime reporting had changed, officer Johan reflected: "We've always had to report certain crimes, but back then [before 2008] we often didn't report some of them and it was never checked." As more advanced methods for digital reporting became available, police officers' personal call signs became automatically attached to every crime event they were dispatched to. This gave police chiefs full insight into whether officers fulfilled their reporting duties and reporting became an obligatory and integral part of police daily operations.

### 2.4.2 Data collection

Our study builds on three years of ethnographic fieldwork with the Dutch police, specifically using insights of eight months of full-time research – between September 2018 and April 2019 – at the police emergency response department of a large Dutch city. Before joining the emergency response department, the first author spent nearly two years at the intelligence department studying the use of a learning algorithm for crime prediction, during which she negotiated eight months of unrestricted and unsupervised access to the emergency response department. She spent over 100 shifts (day, evening, and night) following how police officers went about their work. Initially, she was surprised to see how much time officers spent at their desks, writing crime reports at their computers (i.e., performing data work). Our interest in how the act of writing reports influences situated work was triggered when we realized that performing data work was not a 'side job' for police officers, but was deeply embedded in their day-to-day work. The first author tracked the exact amount of time spent on data work by keeping track of the officers' activities every 15 minutes. Eventually, she calculated that, across 99 shifts, data work counted for approximately 3 out of 9 hours.

The shifts at the emergency department were divided into morning (07:00 till 16:00), afternoon (14:00-23:00), and night (22:00-07:00) shifts. While police officers were heavily armed (e.g., they had a gun, pepper spray, and a baton) and wore a recognizable police uniform, the first author was not armed and wore her own clothes (except for a transceiver with a matching earpiece). Shifts typically comprised around 4–10 police officers and 1 senior officer acting as the team chief. Police officers mostly worked in teams of 2, moving around the city in a recognizable police vehicle. At the start of each shift, the first author typically joined two police officers working as a couple whom she shadowed all through the 9-hour shift. During patrols, she sat in the back of the car, closely following police officers' activities and their interactions with each other and their environment. When called to assist in an event, the first author joined the police officers in every activity. While this sometimes resulted in questions from citizens, she was quickly nicknamed "the professor" and introduced as such. While always taking into account her safety, all officers allowed her to fully join in every event, due to which she was able to gain a holistic experience of police work at the emergency response department.

The first author took detailed notes of all police officers' actions, responses, and reflections, describing in detail the activities as well as writing down quotes when officers, for example, reflected on experiences. This happened outside in the street, 'inside' in the car, during breaks at the office, and when performing desk work. During desk work, she would typically join one of the police officers and closely observe the steps they took to report a specific event. She wrote down, for example, how they went about creating and submitting a report in the information system, how they described an event, as well as what officers said and reflected on while performing desk work. For cross-referencing, the first author also gained access to the reports submitted to the database by the officers. This resulted in approximately 500 pages of crime reports.

While the detailed field notes comprise the bulk of the empirical data used for this study, the first author also organized 12 in-depth, audio-recorded conversations (lasting between 1 and 2 hours) with police officers in which she asked them to reflect on data work and their experience of this work in practice. With these conversations, she aimed to get a deeper understanding of how performing data work was related to police officers' situated practices and to further unpack the general 'rules' associated with working at the desk. For example, in 7 of these conversations, police officers were asked to read and reflect on a specific crime report (written by another, anonymous officer) to better understand how and why crime was reported in that way. Besides, throughout the fieldwork, countless informal conversations took place where the first author could ask questions to solicit interpretations of specific events or decisions. We summarize each of the data sources in Table 2.1.

**Table 2.1 Data sources**

| Data source | Amount/duration | Use in analysis |
|---|---|---|
| *Observations* | | |
| Shifts<br>- Morning<br>- Afternoon<br>- Night | Total: 109 (± 1020 hrs.)<br>- 32 (± 300 hrs.)<br>- 64 (± 600 hrs.)<br>- 13 (± 120 hrs.) | Provided rich insight into the daily practices at the emergency response department at different times of the day. |
| Police street work | ± 650 hrs. | Provided deep insight into the lived experience of police street work. |
| Police desk work | ± 350 hrs. | Provided deep insight into the activities involved in performing data work as a police officer. |
| *Interviews* | | |
| Recorded conversations with police officers | 12 (± 14 hrs.) | Enriched and deepened our understanding of how data work was performed and experienced and the 'rules' behind this work. |
| *Documents* | | |
| Crime reports | 237 (± 500 pages) | Allowed for cross-referencing our observations of how police situated work was translated into reports. |

### 2.4.3 Data analysis

During the full process of data collection, the full author team regularly came together to reflect on the observations, ask critical questions, and to suggest connections with related literature. During the coding process, the first author took the lead, with the second and third author frequently checking in and adding suggestions. The coding process started with reading all field notes, leaving potential codes and interesting themes in the margins. For this paper, we set out to understand how police officers performed data work and with what consequences and, due to the sheer size of the dataset, we decided to focus our coding on identifying the different responses and activities related to data work.

During the first rounds of coding, we found a variety of activities enacted by police officers in their street work in relation to data work. For example, coded activities such as "being untraceable," "staying silent," "not arresting a suspect," and "trying to find alternative solutions." We saw similarities between these activities and grouped them into three main categories: (1) avoiding street-level work, (2) deviating from street-level protocol, and (3) capturing street-level experiences. We engaged in further rounds of axial coding (Strauss & Corbin, 1990) and noticed that the practices we identified were related to a specific experience of the data work performed. We grouped these three types of experiences as: (1) bodily exertion, (2) data categorization, and (3) unknown audiences.

Using the literature on data work and anticipation then helped us to better understand the relationship between the experiences and activities we identified. We realized that the three experiences were actually anticipatory triggers for police officers to enact the activities we identified, which helped us to term the three activities "coping strategies." Understanding that the three types of experiences were anticipatory triggers also helped us identify that these triggers did not exist on their own, but were actually tensions between the nature of data work and the nature of the situated work of police officers. We grouped these tensions as "bodily constrained vs. embodied," "materially rigid vs. contextual," and "ethereal vs. lived." Below, we use the anticipatory triggers and the tensions between data work and situated work to explain how police officers cope with data work in their situated practices.

## 2.5 Findings

Whatever the time of day, police officers typing away at their computers was a common observation at the police department. It was so embedded in their work that the officers spoke of "outside time" (i.e., responding to crime events) and "inside time" (i.e., reporting crime events). During the fieldwork, a 9-hour shift consisted of, on average, 2.5 hours responding to events and 3 hours reporting those events (the other hours were typically filled with activities such as patrolling). Writing a report was obligatory for officers whenever they were dispatched to a crime event by the control center. The control center received all initial crime calls. When the control center decided to dispatch a call, they created a new crime event in the information system where events had to be reported. The callsign of the officers dispatched to the event were automatically added in the information system, which they became responsible for the data work. In the information system, police chiefs could see which events lacked the necessary reports and could thus keep control over the data work. As such, data work was an obligatory and integral part of daily police operations.

Officers had two options for reporting crimes: they could use their smartphone while still 'on the beat' or they could return to the office and use a computer. The smartphone offered officers more flexibility, but most of them considered the screen too small to write reports and preferred to go back to the office to use a computer. Back at the office, they would sit down at one of the computers and log into the secured police environment using their callsign and password. The opening screen of the system showed the list of all crime events an officer was sent to and for which a report had to be submitted. To start writing a report, officers clicked on a call. A new screen opened where they could add general characteristics of the event by selecting tags (e.g., type of crime, crime code, location, people involved, children involved). After submitting this, another screen opened with an overview of all report options (e.g., general description, official description of findings, witness statement, declaration). Not all events required the same types of reports. For example, a witness statement was not always possible or necessary. Officers had to decide themselves what to fill in and what to leave empty.

Selecting a specific type of report opened yet another screen with a fixed format for that type of report. These formats included predetermined categories that could be selected from a drop-down menu. For example, when reporting details of victims, drown-down menus were available for categories such as a person's gender, whether the person belonged to a vulnerable or minority group, and types of vulnerable or minority groups. Some formats also included “free writing space” where officers could provide more details. Yet, officers were taught to use a fixed format for this too, which included seven points: “(1) What was the cause? (2) Which actions did you take on the spot? (3) What agreements have you made? (4) What still needs to be done? (5) Who approved the description? (6) Who is the description transferred to? (7) Did you speak to the person who reported the incident?” Though there was some interpretative flexibility in terms of writing styles, most reports were structured to answer these points.

The structured, rational nature of data work was distinct from the often adrenaline-filled nature of police street practices. Officers themselves were aware of this distinction and frequently expressed this after being involved in crime events. For example, during one of the observations, officer Arnold returned to the police station after an adrenaline-filled emergency that involved a teenager being threatened at knifepoint at a high school. Back at the office, Arnold sighed: "Well, that was ten minutes of fun and now a lot of time inside [writing reports]." In addition to reflecting on data work after the fact, they also actively anticipated data work requirements before and during crime events. As officer Misha explained:

> "We start [anticipating reporting work] the moment we receive a call from the control center and drive to the given location. During that time, we are actually already busy anticipating the message … So, before you arrive at the scene, you are actually already dealing with the call and writing your report in your head. And then in that moment, I try to focus on and remember the most important aspects of the crime event. Things like the details of the criminal offense."

Anticipating data work had an important influence on how officers performed their street-level work. In what follows, we unpack how police officers experienced data work as bodily constrained, materially rigid, and ethereal, and how the police officers enacted coping strategies that were consequential for their street-level practices (see Table 2.2).

### 2.5.1 Bodily exhaustion and avoiding street-level work

To officers, data work was an embodied performance, inherently distinct from their street-level work. The office could be filled with banter and laughter from officers taking a break, but to do data work they had to sit down behind their computers, preferably in silence, for prolonged periods and had to put considerable effort into concentrating and staying focused on a computer screen that contained small fields (see Figure 2.1). To ban surrounding noise some officers put in earphones. Moreover, police officers were extensively trained to shoot, but typing was not part of their skillset and typing was therefore a bodily exertion for the officers. For example, when officer Arnold was writing reports of a chase at the end of an afternoon shift, he was struggling with typing correctly.

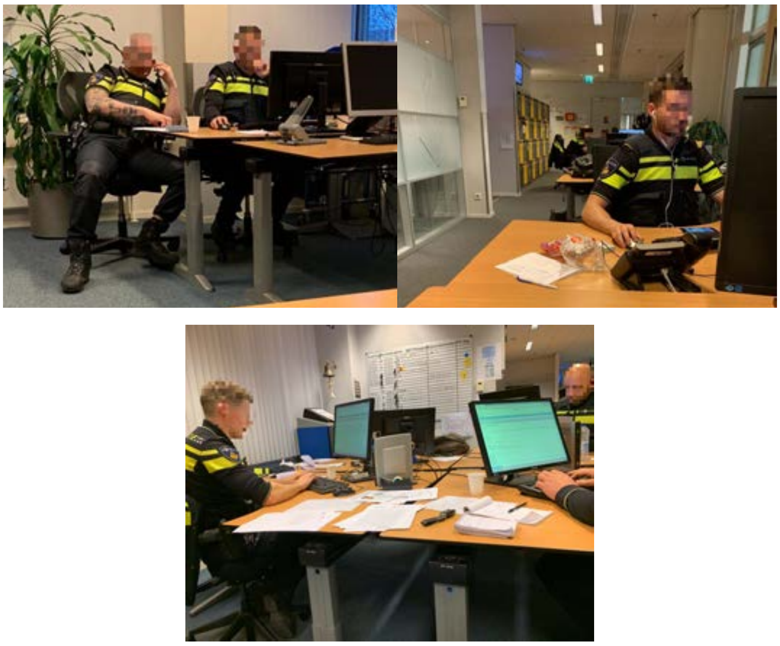
**Table 2.2 An overview of the experiences of data work and coping strategies**

| | Experience of data work | | Experience of situated work | | Coping strategy | |
|---|---|---|---|---|---|---|
| | *Characteristics* | *Data excerpts* | *Characteristics* | *Data excerpts* | *Characteristics* | *Data excerpts* |
| Tension 1: Bodily exhaustion | Bodily constrained<br><br>(Concentrated, seated desk work) | Police officer Thomas is almost falling asleep behind his computer. It's 5 a.m. and he's been writing reports for 4 hours now in the middle of the night. (Observation notes)<br>Danny shows to me how many pages of typed-out text it often requires to turn a crime event into words. The report he shows contains about 24 A4 pages of typed-out text. (Observation notes)<br>"At the moment [of the crime event] you have to do your job, you have to act, you have to react. And then, immediately afterwards, you have to write it down in the system. That's difficult." (Officer Misha) | Embodied<br><br>(Adrenaline-based, moving street work) | Officer Anna explains how, when she was back at the police office and had to write the report, sat staring at the monitor for fifteen minutes, hands shaking and unable to type. She couldn't get rid of the adrenaline and emotions, which was necessary to start writing the report. (Observation notes)<br>Researcher: "Do you ever feel like you cannot write a report immediately because the experience was too intense? And what do you do then?" Misha: "Yes. I walk to the vending machine and buy, and this is important, something that will make me happy. And then I eat it alone, in the fresh air. Chocolate produces endorphins and a temporary happy feeling so that I can write the story down." | Avoiding work | They drive back to the office and have just parked their car when they are sent to check [street] because of a call about public order disturbance. Matt is nowhere to be seen. Danny says he thinks Matt wants the next shift to take over [because this would be yet another report]. (Observation notes)<br>Danny is typing away at his computer, writing another report of the previous emergency. He is busy making a summary of the events. He explains that bicycle theft is an example of an event that takes a lot of work. He says that when at the end of a night shift they are sent to such a case: "Then it remains very quiet on the radio [following the orders of the control center]" (Observation notes) |
| Tension 2: Data categorization | Materially rigid<br><br>(Categorical, IS with fixed format) | One of the officers is checking a license plate number. It's often linked to 'troublesome youth' in another country in the Netherlands. However, the driver is already 24 years old, so not really youth anymore. "There's probably no other label for it," he reflects. (Observation notes)<br>"Previously, it was very much left to the officer whether or not you added a child tag to a report. If you were really worried, you'd add the tag. If you thought that it would be ok, then you'd not add the tag. There was no one who checked that. Nowadays, whenever I put somewhere in the | Contextual<br><br>(No case is the same twice) | "The moment someone opposes an arrest and gets the tag 'resistance perpetrator', it's very difficult for that person to get rid of it. It could be attached to that person for a long time, while it could have been an incident because that person had a really bad day at the time and literally got out of bed on the wrong foot. And then that person could still be confronted with that two years later, while he's actually a good guy." (Officer Neil)<br>"Every case is different. That's also the tricky part of police work. You can never compare everything one to one. | Deviating from protocol | The two police officers indicate to the others that they did not want to arrest the boy for disturbing public order because reporting it would "cause too much hassle" afterwards. (Observation notes)<br>Officers Boyd and William are sent to a shoplifter. Boyd tries with the control center whether they can get the shop to handle this business, but apparently, this person stole quite some stuff and so they have to arrest the person. It's not enough to just give the person a ban for the shop and a fine. (Observation notes) |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | report that a child was involved in the event, then I am sure that I will receive an email a day later saying, listen, you have to add the child tag." (Interview with officer Neil)<br>Two police officers are writing a report about a shoplifting case. They have the bag with the stolen goods (mainly clothes) on the table and now have to describe what every piece looks like. They argue about the color of the garments; "I think this is more, like, teal" says Rory about one of the garments. (Observation notes) | | Someone exhibiting a certain type of behavior may react differently tomorrow. Unfortunately, it's impossible to draw a fixed format or make a handout, like, this is what happens in case of [tagging] article 3 [providing assistance to those in need] and this is what you do and then everything is fine. It's different every time." (Officer Misha) | | |
| Tension 3: Unknown audiences | Ethereal<br><br>(Audiences are unlimited and potentially unknown) | "Because of the visibility of police work, reporting changes" says Arnold. According to him, the visibility to the outside world influences the police organization's focus on reporting. Because police officers are visible to society, they have to "follow up on it" and adapt to the [transparency] wishes of the moment [in how they report]. (Observation notes<br>"As a police officer, you're very visible and vulnerable and I don't think the organization always has our back in that regard." (Officer Walter)<br>Bram and Peter talk about how, after a chase where the police hit the car, the reporting work involved was a real "hassle." They have to follow strict rules when writing the report, because otherwise you'll get an investigation of the "safety, integrity & complaints" department. (Observation notes) | Lived<br><br>(Only those who experience it can understand) | "You can write down ten times that someone is as crazy as he gets and that that person is big, but you never experience it the way you do when you're standing in front of that person's door and he opens the door." (Officer Neil)<br>Officer Sam explains how difficult it is to describe the street-level experiences. He says that a report should be a "business-like summary" of what happened in the street, but that it should actually should be just as important to really feel what it was like by reading the report. Only then will the reader be able to understand the danger they've been in. (Observation notes) | Capturing work | "Don't underestimate the value of a bodycam. It makes portraying details and getting the message across so much easier." (Officer Misha)<br>"When a case is caught on camera [using the bodycam], it's solid evidence." (Misha)<br>Jack is picking up his bodycam. He always wears it because it's a source of evidence. (Observation notes) |

"I'm so tired, I only make typos," he complained. An additionally exerting condition was that officers had to perform this already bothersome data work at all times during the day and night.

**Figure 2.1 Police officers sitting down to write reports**



Writing reports was especially experienced as heavy and demanding after incidents that included high levels of action and adrenaline. For example, officer Anna explained how she, after being involved in a crime where multiple people were murdered, sat down behind a computer to do the desk work but ended up spending the first fifteen minutes staring blankly at the screen, her hands trembling and unable to focus or to start typing. Officer Misha further elaborated on how the bodily exertion of reporting was distinct from street-level work:

> "At the moment [of a crime event] you have to do your job. You have to act. You have to react. And then, immediately afterward, you have to [sit down and] do the typing work to get it into the system. That's difficult."

In addition, it was exceptionally difficult that, during most 9-hour shifts, officers had to switch between writing reports and doing street-level work multiple times. Because of this, officers felt that they were going "from pillar to post," constantly switching between two modes of work. For example, it was not uncommon for shifts to start with a heavy two-sided car accident with heavily injured victims. Then, while the officers were working on the reports of this case, for a robbery call to come in which required them to immediately jump up and rush to the crime location. Then, when back doing data work of now two events, for the third call to come in about a dangerous situation including violence. Not only was this constant switching physically straining for officers, at the end of the third call the stress of still having so much data work would make them nearly run back to their desks.

Unsurprisingly, officers were happiest when they were able to do "a lot of street-level work without having to do any reporting" (officer William). However, given that they were automatically attached in the database to each crime event they were involved in, doing street-level work without having to report was almost impossible. To cope with the bodily exertion of data work and the need to constantly switch, officers therefore tried to *avoid street-level work* by signaling 'unavailable' with their transceivers. They commonly used the numbered buttons on the transceiver to show to the control center whether they were available or not. For example, when they were available for crime calls, they pressed the '1' button and they had to press '4' when they were unavailable. The status 'unavailable' should be used, for example, when they had to transport a suspect to the police station, since having a suspect in the back of the car meant they could not leave their car to join another crime call. It was commonly assumed that, whenever they finished duties that urgently hindered their availability, officers should switch back to 'available' to be dispatched to new crime events. However, anticipating the bodily exertion of data work, officers used the 'unavailable' status to avoid street-level work. For example, officer Danny explained how reporting bicycle theft was an especially exhaustive activity, for that required sitting down for many hours at the computer. When, at the end of a night shift, the control center would call out for officers available to assist in a case of bicycle theft it would "stay very quiet," meaning that no one would signal available.

By trying to avoid street-level work to reduce the exertion of reporting, officers created stressful and sometimes troublesome situations in the field. For example, during a patrol with officers Joyce and Mary, all officers had their transceivers signaling 'unavailable' while they were actually driving around and fully available. An emergency call came in and the control center asked for available officers but nobody responded. Joyce and Mary were also reluctant, as they had already spent a large amount of time they spent at their desk during that shift. The control center decided to give a quick description of the emergency – a girl was screaming and being pushed into a car by several men – and a broad indication of the location, in the hopes to provoke some officers to go there. Joyce and Mary were immediately triggered because they were driving in the middle of that area. However, suddenly, at least five other police couples reported being available and Joyce and Mary were unable to share with the control center that they were very close by. The only thing they could do was change their status. Finally, when the control center answered all requests, they noticed that Joyce and Mary literally drove past the location of the emergency and the control center asked them whether they observed something. They did not see anything, since it was dark and they did not know where to look. "Damn it, we could have prevented it," Joyce said disappointed.

In sum, for police officers, the bodily constraints of data work conflicted with their adrenaline-driven situated work. Anticipating the bodily exhaustion of reporting, the officers coped with the tension by avoiding crime events (see Table 2.2).

### 2.5.2 Data categorization and deviating from street-level protocol

In performing data work, officers also encountered the material and discursive nature of the information system that was used for writing and submitting reports. One of their most challenging tasks was to categorize street-level experiences using fixed labels. This was especially difficult given the complex and ever-changing nature of their street-level work. As officer Misha explained:

> "Every case is different, you know. That's the tricky part of police work. You can never compare cases one to one. Someone who exhibits one type of behavior one day might respond very differently tomorrow. Unfortunately, it's not at all possible to make some kind of fixed handout. It's different every time."

Officers frequently spent a large amount of time finding ways to fit their unique cases to predetermined labels. For example, during one of the observations, officer Jan encountered a man sleeping at a train platform, who appeared to have a location ban for that area. The man was what they called in police terms "trespassing." Back at the desk, Jan had trouble adding the right label. After fifteen minutes of trying different settings, he still could not select the trespassing label and asked a more senior officer (Matt) to help him out. Matt looked at his settings and suggested that Jan changed the location of the case to the waiting area of the train station (instead of the platform). Finally, Jan was able to label the case 'trespassing'.

Moreover, officers were concerned about the persistence of labels they attached to a person or a case. For example, officer Neil explained:

> "The moment someone opposes an arrest and gets labeled 'resistance perpetrator,' it's very difficult for that person to get rid of it [the label]. It could be attached to that person for a long time, while it could have been a one-time incident because that person had a really bad day at the time and literally got out of bed on the wrong foot. And then that person could still be confronted with that two years later, while he's actually a good guy."

Especially when children were involved, attaching a label put a lot of pressure on officers. To track child-related incidents they were obliged to add a so-called "safe-at-home" label to every report involving children. Adding this label automatically alerted child safety agencies when submitting the report. However, the officers were convinced that not all child-related cases needed such a label and that, once it was used, parents could experience unreasonably difficult times. For example, officers Rory and Luke were sent to check up on a baby that had been crying for over an hour. Upon arrival, it turned out to be a colicky baby and the parents were trying everything they could to comfort the child. Yet, because a baby was involved in this case, police protocol was to add the safe-at-home label. Still involved in the case at hand, the officers started to visualize what would happen if they would label this case accordingly and said that, if one of the neighbors would call more often, the parents would have "a mountain of nonsensical reports with safe-at-home labels and child protection knocking at their door" (officer Luke).

The categorical and persistent nature of reports went against officers' feeling of justice, which was generally based on intuition and empathy for the situation at hand. For example, officer Randy empathized with the conditions of a suspect he had just addressed for unlawful begging:

> "Someone like that will never be able to integrate again. He was just released from prison and had no money, of course, so he was forced to beg. But then he gets yet another label. It didn't seem like he was going to end his life anytime soon, but I wouldn't be surprised if he eventually did out of desperation."

To cope with the clash between the categorical and homogeneous perspective on crime as embedded in the information system and their own feelings of justice based on their lived experiences, officers found ways to turn a blind eye on crime events. By doing this, they intentionally *deviated from street-level protocol*, which prescribed that in case of crime a suspect should be arrested. This practice was commonly observed in the case of shoplifting. If, for example, the suspect was a so-called "first offender" (i.e., had not been registered for committing a crime before) and if the costs of the stolen goods were low (e.g., when the suspect tried to steal an energy drink and a chocolate bar), officers tried to compromise with shop owners to not arrest the suspect but to give them a fine and ban them from the shop. This way, officers did not have to label someone a 'shoplifter' in a report and they would therefore stay out of the database.

Deviating from protocol to synchronize with their empathy-based feeling of justice was not possible in every case, which led officers to experience extreme pressure from having to choose between the influence of labels and the situation that demands them to take 'official' police action. For example, officers Robert and Oliver were called to assist at the train station where the local security guards were holding a girl who was trying to commit suicide by jumping in front of one of the arriving trains. Once there, they found the girl to be in such distress that they could not leave her in the hands of the inexperienced local guards, for then she might end up indeed taking her life. Robert and Oliver saw no other way than to take the girl back to the office and lock her into one of the cells while trying to contact a crisis center for people with a mental breakdown. While they acted exactly according to one of the fundamental police principles – offer help to those in need – once back at the office, Robert and Oliver experienced heavy social reprimanding by their colleagues. They were chastised for bringing the girl into the physical police environment and putting her in a cell, which could have serious negative consequences on her already volatile mental state. Next to that, they were also scoffed for simultaneously bringing her into the 'virtual' police environment, since locking her up meant that they would have to report it, which meant that the girl would from now on carry a label of having been associated with the police while, no matter how worrisome, what she tried to do was not criminal.

In sum, the materially rigid information system conflicted with the police officers' contextual understanding of justice. Anticipating the categorical and persistent nature of doing data work, the officers coped with the tension by deviating from street-level protocol (see Table 2.2).

### 2.5.3 Unknown audiences and capturing street-level experiences

As reports were submitted to the database, they could travel across a wide variety of potentially unknown audiences, which officers experienced to exacerbate the accountability of their already highly visible street-level work. For example, officer Bram reflected on this as follows:

> "Nowadays, everything has to be visible and explainable, otherwise you'll get investigated. As a result, we as police are now much more focused on the 'outside world', on how the outside world can perceive us."

For officers, the main consequence of widespread and potentially unknown audiences of reports was that they could unexpectedly be held accountable for their street-level behavior. Officer Andrew explained how he almost lost his job when he wrongly anticipated the potential audience of a burglary report. He thought he added an illustration for exclusive internal use to the report and wrote: "This lady [the victim] comes across as unstable." As he submitted the report, it was automatically forwarded to the victim, including the note intended for mere internal use, who filed an official complaint against Andrew.

Being well aware of their accountability, officers took efforts to *capture their lived experiences* to control whether and how their street-level work would be perceived by unknown others. To do this, they augmented their vision and memory with camera recording capabilities that could replicate and capture at least part of their experiences in more detailed ways than by just writing reports. Specifically, officers adopted bodycams – which were provided to them by their department but were not mandatory to use – to record their street-level work. Bodycams were small, rectangular devices attached to the front of the police uniform, around the chest area (see Figure 2.2). It consisted of one lens that captured all that happened in front of the officer. When used, the bodycam was continuously recording but did not save the recorded footage unless officers pressed the 'save' button at the front of the device. When pressed, audio and visual data were saved from 30 seconds before the starting time until the button was pressed again. Officers were convinced that using a bodycam provided an additional account to their lived experience, which they could not offer when being fully occupied with acting in the moment. For example, bodycams could capture the time it took to act or respond and it could bring into view what they saw and heard at the time. This made officers feel like bodycam footage gave them "100% believability" (Misha). "Don't underestimate the value of a bodycam," officer Misha said, "it makes portraying details and getting the message across so much easier."

**Figure 2.2 Example of a bodycam worn by officers[8]**

One of the most pressing examples of how officers used a bodycam to capture their embodied experience happened in the second week of our fieldwork, which allowed us to

[8] By Sanderflight - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=76206520

trace how the reports traveled across (unexpected) audiences over time. On a Monday afternoon, officer Jack, together with about six other colleagues, was sent to a man who appeared to be in a psychosis. Once there, the first thing Jack did was switch on his bodycam. He later explained that pushing the 'save' button was common practice:

> "Using the bodycam was a matter of conditioning. I pushed that button every time I got out of the car. It was routine for me to press it. I didn't know at all that I was getting into this situation. I just always pressed it."

Indeed, little did Jack know that about 15 minutes later he would shoot the man in an act of self-defense, for the man threatened to stab him with a kitchen knife.

In the year after this incident, the reports reached a variety of audience groups and the bodycam footage played a key role in how the case was perceived. First, before being allowed to continue doing street-level work, Jack was obliged to hand in his gun and undergo an internal investigation of whether his behavior was rational during the incident. Having the bodycam footage ready-at-hand, which portrayed Jack's decisions in the heat of the incident, helped the criminal investigation department to quickly reach a decision and to return the gun to Jack. Second, Jack's immediate colleagues, who were not involved in the incident, were interested to learn from the incident. In addition to having access to the reports, Jack showed them the bodycam footage. Third, Jack was subjected to a judicial investigation, which involved judges and lawyers, to determine whether he had lawfully shot the person. The case turned out to be complicated, because the person was not moving towards Jack when he was shot. In previous cases, this was not considered self-defense. In this case, the bodycam footage was decisive for the final verdict that Jack was acting out of self-defense, for the detailed images showed that Jack had no other choice than to shoot. Fourth, the person who was shot also accessed the reports and bodycam footage. This resulted in the person requesting a meeting with Jack to apologize for his actions. Finally, since shootings were extreme events and this case had an unprecedented verdict, the case with its reports and bodycam footage became part of the curriculum for new police recruits, in which specific attention was paid to the importance of capturing street-level experiences by using bodycams.

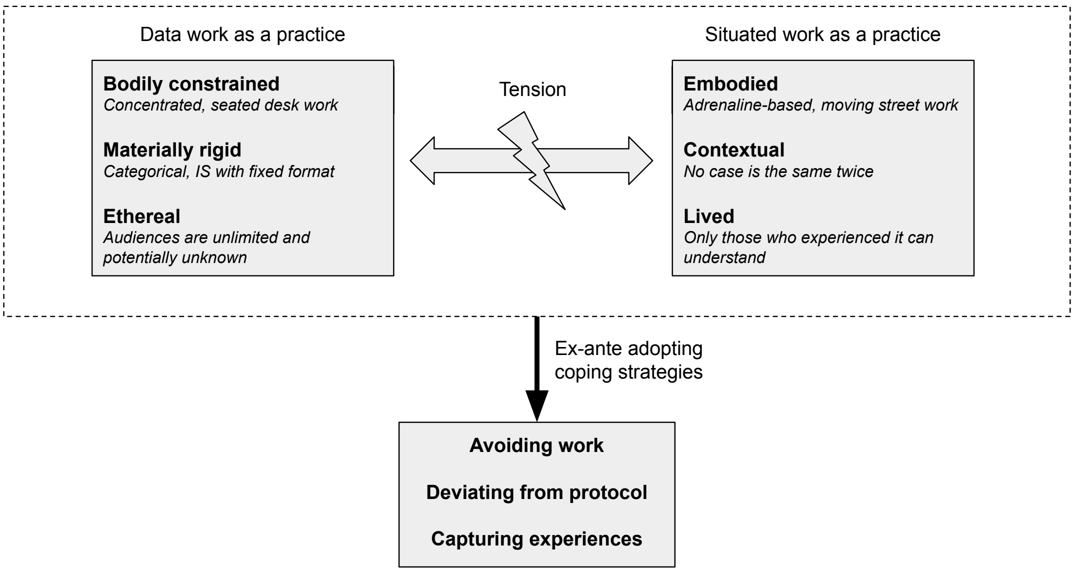
Using a bodycam to capture lived experiences for a variety of audiences created a previously unknown level of transparency in police work, which had both positive and negative consequences for police accountability. For example, in the case of the shooting, having bodycam footage had a positive outcome for officer Jack, but there was a downside to it too, as the details of the recording were the sole reason why the case was brought to court in the first place. In the heat of the moment, the officers had been so absorbed with the threatening situation that no one had noticed that the person was actually not moving towards them with the knife. It was only when watching the recording that they realized this. Jack explained: “In hindsight, if I wouldn’t have had the bodycam footage, nobody would have ever said that the person I shot was not moving forwards.” Moreover, while it helped them to bring into view and compensate for what their body could not capture in the heat of the moment, officers struggled with the fact that even this ‘bodily’ tool could not fully convey their lived experience. As Jack reflected: “Bodycam footage is great, it can have a lot of advantages, but it doesn’t show what happens inside the body of the one wearing the bodycam.” Using a bodycam to augment their vision and memory, officers thus ran the risk of capturing more details without actually conveying their lived experience, thereby creating only limited transparency and not solving issues of accountability.

In sum, the ethereal nature of crime reports conflicted with the officers’ lived understanding of their work. Anticipating the widespread and potentially unknown audience of their data work, the officers coped with the tension by capturing their experiences (See Table 2.2).

## 2.6 Discussion

In this paper, we set out to examine how workers cope with data work in their situated practices in order to understand how data work influences situated work performance. We took as our subject a team of police officers at the emergency response department who experienced strong organizational and institutional pressures to record their everyday activities and move towards 'data-driven policing'. Our analysis showed that, instead of 'misrepresenting' activities in reports, police officers adjusted their situated work to fit the practice of data work. On a daily basis, they experienced data work as a bodily constrained, materially rigid, and ethereal practice, which produced tensions with the deeply embodied, contextual, and lived experience of their situated work (see Figure 2.3). To cope with these tensions, they enacted three coping strategies in their situated work (i.e., avoiding work, deviating from protocol, and capturing experiences). Through these coping strategies, they *ex-ante* enacted data work in their situated practices; they adjusted the situated activities that had to be recorded and aligned their situated work to reflect the practice of data work.

**Figure 2.3 Empirical model of anticipating data work**



### 2.6.1 Anticipating data work as a practice

One of the core findings of the study presented in this paper is that when workers experience tensions between their data work and their situated work, they *ex-ante* adopt coping strategies in their situated practices. This insight has implications for our current understanding of data work and anticipation.

Previous studies on data work have looked at the practices involved in the construction of data (Cunha & Carugati, 2018; Pachidi et al., 2020; Pine & Bossen, 2020; Pine & Liboiron, 2015; Truelove, 2019) and have emphasized the new skills that are required for doing data work (Gray & Suri, 2019; Kellogg et al., 2020; Kittur et al., 2013; Pine, 2019; Pine & Bossen, 2020; Sachs, 2020). Our case contributes to these studies by unpacking how doing data work also changes situated work practices. We emphasize that, in contrast to how data work has previously been understood, it is not a separate activity but is inherently entwined with situated work. Moreover, this study shows that workers, in their efforts to cope with the tensions between data work and situated work, can create a pattern of action in which they reproduce the burden of data work by engaging in coping strategies that temporarily alleviate but not fundamentally remove these tensions.

The insights from this study also contribute to research on the social construction of data. Studies in this field have argued that data is not objective but includes the decisions and actions of those who make the data (e.g., boyd & Crawford, 2012; Christin, 2020; Gitelman, 2013; Kitchin & Lauriault, 2014; Pine & Liboiron, 2015; Slota, Hoffman, Ribes, & Bowker, 2020). This case builds on and adds to this perspective and emphasizes that social construction not only happens when making data, but that this is already performed in the field, before the data is made. This means that, to understand how data is socially constructed requires one to look beyond the data work practices, towards a holistic perspective on the situated work performance that forms the basis of the data that is made. In line with this, this case also contributes to research on anticipation and anticipatory work (Barley, 2015; Bucher et al., 2020; Flyverbom & Garsten, 2021) which considers data as input for anticipation about the future. Specifically, we emphasize that by *ex-ante* coping with tensions between data work and situated work, workers are creating the data in their situated performances. While we agree that "data may be combined in creative ways in anticipatory practices" (Flyverbom & Garsten, 2021, p. 7), our study shows that data can also be *created* in creative ways *through* anticipatory practices.

### 2.6.2 From impression management to anticipating data work

A second core finding of this study is that workers can anticipate data work in different ways, depending on the tensions they experience with their situated work. This insight contributes to research on representation practices in data work.

Previous research on representation in data work has largely focused on what and how data represents reality and how this representation does not align with 'reality' (Cunha & Carugati, 2018; Pachidi et al., 2020; Pine & Liboiron, 2015; Van Maanen, 1980). While not directly addressing the anticipatory aspect of data work, these studies address this type of work as a kind of 'impression management' in which those who perform data work take into consideration what the data they report reflects to those who read it. This study builds upon and extends this perspective by showing the important role not only of the audience, but also of the nature of data work itself for how data is reported. Our case emphasizes that performing data work is a constrained activity with consequences beyond creating a good but misrepresented impression of oneself, towards changing the situated work.

In addition, our study contributes to research that uses the foundations of critical accounting studies for understanding and questioning the nature of representations (e.g., Bevan & Hood, 2006; Hull, 2012; Power, 2021; Quatrone, 2015; Roberts, 1991, 2009; Van Maanen & Pentland, 1994). These studies question the current focus on data and numbers as a means for representing work and informing management activities. While we share the concern presented in these studies that data can fundamentally misrepresent reality, our study highlights the performative nature of data work in that, to cope with the tensions between data work and situated work, workers can also adjust 'reality' in such a way that it fits with the data that is being reported. In such instances, it becomes increasingly difficult to discern what is 'real' and what is not.

### 2.6.3 Practical implications and future research

Our study has practical implications for managers and workers involved in the making and use of data. First, our study shows that implementing data-driven approaches to work requires careful consideration and understanding of the situated practices and mapping out where and how tensions may appear between the two. This requires managers, or those who are responsible for the implementation process, to understand the nature of the work that is being datafied. Implementing data-driven approaches thus requires new responsibilities on the side of managers to monitor the relationship between data work and situated work. This is also important, because increasing attention is paid to the problems of data work for domain experts such as doctors. Studies increasingly point at the potential of burnouts due to overwhelming data-related activities. To prevent data work from becoming a societal problem requires a better alignment between the activities of data production and other, more situated work.

At the same time, implementing data-driven approaches also requires new data-related skills on the side of those who make the data to understand the consequences of decisions and actions for the data that is being made (and how it is being used afterwards). As our study showed, because of the tension between the practice of data work and their situated practices, workers are urged to be reflective about the situated work they perform and how these activities are 'translated' into data. However, this reflection goes one-way and does not take into account the consequences for the nature of data. To become a "reflective data practitioner," requires workers to reflect on how their work is translated into data and what this means for their situated practices, but also what this means for the data that is being made and used (for example, for training learning algorithms to create artificial intelligence systems).

It is also worth noting some boundary conditions to our study. First, we offer a study in which the data work to be performed is largely 'manual.' While there are different contexts in which data work is not yet automated (think, for example, of doctors filling in the electronic health records of patients), there are also cases in which dataficiation is indeed a largely automated process (e.g., Amazon's shelf workers). As such workers might experience different tensions between their situated work and the data that is being produced, it would be interesting for future research to go beyond the 'self-reporting' nature of data and also include the automated data production in understanding how situated work changes. In addition, our more holistic approach to the experience of data work in practice offers first insights into the role of the body in data work (e.g., in the tension between the exhausting data work and the adrenaline-driven situated work). We encourage future research to further explore not only the role of the body but also, for example, the role of emotions in data production. Finally, with our case we offer an extreme example of the tensions between situated work and data work. There are other examples in which the difference between the two are less severe, such as where the data work and situated work are performed in the same environment (e.g., customer service employees). As the changes in situated work might be more nuanced and may be even more difficult to observe, we encourage future studies to also include such contexts in understanding the relationship between data production and situated practices.

## 2.7 Conclusion

With the growing prevalence of data in everyday work and organizing, data work is becoming an increasingly central activity. While previous research on data and data work has already emphasized the misrepresentation of work in data and the potential misalignment with reality, this study emphasized data work as performative in such a way that workers can adjust their 'reality' in such a way that it aligns with the practice of data work. As such, to deeply grasp the nature of data, our study emphasizes the importance of understanding the burden of data production in workers' every day, situated work practices. It is only then that we will see that, sometimes, it is not the data that is adjusted, but the reality of everyday work that surrounds it.

## References


Azad, B., & King, N. (2008). Enacting computer workaround practices within a medication dispensing system. *European Journal of Information Systems, 17*(3), 264-278.

Barley, W. C. (2015). Anticipatory work: How the need to represent knowledge across boundaries shapes work practices within them. *Organization Science, 26*(6), 1612-–1628.

Bevan, G., & Hood, C. (2006). What's measured is what matters: Targets and gaming in the English public health care system. *Public Administration, 84*(3), 517–538.

Bietz, M. J. & Lee, C. P. (2009). Collaboration in metagenomics: Sequence databases and the organization of scientific work. In: *ECSCW*. Berlin, Germany: Springer, 243– 262.

Borgman CL (2015) *Big Data, little data, no data: Scholarship in the networked world.* Cambridge, MA: MIT Press.

Bossen, C., Pine, K., Ellingsen, G., & Cabitza, F. (2016). *Data-work in healthcare: The new work ecologies of healthcare infrastructures.* Paper presented at the Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion - CSCW '16 Companion.

boyd, d., & Crawford, K. (2012). Critical questions for Big Data. *Information, Communication & Society, 15*(5), 662–679.

Bradbury, H., & Lichtenstein, B. M. B. (2000). Relationality in organizational research: Exploring the space between. *Organization Science, 11*(5), 551–564.

Brayne, S. (2017). Big Data surveillance: The case of policing. *American Sociological Review, 82*(5), 977–1008.

Bucher, E. L., Schou, P. K., & Waldkirch, M. (2020). Pacifying the algorithm – Anticipatory compliance in the face of algorithmic management in the gig economy. *Organization.* doi:10.1177/1350508420961531

Christin, A. (2020). What data can do: A typology of mechanisms. *International Journal of Communication, 14*, 1115–1134.

Cunha, J., & Carugati, A. (2018). Transfiguration work and the system of transfiguration: How employees represent and misrepresent their work. *MIS Quarterly, 42*(3), 873–894.

Engle Merry, S. (2011). Measuring the world: Indicators, human rights, and global governance. *Current Anthropology, 52*(S3), S83–S95.

Feldman, M. S., & Orlikowski, W. J. (2011). Theorizing practice and practicing theory. *Organization Science, 22*(5), 1240–1253.

Ferguson, A. G. (2019). *The rise of big data policing: Surveillance, race, and the future of law enforcement.* NYU Press.

Flyverbom, M., & Garsten, C. (2021). Anticipation and organization: Seeing, knowing and governing futures. *Organization Theory, 2*(3). doi:10.1177/26317877211020325

Gherardi, S. (2006). *Organizational knowledge: The texture of workplace learning.* Oxford: Blackwell.

Giddens, A. (1984). *The constitution of society.* Cambridge, UK: Polity Press.

Gitelman, L. (2013). *"Raw data" is an oxymoron.* Cambridge, MA: MIT Press.

Gray, M. L., & Suri, S. (2019). *Ghost work: How to stop Silicon Valley from building a new global underclass.* San Francisco, CA: HMH Books.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly, 28*(1), 75–105.

Hindmarsh, J., Hyland, L., & Banerjee, A. (2014). Work to make simulation work: 'Realism', instructional correction and the body in training. *Discourse Studies, 16*(2), 247–269.

Hull, M. S. (2012). Documents and bureaucracy. *Annual Review of Anthropology, 41*(1), 251-267.

Jasperson, J., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly, 29*(3), 525–557.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.

Kitchin, R. & Lauriault, T. (2014). Towards critical data studies: Charting and unpacking data assemblages and their work. In: J. Eckert, A. Shears, & J. Thatcher (eds.) *Geoweb and Big Data.* University of Nebraska Press. Available at: https://ssrn.com/abstract=2474112

Kittur, A., Nickerson, J. V., Bernstein, M., Gerber, E., Shaw, A., Zimmerman, J., Lease, M., & Horton, J. (2013). *The future of crowd work.* Paper presented at the Proceedings of the 2013 Conference on Computer Supported Cooperative Work.

Latour, B., & Woolgar, S. (2013 (1979)). *Laboratory life: The construction of scientific facts.* Princeton University Press.

Loxley, J. (2007). *Performativity.* London: Routledge.

Manning, P. K. (2001). Technology's ways: Information technology, crime analysis and the rationalizing of policing. *Criminal Justice, 1*(1), 83–103.

Muller, J. Z. (2019). *The tyranny of metrics.* Princeton, NJ: Princeton University Press.

Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'. *The Journal of Strategic Information Systems, 24*(1), 3-14.

O'Neil, K. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy.* New York: Crown.

Oborn, E., Barrett, M., & Davidson, E. (2011). Unity in diversity: Electronic patient record use in multidisciplinary practice. *Information Systems Research, 22*(3), 547–564.

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization science, 11*(4), 404–428.
Østerlund, C., & Carlile, P. (2005). Relations in practice: Sorting through practice theories on knowledge sharing in complex organizations. *The Information Society, 21*(2), 91–107.
Pachidi, S., Berends, H., Faraj, S., & Huysman, M. (2020). Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organization Science.* doi:10.1287/orsc.2020.1377
Pine, K. H. (2019). The qualculative dimension of healthcare data interoperability. *Health Informatics Journal, 25*(3), 536–548.
Pine, K. H., & Bossen, C. (2020). Good organizational reasons for better medical records: The data work of clinical documentation integrity specialists. *Big Data & Society, 7*(2). doi:10.1177/2053951720965616
Pine, K. H., & Liboiron, M. (2015). *The politics of measurement and action.* Paper presented at the Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems.
Power, M. (2021). Modelling the micro-foundations of the audit society: Organizations and the logic of the audit trail. *Academy of Management Review, 46*(1), 6–32.
Quattrone, P. (2015). Governing social orders, unfolding rationality, and Jesuit accounting practices. *Administrative Science Quarterly, 60*(3), 411–1445.
Reckwitz, A. (2002). Toward a theory of social practices: A development in culturalist theorizing. *European Journal of Social Theory, 5*(2), 243–263.
Roberts, J. (1991). The possibilities of accountability. *Accounting, organizations and society, 16*(4), 355–368.
Roberts, J. (2009). No one is perfect: The limits of transparency and an ethic for 'intelligent' accountability. *Accounting, Organizations and Society, 34*(8), 957–970.
Sachs, S. E. (2020). The algorithm at work? Explanation and repair in the enactment of similarity in art data. *Information, Communication & Society, 23*(11), 1689–1705.
Schatzki, T. (2002). *The site of the social: a philosophical account of the constitution of social life and change.* State College, PA: Penn State Press.
Sein, M. K., Henfridsson, O., Purao, S., Rossi, M., & Lindgren, R. (2011). Action design research. *MIS Quarterly, 35*(1), 37–56.
Sergeeva, A., Faraj, S., & Huysman, M. (2020). Losing touch: An embodiment perspective on coordination in robotic surgery. *Organization Science, 31*(5), 1248–1271.
Sergeeva, A., Huysman, M., Soekijad, M., & van den Hooff, B. (2017). Through the eyes of others: How onlookers shape the use of technology at work. *MIS Quarterly, 41*(4), 1153–1178.

Slaughter, R. (1993). The substantive knowledge base of futures studies. *Futures, 5*, 227–233.

Slota, S. C., Hoffman, A. S., Ribes, D., & Bowker, G. C. (2020). Prospecting (in) the data sciences. *Big Data & Society, 7*(1). doi:10.1177/2053951720906849

Stein, M. K., Wagner, E. L., Tierney, P., Newell, S., & Galliers, R. D. (2018). Datification and the pursuit of meaningfulness in work. *Journal of Management Studies, 56*(3), 685-717.

Truelove, E. (2019). *The changing nature of professional work inside an incumbent firm in the age of social media: examining the challenge of coproduction* (Doctoral dissertation, Massachusetts Institute of Technology).

Van Maanen, J. (1980). Beyond account: The personal impact of police shootings. *The annals of the American academy of political and social science, 452*(1), 145–156.

Van Maanen, J., & Pentland, B. T. (1994). Cops and auditors: The rhetoric of records. In S. B. Sitkin & R. J. Bies (eds.) *The legalistic organization*: 53–90. Thousand Oaks: Sage Publications.

Vertesi, J. (2012). Seeing like a Rover: Visualization, embodiment, and interaction on the Mars exploration Rover mission. *Social Studies of Science, 42*(3), 393–414.

# 3. In the land of the blind, the one-eyed man is king

## Knowledge brokerage in the age of learning algorithms

## Abstract

This paper presents research on how knowledge brokers attempt to translate opaque machine learning knowledge. The research is based on a 31-month ethnographic study of the implementation of a learning algorithm at the Dutch police to predict the occurrence of crime incidents and offers one of the first empirical accounts of algorithmic knowledge brokers. We studied a group of intelligence officers, who were tasked with brokering between machine learning knowledge and domain knowledge by translating the outcomes of the learning algorithm to police management. We found that, as knowledge brokers, they enacted different translation practices over time and performed increasingly influential brokerage roles i.e., messenger, interpreter, curator. We explain this outcome by the opaque nature of learning algorithms which hindered the translation from the knowledge source to the domain. Triggered by an impassable knowledge boundary between the brokers and the machine learning domain, the brokers acted like 'kings in the land of the blind' and substituted the algorithmic predictions with their own judgments. By emphasizing the dynamic and influential nature of algorithmic brokerage work, we contribute to the literature on knowledge brokerage and translation in the age of learning algorithms.

**Keywords:** learning algorithms, machine learning knowledge, artificial intelligence, knowledge brokerage work, algorithmic brokers, knowledge translation,

## 3.1 Introduction

From healthcare to recruitment, litigation, and law enforcement, learning algorithms are increasingly prevalent in everyday work (e.g., Brayne, 2020; Rezazade Mehrizi et al., 2020; Van den Broek et al., 2021; Zhang et al., 2020). By autonomously combining large datasets with advanced computational and statistical methods to make connections between data points – a process which is called "machine learning" (Brynjolfsson & McAfee, 2017; Burrell, 2016; Davenport, 2018) – learning algorithms generate "machine learning knowledge" (Van den Broek et al., 2021). Learning algorithms deserve specific scholarly attention, as we cannot rely on the existing understanding of knowledge technologies in organizations (Huysman, 2020; Newell, 2015; Pachidi et al., 2020; Von Krogh, 2018). Earlier 'rule-based' technologies, such as expert systems, required developers to manually extract expert rules and transform these into code. These systems thus reflected the expert knowledge that was coded into them (Forsythe, 1993). In contrast, through machine learning, learning algorithms promise to generate more objective, efficient, and new knowledge that might even surpass human-generated insights (Leavitt et al., 2020; Tshitoyan et al., 2019; Van den Broek et al., 2021). The downside of machine learning is that it is difficult for humans to discern how and which connections between data points are made, which is often referred to as the "opaque nature" (Burrell, 2016; Christin, 2020) or "black box problem" (Ajunwa, 2020; Introna, 2016; Pasquale, 2015) of learning algorithms. It is therefore challenging to understand how machine learning knowledge is generated.

The opaque nature of learning algorithms makes trusting and using algorithmic predictions in practice problematic (Bader & Kaiser, 2019; Glikson & Woolley, 2020; Lebovitz et al., 2019). Recent studies posit that "algorithmic brokers" (Kellogg et al., 2020) or "algorithmists" (Gal et al., 2020) could emerge to facilitate the use of these systems by translating algorithmic predictions towards users (Henke et al., 2018; Sachs, 2019). Such a role resembles what is referred to in organizational theory as "knowledge brokers" (e.g., Brown & Duguid, 1998; Meyer, 2010; Pawlowski & Robey, 2004); actors who solve knowledge boundaries between groups by translating knowledge between them (Carlile, 2004). What we call '*algorithmic knowledge brokers*' would thus need to translate machine learning knowledge towards the user domain. Interestingly, a prerequisite for being able to translate knowledge is to have a thorough understanding of the knowledge of both the knowledge source and the target domain (Carlile, 2004; Røvik, 2016; Sturdy & Wright, 2011). For algorithmic knowledge brokers, this means understanding both the machine learning domain and the user domain. The opaque nature of learning algorithms then leads to a puzzle that goes beyond the current understanding of knowledge brokers, for how do knowledge brokers translate machine learning knowledge when they cannot understand how this knowledge is generated?

To answer this question, we offer a 31-month ethnographic study of a Dutch police department that implemented predictive policing; the use of a learning algorithm to predict where and when a crime is likely to occur. By analyzing the implementation process over an extended period, we found that a group of 'intelligence officers' enacted different translation practices that afforded them to perform increasingly influential knowledge brokerage roles (i.e., messenger, interpreter, curator). We explain the change in roles by unpacking the knowledge differences that emerged when the intelligence officers attempted to translate machine learning knowledge in practice. At first, the intelligence officers were unfamiliar with both the learning algorithm as well as the police, and their attempts to simply list and transfer algorithmic predictions towards the police were unsuccessful. They realized that to perform brokerage work, they needed to better understand the technical as well as the domain details. As they tried to understand the inner workings of the learning algorithm, they figured that the boundary between machine learning knowledge and their human interpretations was impassable. On the other hand, due to their efforts to better understand the police domain, the knowledge differences between the intelligence officers and the police dissolved. Their brokerage work increasingly fitted police requirements, yet they remained unable to open the black-boxed learning algorithm, which eventually triggered them to substitute machine learning knowledge with their own judgments.

Our study offers an integrative perspective on organizational theory and emerging technologies and reveals the emergence of a new phenomenon, meaning that of the algorithmic knowledge broker with its dynamic and influential nature. Through our process perspective on knowledge brokerage work, we offer new insights into the literature on knowledge brokers (e.g., Brown & Duguid, 1998; Burgess & Currie, 2013; Meyer, 2010; Pawlowski & Robey, 2004). The study shows that the translation practices that knowledge brokers enact over time afford them a unique position in which they can grow to become increasingly influential. Moreover, this case highlights that knowledge brokerage work is more complex than resolving a knowledge boundary between groups (e.g., Boari & Riboldazzi, 2014; Carlile, 2004; Dougherty, 1992) as, in their efforts to resolve such boundaries, brokers can generate new boundaries between themselves and those groups they are intended to connect. In addition, our findings contribute to translation theory (e.g., Czarniawska & Sevón, 2005; Mueller & Whittle, 2011; Nielsen et al., 2014; Røvik, 2016). While these studies mainly focus on how knowledge is translated *to* specific fields and organizations, we show the importance of unpacking how knowledge is translated *from* its original source and provide insights into what happens to translation in the case of opaque machine learning knowledge.

## 3.2 Research on knowledge brokers

Knowledge brokers gather and disseminate knowledge and thereby create connections between groups with different kinds of tasks, expertise, meanings, status levels, or occupational or institutional worlds (Allen, 1977; Barley & Bechky, 1994; Brown & Duguid, 1998; Burgess & Currie, 2013; Chiambaretto et al., 2019; Evers & Menkhoff, 2004; Haas, 2015; Howells, 2006; Lomas, 2007; Meyer, 2010; Pawlowski & Robey, 2004; Van Zoonen & Sivunen, 2020). Due to their interesting intermediary position between disconnected groups, organizational scholars increasingly pay attention to the role of knowledge brokers in areas such as engineering (Johri, 2008), science (Barley, 1996; Kissling-Naf, 2009), IT

(Pawlowski & Robey, 2004), and recently also regarding emerging technologies such as learning algorithms (Kellogg et al., 2020).

Research on knowledge brokers is a sub-field of the larger brokerage studies (e.g., (Appelbaum & Batt, 2014; Burt, 1992; Gould & Fernandez, 1989; Heaphy, 2013; Obstfeld, 2005; Obstfeld et al., 2014; Stovel & Shaw, 2012) and traditionally resides in the structural network approach (e.g., DiMaggio, 1993; Fernandez & Gould, 1994; Gould & Fernandez, 1989; Leonardi & Bailey, 2017; Obstfeld, 2005; Reagans & McEvily, 2003; Stovel & Shaw, 2012). Taking this perspective, knowledge brokers are considered to occupy a "structural hole" (Burt, 1992) between disconnected actors and benefit from unique access to various groups and knowledge sources (DiMaggio, 1993; Fernandez & Gould, 1994). Knowledge brokers perform a kind of "boundary work" (e.g., Langley et al., 2019; Soundarajan et al., 2018) between different groups. They differ, however, from what is commonly known in organizational and information systems literature as "boundary spanners" (e.g., Ancona & Caldwell, 1992; Levina & Vaast, 2005) in that knowledge brokers do not belong to or come from the groups they intend to connect (Gould & Fernandez, 1989; Fleming & Waguespack, 2007; Haas, 2015; Meyer, 2010). In performing brokerage work, knowledge brokers thus cannot tap on their own knowledge bases but rely on their interactions with the groups to establish an understanding of the groups' knowledge (Brown & Duguid, 1998; Haas, 2015).

Without specifically focusing on knowledge, studies on *brokerage work* move away from the structural network perspective to take a more micro perspective and examine the practices of brokering that are aimed to "fill critical gaps in complex networks of relations by connecting, buffering, and mediating across multiple organizational and occupational boundaries" (Anteby et al., 2016, p. 218). These studies scrutinize the practices through which brokers can help two or more groups of actors collaborate, coordinate, or maintain institutionalized roles (e.g., Canales, 2011; Edacott & Leonardi, 2020; Fernandez-Mateo, 2007; Fleming & Waguespack, 2007; Hoffer Gittel, 2002; Obstfeld et al., 2014; Pawlowski & Robey, 2004; Sele & Grand, 2016; Wenger, 1999). For example, Lingo and O'Mahony (2010) studied brokerage work carried out by country music producers to coordinate the work of various groups of actors (e.g., songwriters, performers, sound engineers) to produce a hit song. Studies on brokerage work attribute the emergence of specific brokering practices to triggers such as institutional reform or organizational change (Barley, 1996; O'Mahony & Bechky, 2008; Hargadon & Sutton, 1997; Heimer & Stevens, 1997; Huising & Silbey, 2011; Reay et al., 2006; Silbey et al., 2009). These studies emphasize how brokerage work emerges when reforms create new tasks that existing groups are unwilling or unable to take on. In such cases, brokers can absorb the newly created tasks and maintain the stability of the occupational system while simultaneously facilitating reform (Obstfeld, 2005). For example, Kellogg (2014) examined how, in the face of organizational reform at a hospital, low-status brokers took on tasks that medical professionals and lawyers did not consider to be part of their occupational field. In an effort to deal with the groups' unwillingness to collaborate, the brokers enacted buffering practices that kept the groups from interacting with each other and thereby maintained the occupational system.

Brokerage work can take many forms – e.g., in a business context a broker can perform the tasks of an agent, promoter, or dealer, in politics it can be tasks such as those of a mediator or diplomat (Meyer, 2010). In the case of knowledge brokerage, the tasks are specifically associated with gathering and disseminating knowledge. Knowledge brokerage work can involve many different knowledge-related activities, such as "the identification and localization of knowledge, the redistribution and dissemination of knowledge, and the rescaling and transformation of knowledge" (Meyer, 2010, p. 120). Yet, what binds these activities is that there exists a semantic (or interpretative) boundary regarding, for example, words, outcomes, or measurements, which hinders the flow of knowledge between the groups that a knowledge broker is intended to connect (Carlile, 2004; Dougherty, 1992). Knowledge brokerage work is not needed when knowledge boundaries exist on the syntactic or pragmatic level. If the knowledge boundary is syntactic (or grammatical), knowledge can be *transferred* without too much effort and no brokering is necessary. If the knowledge boundary is pragmatic (or political), the efforts required to *transform* knowledge from one group to the next is beyond the limits of brokerage work (Carlile, 2004).

A semantic boundary makes gathering and disseminating knowledge a complex endeavor that requires alignment between perspectives through *translation* practices (Barley, 1996; Boari & Riboldazzi, 2014; Grady & Pratt, 2000; Paul & Whittam, 2010; Tushman & Katz, 1980; Wenger, 1999). Translation means altering knowledge in such a way that it gains a common meaning that can be understood by the receiving party (Callon, 1986; Carlile, 2004; Dougherty, 1992; Latour, 1986, 2005; Law, 2002). Translation generally consists of two phases (Røvik, 2016). In the first phase, a practice or idea is *translated from* the source domain into more abstract representations, such as words or texts, which is also called de-contextualization. In the second phase, the more abstract representations are *translated to* the concrete practices of the target domain, which is also referred to as contextualization (Røvik, 2016). When a semantic boundary limits the source and target domains to engage in these two phases, translating tasks can be taken up by knowledge brokers to continue the knowledge flow (Allen, 1977; Brown & Duguid, 2001; Carlile, 2004; Hargadon & Sutton, 1997; Law, 2002; Wenger, 1998).

To perform translation tasks as a knowledge broker, "contextual bilingualism" (Røvik, 2016, p. 299) – in other words, comprehensive knowledge of the source and target domains (Brown & Duguid, 1998; Carlile, 2004; Shulman, 1987; Sturdy & Wright, 2011) – is important. For example, in case of translating knowledge from the source domain, "the main challenge is to ensure that the representation contains all the relevant information required to explain and understand how the practice functions in the source context" (Røvik, 2016, p. 294).[9] If you take knowledge out of its original context without having enough background knowledge, this can result in incorrect translations. Consider the first sentence of Albert Camus' "L'Étranger": "*Aujourd'hui, maman est morte*." Even though most know the English translation to be "Mother died today," translators who are knowledgeable of Camus' background and the nature of the French language are pointing

[9] It is important to note that Røvik (2016) refers to the translation of practices and ideas and does not include machine learning knowledge.

at the wrong translation of "maman" into "mother" (it should be something like "mom"). Moreover, to correctly translate this sentence also requires translators to understand that Camus is an existentialist, meaning that time plays a very important role in his worldview. Camus thus put "aujourd'hui" purposefully at the start of the sentence. Putting "today" at the end of the sentence in the English translation leads to a main emphasis on "mother" instead of "time", which is not what Camus intended to do.[10] This example shows the importance of translators to be "sufficiently knowledgeable" (Brown & Duguid, 1998) about the knowledge source to ensure that one does not get lost in translation.

For knowledge brokers, who are not members of the source or target domain (Gould & Fernandez, 1989; Fleming & Waguespack, 2007; Haas, 2015; Meyer, 2010), understanding both can be a challenging task (Brown & Duguid, 1998). Interestingly, despite the growing attention of organizational scholars in the role of knowledge brokers for transmitting knowledge (e.g., Chiambaretto et al., 2019; Pawlowksi & Robey, 2004), the actual practices through which knowledge brokers become knowledgeable of the domains remains largely invisible in current research (Barley, 1996; Meyer, 2010; Vogel & Kaghan, 2001). In doing so, knowledge brokerage research leaves unexplored how brokers cope with the challenge of dealing with different knowledge domains and what this means for performing brokerage work. This implies that the prerequisite of understanding both domains for performing knowledge brokerage work has largely remained implicit and apparently unproblematic. Yet, the recent emergence of learning algorithms – technologies that can autonomously generate knowledge (Faraj et al., 2018) – requires us to reconsider and further elaborate how knowledge brokers enact translation practices. Learning algorithms are known for making knowledge 'invisible' and trigger concerns about the inability for users to understand how these tools arrive at insights (e.g., Ajunwa, 2020; Burrell, 2016; Zhang et al., 2021). To solve these concerns, organizational practitioners and scholars suggest introducing a new role that we term '*algorithmic knowledge brokers*,' who can translate the knowledge generated by learning algorithms to the intended users (Gal et al., 2020; Henke et al., 2018; Kellogg et al., 2020). Below, we unpack why learning algorithms,

[10] https://www.newyorker.com/books/page-turner/lost-in-translation-what-the-first-line-of-the-stranger-should-be

more than any other previous phenomenon, offer insights into what it means for knowledge brokerage work when knowledge cannot be understood.

## 3.3 Brokering learning algorithms

Learning algorithms are technologies that autonomously generate decisions, classifications, or predictions (Faraj et al., 2018). Generally, algorithms contain a series of logical steps for performing computational tasks on data (Christin, 2020). In previous, 'rule-based' technologies, such as expert systems, developers had to manually extract steps (or rules) from human experts and code them into an algorithm. Thereby, rule-based systems always replicated expert rules (Forsythe, 1993). In contrast to rule-based technologies, learning algorithms do not depend on expert rules stated up-front but can generate their own rules by automatically and autonomously creating connections between a large number of data points (Balasubramanian et al., 2020; Dourish, 2016; Kellogg et al., 2020; Zhang et al., 2021). This is what is commonly referred to as "machine learning" (Brynjolfsson & McAfee, 2017; Burrell, 2016; Davenport, 2018).

Through machine learning, learning algorithms produce *machine learning knowledge* that is different from human knowledge and might even exceed it (Leavitt et al., 2020; Lebovitz et al., 2021; Tshitoyan et al., 2019; Van den Broek et al., 2021). For example, consider a spam filter as discussed by (Burrell, 2016, p. 9): "Humans likely recognize and evaluate spam according to genre: the phishing scam, the Nigerian 419 email, the Viagra sales pitch. By contrast, the 'bag of words' approach [i.e., machine reasoning] breaks down texts into atomistic collections of units, words whose ordering is irrelevant." In other words, while humans use their ability to interpret a message in order to assess if an email is spam, a learning algorithm uses words commonly associated with spam (e.g., click, dollar, price) and is trained to rank these words by weight and to flag an email based on the aggregate of the weights of all the words. In general, machine learning knowledge is promised to be more objective, efficient, and new (Van den Broek et al. 2021).

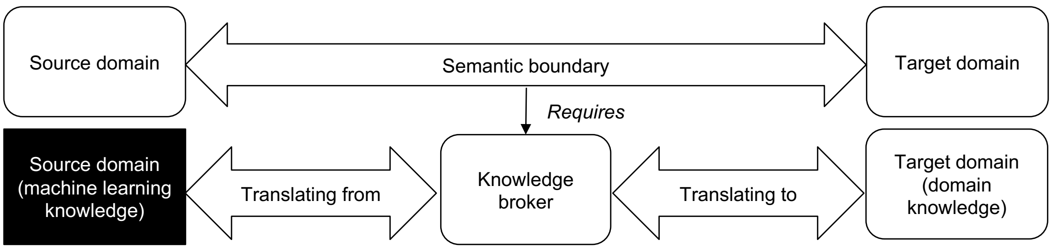
Yet, there is also a problem with the use of learning algorithms, as the procedures used for machine learning differ fundamentally from "demands of human-scale reasoning and styles of semantic interpretation" (Burrell, 2016, p. 2). Understanding machine learning knowledge requires one to discern how the internal decision logic of learning algorithms changes when they learn from data. However, because machine learning is based on combining large datasets and advanced computational methods, it becomes increasingly challenging for humans to understand how learning algorithms arrive at insights (Brynjolfsson & McAfee, 2017; Burrell, 2016; Carrizosa & Morales, 2013; Campolo & Crawford, 2020; Christin, 2020; Davenport, 2018; Faraj et al., 2018; Gal et al., 2020). This is commonly referred to as the "opaque nature" (Anthony, 2021; Burrell, 2016; Christin, 2020) or the "black box problem" (e.g., Ajunwa, 2020; Introna, 2016; Pasquale, 2015) of learning algorithms. The inherent difference between machine learning and human knowledge makes this opaque nature (or opacity) a fundamental issue in the case of learning algorithms and keeps even developers in the dark about how the internal decision logic of these systems evolves (Faraj et al., 2018; Michalski et al., 2013; O'Neil, 2016). For example, when in 2016 the learning algorithm AlphaGo defeated Go grandmaster Lee Sedol, the developers were unable to explain how the system exactly generated the strategies that led to its victory.

As a consequence, the opacity of machine learning is a specific area of concern in the field of computer science and has triggered a community of scholars to study 'explainability issues' and how to alleviate them (e.g., Barredo et al., 2020; Doran et al., 2017; Kirsch, 2017; Lipton, 2018; Miller, 2019; Mittelstadt et al., 2019; Preece et al., 2018; Robbins, 2019). Scholars engaged in this community argue that the nature of learning algorithms is a double-edged sword: their key strength (i.e., processing and learning from large data sets to arrive at new knowledge) is simultaneously their main problem. To solve this problem, these scholars focus on finding technical solutions for opacity and rarely look at questions such as how explainability issues are dealt with in practice, who needs explanations, or why, what kind of, and when explanations are needed in the first place (Hafermalz & Huysman, 2019). Yet, these are important organizational questions, for organizational scholars increasingly argue that when users are confronted with machine learning knowledge that cannot be explained or understood, they experience difficulties trusting, using, and maintaining control over the role of learning algorithms in their decision-making process (Bader & Kaiser, 2019; Christin, 2017; Gal et al., 2020; Glikson & Woolley, 2020; Lebovitz et al., 2019; Zarsky, 2019). For example, examining machine learning knowledge in a medical context, Durán and Jongsma (2021) asked: "If we are unable to entrench reliable knowledge from medical [learning algorithms], what reasons do physicians have to follow their diagnosis and suggestions of treatment?" (p. 330).

To overcome the explainability issues of machine learning knowledge in organizations, organizational scholars argue for the need to translate this knowledge to make it comprehensible for humans (Bolin & Andersson Schwarz, 2015). This requires new tasks related to translating the knowledge generated by learning algorithms in practice (Gal et al., 2020; Henke et al., 2018; Kellogg et al., 2020; Sachs, 2020; Shestakofsky & Kellar, 2020), which are usually outside the domain of expertise of technology developers and users – i.e., developers generally do not have sufficient knowledge of the user domain, and users often do not possess enough technical knowledge. The need for translation creates an opportunity for knowledge brokers to step in and take up these translation tasks. Such '*algorithmic knowledge brokers*', at first sight, could be an organizational solution to the explainability problem established in computer science. Yet, in the case of algorithmic knowledge brokers, an interesting puzzle arises regarding the ability to translate machine learning knowledge if learning algorithms are indeed opaque.

As we discussed above, theories on translation taught us that to translate knowledge from one domain to the next requires one to understand the source and target domains (e.g., Brown & Duguid, 1998; Røvik, 2016). Translation scholars argue that to adequately translate from the source to the target domain depends on the complexity, embeddedness, and implicitness of knowledge (Røvik, 2016). Complexity refers to the ability to understand the relationships between observed results and underlying practices. Embeddedness means how much of the knowledge is ingrained in the specific context (and is therefore difficult for a knowledge broker to access). Implicitness refers to how much of the knowledge can be articulated. The higher the complexity, embeddedness, and implicitness of knowledge, the more challenging translation becomes (Røvik, 2016). In the case of machine learning knowledge, the complex, embedded and implicit nature of the knowledge that needs to be translated can be considered as extreme, yielding an insurmountable knowledge boundary between the source domain and the target domain. To translate machine learning knowledge towards the target domain, algorithmic knowledge brokers are thus confronted with a new situation in which they, by definition, cannot understand how knowledge is generated by the source domain (see Figure 3.1). Accordingly, in this paper, we aim to understand which practices algorithmic knowledge brokers build on and use when they cannot scrutinize the knowledge generated by learning algorithms – in other words, when they operate 'in the land of the blind' – and ask: How do knowledge brokers translate machine learning knowledge when they cannot understand how this knowledge is generated?

**Figure 3.1 The challenge of brokering machine learning knowledge**




## 3.4 Methods

### 3.4.1 The learning algorithm

Our study focuses on the implementation of the so-called 'Crime Anticipation System' (CAS), which was internally developed by a team of data scientists at the Dutch police. The development was initiated by the national police management to allocate police resources (e.g., patrol officers, specialized teams, material resources) more effectively and efficiently by predicting where and when a crime was most likely to occur. To create CAS, the data scientists were inspired by the U.S. version 'PredPol.' While the police could have bought-in the external PredPol-algorithm, national management decided that the in-house data scientists could better develop a new version so that it would not require the police to share vulnerable data with external sources. Moreover, through in-house development the police planned to hold a grip on which data and variables were included in the learning algorithm (e.g., to prevent profiling they decided to not include individual-level data).

The data scientists used logistic regression analysis as the technique for the CAS learning algorithm. Logistic regression analysis is a very popular method in machine learning, specifically for binary classification tasks (i.e., a problem with two class values, such as 'crime' and 'no crime'). It is used to predict, for example, whether an email should be classified as spam or not, whether a tumor is benign or malignant, or whether a loan will or will not be repaid. Because learning algorithms are typically trained using large amounts of data, CAS was developed with data of the crimes with the highest reporting numbers, which are called 'high-impact crimes' (e.g., burglary, car theft, robbery). Such crimes are relatively easy to carry out, and thus happen frequently, and have a high impact on citizens, which means that they are also often reported. The reporting of these crimes results in a large number of data points, which makes them specifically suited for developing and training learning algorithms.

For the CAS algorithm to learn, the data science team constructed a dataset with historic high-impact crime data. They divided the country into squares of 125m$^2$ and used three years of historical data for every square. Across these three years, they used bi-weekly reference moments, which resulted in 76 lines of data per square. Each line of data consisted of 8 technical variables and 47 predictive variables (limited by strict data regulations). The technical values included, for example, time indicators, the name of the police station, and the name of the police district. The 47 predictive variables consisted of 19 population-related variables, e.g., number of one-parent households, total number of addresses, average house price, number of male inhabitants, number of female inhabitants, average age of inhabitants, and 28 crime-specific variables, e.g., for burglary, variables such as time since the last burglary, number of burglaries in the last two weeks. In addition, each line included whether the specific crime happened in the two weeks between the reference moments (see Appendix 1, Table A1). To predict the probabilities of future crimes, the logistic regression model of CAS was trained to learn a mapping between the 47 predictive variables and whether a crime happened or not (see Appendix 1, Table A2). To transform the numerical probabilities into a visualization of the crime predictions on a map, threshold values were added to determine whether and in what color predicted squares appeared on the map; the darker the color, the higher the predicted probability (see Figure 3.2). Data extraction, data preparation, model building, and generating maps were automated and happened on a weekly basis. The model was thus able to autonomously learn and generate predictions. This, in combination with the size of the data set and the high number of predictions, made the internal decision logic of predictions opaque in practice, even for the data scientists.

**Figure 3.2 Visualization of predictions as perceived in the user interface**


### 3.4.2 Research setting

In contrast to, for example, the fragmented organizational structure of the U.S. police force (see e.g., Brayne, 2020; Van Maanen, 1973), the Dutch police is nationally organized and coordinated, which facilitated the nationwide implementation of CAS. The Dutch police started the predictive policing project in 2012 by hiring three data scientists and, between 2012 and 2017, gradually expanded the data science team to about 20 members. Maintaining CAS remained one of the responsibilities of these data scientists, also after the implementation at local police departments, but most of the members of the data science team were also actively involved in other projects, such as developing counterterrorism learning algorithms and image recognition for investigating and preventing child sexual abuse. One data scientist (Dennis[11]) took the lead in the development of CAS and was therefore the main 'brain' behind the learning algorithm. All other data scientists were responsible for the maintenance of the system and performing updates.

In 2013, the data scientists finished the first version of CAS, which predicted a week in advance where and when a crime was most likely to occur. During the test phase, an important role for a group of 'intelligence officers' emerged, who could help local police managers to use the crime predictions. In the Findings section, we will go into detail about the emergence of these intelligence officers as algorithmic knowledge brokers. Here, it is important to emphasize that the implementation of CAS therefore included three separate groups: data scientists as developers, intelligence officers as algorithmic knowledge brokers, and local police managers (hereafter 'police managers') as users. The interaction between intelligence officers, data scientists, and police managers in the implementation and use of CAS was influenced by the 'siloed' organizational structure of the Dutch police. The police managers engaged in tasks related to police operational decision-making. They transferred data-related tasks to intelligence officers and, because the nature of police work was action-oriented and police managers considered CAS to be extremely complex and 'foreign', they did not feel the need to engage with CAS directly and trusted intelligence officers to do so. As one police manager responded to an intelligence officer: "You lost me at http." The data scientists were located in a different building, far removed from daily police operations and the intelligence officers. They were hired for their expertise in computer science and were expected to create systems that would generate new insights for police operations across the country. The data scientists were not bothered by their distance from daily police operations. They considered machine learning knowledge fundamentally different from police occupational knowledge and were convinced that such knowledge could and should be generated away from the police domain. As a result, the data scientists only occasionally interacted with intelligence officers (via email or organized meetings held on average twice a year) and they rarely

[11] All original names have been removed, the names mentioned are pseudonyms.

spoke with police managers. In the Findings, we describe how the intelligence officers attempted to broker these two disconnected groups by translating the machine learning knowledge to the police domain.

### 3.4.3 Data collection

We performed ethnographic research with the aim of theory elaboration to make theoretical advancements (Fisher & Aguinis, 2017). We conducted our fieldwork at the Dutch police over 31 months, from October 2016 to April 2019. During these three years, the first author observed and took part in the daily work at the intelligence department and the emergency response department. In this study, we report on our data of the intelligence department only. We followed the intelligence officers over these three years, with an intensive observation period in the second year of the study, in which the first author joined the intelligence department approximately 3 days a week, observing and taking part in the intelligence officers' work. All observations were conducted when CAS was already in use, details about the development of CAS and the techniques used were obtained through (retrospective) interviews with data scientists and archival documents. Our interest in the role of the intelligence officers was triggered when, at the start of our fieldwork, we were surprised to see that the police managers did not directly interact with CAS but that the intelligence officers performed this work. We saw parallels with Barley's (1996) broker technicians and observed the intelligence officers' struggles with understanding the meaning of the crime predictions in practice.

The first author had unrestricted access to the intelligence department – which consisted of about 15 full-time employees – of a police station in a large Dutch city. She shadowed the intelligence officers in all their work, including their interactions with CAS, data scientists, police managers, and police officers. Her main focus was on the intelligence officers but joining the various interactions also gave her thorough insights into the other groups involved. She would usually sit at the desk next to one of the intelligence officers and write down in detail which features they used when working with CAS, how they tried to make sense of the learning algorithm and the crime predictions, and how they reasoned and went about representing the predictions to police managers. Through her prolonged presence at the intelligence department, she gained the trust of the intelligence officers to perform some of the intelligence activities herself, which gave her deep insights in the efforts involved in performing intelligence officers' work. For example, they asked her to help out with extensive database searches, she was given access to the CAS user interface to go through crime predictions, and eventually even helped new intelligence officers settle in by explaining how to use CAS. The first author also followed other activities of the intelligence officers, which gave her a rich contextual understanding of the empirical site. For example, participating in briefings at the start of police shifts, joining management meetings and meetings with data scientists, and accompanying the intelligence officers for lunch and occasional festivities, such as their yearly team outing and Christmas party. Finally, the first author joined one of the intelligence officers appointed as 'spokesperson' to regional (once a month) and national (once every six months) gatherings of intelligence officers at police stations across the country. Because the intelligence officers all worked at different police stations, these meetings were used to reflect and learn from each other. Initially during these meetings, the intelligence officers shared best practices and their struggles with translating machine learning knowledge. This further established her observations of the challenges faced by the intelligence officers. Near the end of the fieldwork, the first author observed that the intelligence officers collectively emphasized the need to substitute predictions, which validated her observations of how the role of intelligence officers changed over time. By actively participating in all facets of the intelligence officers' work, the first author became fully socialized into the intelligence department, by which she developed a holistic perspective of intelligence officers' work and their relationship to other stakeholders, a deep understanding of the work practices performed, as well as the underlying feelings and experiences, such as confusion, stress due to time pressure, tiredness, but also pride and joy of being able to come up with a fitting recommendation.

The first author also conducted 33 formal semi-structured interviews. Voice recording was possible for 25 interviews, which were transcribed verbatim. For the other eight, detailed notes were taken during the interview and expanded afterward into an elaborate summary. We explicitly searched for and contacted people who could provide rich details and reasoning into how CAS development, implementation, and deployment proceeded and why. The first author interviewed actors from all groups involved to maintain a multi-actor perspective. This included data scientists who were closely involved with CAS for the longest time, intelligence officers who were at the intelligence department already before the implementation of CAS, and police managers who were closely involved in the implementation of the learning algorithm. Moreover, for a deeper understanding of the police occupational world, the first author interviewed five patrol officers, who needed to have at least 10 years of experience to make sure they could deeply reflect on their work. The main questions asked to data scientists were about the techniques used in CAS to get in-depth, retrospective insight into the development and reasoning behind CAS. After one of these interviews, the first author sat with the data scientist to have a close look at the learning algorithm of CAS, which gave her a better understanding of the methods used. Intelligence officers and police managers were asked to describe their occupational trajectory, their daily activities, and what role CAS played in these activities to get an in-depth understanding of the influence of the learning algorithm on their everyday work. In addition, police managers were asked about their views on the usefulness of CAS for allocating police resources and crime prevention to understand their motivation behind working with the system. At the very end of the fieldwork (April 2019), the first author conducted retrospective interviews with two intelligence officers, where she asked them to reconstruct how their work practices and responsibilities changed from the introduction of CAS in 2015 to their current role. These two intelligence officers were selected because they had been with the department for the longest time.

Finally, during the fieldwork, countless informal conversations took place with all groups involved. These informal conversations allowed the first author to ask questions to solicit interpretations of specific events or decisions. For retrospective details, we also collected documentation data that was either internally or externally available. These materials were very valuable as they gave us additional information about the technical specifications of CAS (e.g., the complete list of variables used) and insight into, for example, the evaluations of the CAS implementation, strategic plans, reasoning and expectations about role transformations, and meeting details. We summarized each of the data sources in Table 3.1.

**Table 3.1 Description of data sources and their use**

| Data types | Amount/duration | Use in analysis |
|---|---|---|
| **Primary data** | | |
| *Observations of intelligence officers' work* | *Between Oct. 2016 and Apr. 2019, 565 hours* | *Provided rich insight into the daily practices and lived experience of intelligence work and their interactions with data scientists and police managers.* |
| Meetings with data scientists | 2 (avg. duration: 2 hrs.) | Provided insight into the intelligence officers' attempt at giving feedback to the data scientists and the data scientists' responses. |
| Management meetings | 47 (avg. duration: 2 hrs.) | Provided insight into the changing dominance of intelligence work and how the managers responded to this. |
| Briefings | 123 (avg. duration: 15 min.) | Provided insight into the translation of intelligence work to daily police practice. |
| Intelligence gatherings (regional and national) | 14 (avg. duration: 2 hrs.) | Provided broader insight into how intelligence officers' work evolved regionally and nationally. |
| *Formal interviews* | *Total: 33 (avg. duration: 1 hour)* | *Enriched and deepened our understanding of the worlds of the actor groups involved.* |
| Intelligence officers | 8 (± 50% of the team) | Enriched our understanding of the background and development of intelligence work. |
| Data scientists | 7 | Enriched our understanding of the "machine reasoning" world of the data scientists. |
| Police managers | 13 | Enriched our understanding of the police occupational world, the needs for police operational decision-making, and the managers' trust in data and algorithms. |
| Police officers | 5 | Enriched our understanding of the police occupational world. |
| **Secondary data** | | |
| *Documentation* | *Total: 431 documents* | *Validated observation and interview findings and added context and historical insights.* |
| Management documents | 35 | Provided insight into managerial decisions and helped to establish the chronology. |
| Intelligence documents | 45 | Provided insight into the developments in the role of the intelligence officers and helped to establish the chronology. |
| Additional documents | 261 | Provided insight into the backgrounds to CAS and enriched our understanding of the police occupational world. |

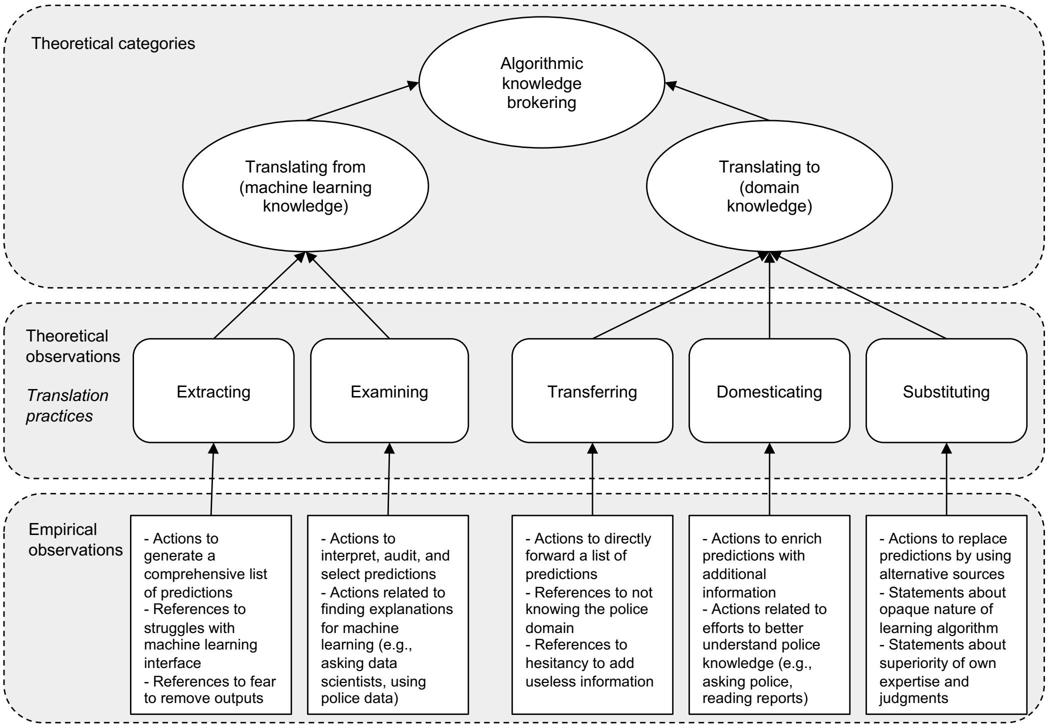
### 3.4.4 Data analysis

Throughout the data collection, we engaged in regular conversations to reflect on observations, ask ourselves what these meant, and link to related literature. The coding was performed by the first and second authors, with the first author taking the lead and the second author frequently checking in and adding input. We began coding by reading field notes and interview transcripts, adding potential codes in the margins. This helped us to identify important themes. For example, we were struck by how the intelligence officers frequently referred to unexpected changes in their role and remarks about their growing influence on police managers. To trace how this growing influence came about, we performed a temporal analysis of our data, broadly mapping the role changes. We also noted the struggles of intelligence officers with understanding and interpreting algorithmic predictions. This triggered us to further scrutinize the nature of algorithmic predictions and how this related to the intelligence officers' brokerage work.

We used open coding (parsing out the data to understand the underlying dynamics) to conduct a more formalized analysis of the field notes and transcripts (Strauss & Corbin, 1990). We initially focused on specifying in detail the activities and interactions of the three groups involved. We categorized the codes by the occupational group to maintain oversight (i.e., 'data scientists', 'intelligence officers', 'police managers') and used these groups to construct a visual map that portrayed how certain activities triggered specific events (Langley, 1999; see Appendix 2 for the visual map). We then engaged in further rounds of axial coding, i.e., unraveling more thematic relationships and contrasts through coding across concepts (Strauss & Corbin, 1990), and noticed that the intelligence officers' efforts to understand both machine learning knowledge and the police domain played a central role in how their work changed over time. We compared and contrasted the intelligence officers' actions with the learning algorithm and the associated machine learning knowledge, as well as with the police domain, through which five key translation practices emerged: (1) extracting, (2) examining, (3) transferring, (4) domesticating, and (5) substituting (see Figure 3.3).

Using the literature on knowledge brokerage work and translation theory then helped us to better understand what these five brokerage practices were examples of. Based on theories on translation (Røvik, 2016), we grouped the practices "extracting" and "examining" under the theoretical category "translating from (machine learning knowledge)" and the practices "transferring," "domesticating," and "substituting" under the theoretical category "translating to (domain knowledge)." Together, these two theoretical categories formed the basis for our understanding of algorithmic brokerage work. This structure with its associated practices also helped us to see how the algorithmic brokerage work evolved through a cumulative process, in which new types of practices were built on earlier ones. In this cumulative process, we identified three algorithmic knowledge brokerage roles: (1) messenger, (2) interpreter, and (3) curator. In what follows, we use these roles to explain the cumulative efforts to translate machine learning knowledge in practice.

**Figure 3.3 Conceptual scheme**




## 3.5 Findings

After a two-year development period of CAS, in 2015, the data science team performed a test to see whether the learning algorithm could be nationally implemented. They deployed it for several months in five large Dutch cities, which was closely monitored by evaluators from the Dutch police academy. After the test, which was considered a success, the evaluators wrote a report in which they indicated an occupational group called 'intelligence officers,' who emerged as important actors who "supported police managers" at local police stations by "being able to generate CAS predictions" (internal document). The important role of intelligence officers was surprising to the evaluators, since before the introduction of CAS, the work of intelligence officers mainly involved supporting police officers by searching the numerous police databases when the police themselves did not have direct access to it (e.g., finding crime numbers, suspect data, or information about criminal networks). Intelligence officers were 'hidden' at a back-office, the work was generally regarded as low-status, the education level required for the position was low – it did not require one to be knowledgeable of technology or police work – and it was considered to offer an opportunity for those who "wanted to join the police without wanting to work on the street" (intelligence officer Louisa).

The evaluators, however, saw the potential benefits of tasking intelligence officers, who were used to working with police data, with translating machine learning knowledge to make it meaningful for police work and ended their report with suggestions for a new work process for contextualizing algorithmic predictions. According to the evaluation report, the work process should include three steps: actualizing, interpreting, and explaining. Actualizing meant adjusting predictions to local changes (e.g., when a burglar was captured). Interpreting meant adding more information to the crime predictions, such as the most-used crime methods. Explaining meant deeply analyzing why a crime is predicted (i.e., finding causal explanations for the algorithmic predictions). The data science team agreed with the suggestion of the evaluators and gathered that intelligence officers could, for example, contextualize a burglary prediction by adding information about the kind of houses in the targeted area. As data scientist Dennis reflected:

> "You need to have somebody [i.e., intelligence officers] who looks at the maps and thinks about the causes of high risk and how to prevent them. How to take the cause away so that you are not fighting the symptoms but taking away the cause of the problem."

While the intelligence officers were thus expected to find underlying causes for predictions, the data scientists assumed that the intelligence officers did not need to understand how the learning algorithm generated knowledge to perform their translation tasks and that access to police databases would be enough. As one of the data scientists explained: "Intelligence officers don't have to interpret model parameters or any kind of technical stuff, they just get the maps." The intelligence officers thus were asked to fulfill brokerage work without understanding how machine learning knowledge was generated. Below, we analyze the efforts of a group of intelligence officers at one police station to translate crime predictions for police managers and how they thereby performed three consecutive roles – i.e., messengers, translators, and curators. We discuss how these efforts were hindered by the inability to understand machine learning knowledge and how this eventually led the intelligence officers to believe that the predictions should be substituted by their own alternatives.

### 3.5.1 Algorithmic knowledge broker as messenger

The main aim of intelligence officers' work was to make abstract crime predictions based on machine learning meaningful for local police managers. The predictions were presented to the intelligence officers by means of an interactive map where they could select the location, the crime type, and the timeframe. Because police managers never really looked at the map, they asked the intelligence officers to generate a weekly overview of the CAS predictions, so that the overviews could be used as input for scheduling police tasks and resources. Generating such an overview was a laborious task for the intelligence officers. For example, they had to click on every timeframe in a drop-down menu[12] and since the system generated predictions for four different crime types per police station, the intelligence officers went through this cycle four times, selecting a timeframe in the drop-down menu a total of 168 times. When a prediction appeared on the map in the form of a colored block, they translated the predictions into words and added it to a Word document – e.g., "burglary, Monday, between 12:00 and 16:00, [name of the neighborhood]." Per crime type, the final list made in Word included on average one predicted timeframe and one or two predicted areas a day.

[12] 4-hour timeframes, 7 days a week, meant clicking (24/4)*7 = 42 times to get a weekly overview.

Through this process of extracting predictions, a comprehensive list of likely future crimes was generated. However, because the map that the intelligence officers used as input did not offer any insight into the causes of crime predictions, they had little clue about the meaning of these predictions in the context of the police. Moreover, since their new tasks caused them to be "in search of their identity as intelligence officers and sometimes didn't know where their work ended" (intelligence officer Wendy), their insecurity grew towards the information needs of the police managers. Afraid to leave out a prediction that might turn out to be right, or add irrelevant information, the intelligence officers decided to stick to comprehensive reporting of all the crime predictions. Better safe than sorry, the intelligence officers gathered that transferring a full overview of potential crimes would be best to support police managers' decision-making and assumed that "all police managers probably know what's behind the predictions" (intelligence officer Eva).

Even though it took the intelligence officers quite some time and effort to construct an exhaustive list of predictions, the police managers did not receive the lists with much enthusiasm; the document was too long and the potential crime causes were unknown. For example, police manager Rudy reflected that the long lists were difficult to use because they lacked a specific focus: "If you keep the [algorithmic predictions] too broad, then we are quick to ignore them. I think the more concrete you are, the more feeling we have for it." The data scientists also acknowledged that simply listing crime predictions was not enough because the "quantitative" predictions needed "qualitative insights" (data scientist Dennis). They emphasized the need for intelligence officers to "add color to" and "enrich" the crime predictions. As Dennis explained:

> "Intelligence officers have to take the predictions and enrich them with qualitative information. For example, [for burglary predictions] adding who could do it or why burglaries might occur in that area or at that time. Intelligence officers could say: we have some narcotics-related issues here, so maybe it could be junkies? Most of the time, junkies aren't well-prepared criminals, so maybe it's just very easy for them to burglarize that area. So maybe those houses have very bad hinges and locks and you can just enter them with a very easy trick. That's the kind of context the intelligence officers should provide."

In sum, confronted with a map that did not provide any background, such as the causes of crime predictions, together with largely unknown requirements from the target domain, intelligence officers initially tried whether the algorithmic predictions would make sense to police managers by extracting them from the system and transferring them as a list (see Table 3.2). As such, their knowledge brokerage role can be described as a "messenger". It soon became clear however, that the differences between machine learning knowledge and the domain knowledge of police managers were larger than the intelligence officers initially expected. Both the police managers and the data scientists criticized the efforts of the intelligence officers and pushed them to deepen their knowledge brokerage work by not just listing but further translating the predictions. The intelligence officers had to better de-contextualize the algorithmic predictions from the machine learning domain in order to contextualize them in the domain of the police.

### 3.5.2 Algorithmic knowledge broker as interpreter

To be able to translate algorithmic predictions to the police domain, the intelligence officers realized they lacked a deep understanding of both the machine learning knowledge and the domain-specific knowledge of police managers and invested in learning more about the technical details of the learning algorithm and the domain details of the police.

*Learning about the source domain.* To be able to translate the crime predictions from the machine learning domain, the intelligence officers recognized they had to better understand the computational and statistical techniques used in CAS. As intelligence officer Richard reflected:

> "There are so many indicators that CAS uses to make these calculations. And then CAS turns a square red on the map. But why does it turn that square red?"

## Table 3.2 Overview of intelligence officers’ brokerage work and roles

| Characteristics of brokerage work | Messengers | | Interpreters | | Curators | |
|---|---|---|---|---|---|---|
| | Details | Data segments | Details | Data segments | Details | Data segments |
| *Understanding of machine learning knowledge* | No knowledge of machine learning and its associated techniques | “It’s just a map. What can we do with it? What do we have to do with it?” (Intelligence officer Sophia)<br>“Sometimes I have such a blackout, then I really don’t know what to do.” (Intelligence officer Louisa)<br>“When we started it really took a day or two to do it really well [to list all predictions].” (Intelligence officer Wendy) | Attempting to gain some knowledge of computational and statistical techniques | “I asked the data scientists, like, is there some kind of value attached to the calculation of the hot times? Does last week count more than a year ago, or two years ago? What kind of table is used for that?” (Intelligence officer Tom)<br>“What I find difficult is, something [a prediction] pops up and turns red. There are so many variables in CAS and there are only a few that make that prediction pop up. I would really appreciate it if I knew which variables.” (Intelligence officer Maya)<br>“We really want to know what’s behind each prediction … Even if it’s only a top three, that’s already something.” (Intelligence officer Wendy) | Experience an impassable knowledge boundary | “I [still] have to guess about the reasons why a hotspot turns red. And then find a fitting recommendation.” (Intelligence officer Fred)<br>“To be really honest, in case of nuisance, I just don’t trust CAS anymore. I have more trust in the data we can get out of the police databases ourselves.” (Intelligence officer Joey) |
| *Understanding of domain knowledge* | Struggling to understand police domain | “We are still struggling to find the best way to use CAS for informing police decision making.” (Intelligence officer Eva)<br>Intelligence officer Nate explains the troubles he has with understanding the needs of police. He does not know how to figure them out. (Observation notes)<br>The intelligence officers say that they are still searching for their identity and that they themselves sometimes do not know where their work ends, but also that the police sometimes expect things from them that they feel are not part of their work. (Observation notes) | Becoming familiar with police requirements | “We ask direct questions to police officers. This neighborhood is the predicted location for burglary. What is going on there? What kind of locks are on the doors? What kind of houses are there? What kind of people live there? Are there a lot of cars, not so many cars, parking spots, good or bad street lighting?” (Intelligence officer Wendy)<br>Intelligence officer Louisa sends the police officers of a specific neighborhood an email to ask for more information about the predicted location. In the email, Louisa asks the police officers to respond before this Friday, because she plans to finish the prediction document by then. (Observation notes) | Experience a passable knowledge boundary | “[The relationship with managers] is much more like a full partner. We are on the same level. Instead of being supportive, we are actually partners.” (Intelligence officer Ben)<br>“Before, we never had to think anything of anything. Back then it was just a question and an answer, that's that. And whatever I thought about that didn't matter. But now we need to think something of it. You have to give a value judgment. That's probably our added value. The information itself, they [police managers] have that themselves too. So that's not the point anymore, that we do that. We need to think something of it." (Intelligence officer Wendy)<br>“When we’re at the management meeting, police managers actually always follow our recommendations.” (Wendy) |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Brokerage practices* | Extracting and transferring crime predictions | Intelligence officer Eva says in a management meeting that she's been struggling with interpreting the predictions, which is why she decided to "take CAS at face value" and present a full list of predictions to the managers. (Observation notes) | Examining and domesticating crime predictions | "Often, when I try to find an explanation for predictions, I look at police data." (Intelligence officer Joey)<br>"We need to look at the data about previous crimes to trust the predictions." (Intelligence officer Michael)<br>"I can imagine that sometimes a prediction is mainly based on the police data and other times on demographic data. If that can be made visible for each prediction, that would really aid my work." (Intelligence officer Fred)<br>"If something is predicted for weeks on end, I look into whether it's constantly the same suspect who's active there, so that I can add a picture and a name and possibly an MO or a more specific timeframe to the prediction." (Joey) | Substituting crime predictions | "We base our recommendations on the figures we generate ourselves. We run a report on [own explainable tool] so that you can see, like, hey I see an upward trend in pickpocketing here. Then we zoom in on that." (Intelligence officer Wendy)<br>Intelligence officer Louisa explains that their new tool helps them to label and retrieve data. On Sunday, she spent a long time working on various car burglaries. She read and labeled several reports, which helped her see a connection and pattern between them. (Observation notes)<br>"We don't refer to CAS anymore." (Wendy) |
| *Data scientists' responses to translation* | Insist that algorithmic predictions need to be moved away from the data science world | "What we wanted [intelligence officers] to do in this work process is not to follow orders but be a bit more proactive and to not be afraid of putting forth their own thoughts about what's happening here [in this crime prediction]." (Data scientist Dennis)<br>"Police just want more information. They want to know, for example, 'are there any people I should pay attention to when I see them? Are there certain buildings that are interesting in one way or another?' This kind of qualitative information is important. That helps them to focus rather than just being somewhere at a certain predicted moment." (Dennis) | Explain the basics of machine learning | "During our meeting, it was asked which variables are used for the predictions. An overview of the variables can be found at: [internal link]." (Data scientist Matt in an email to the intelligence officers)<br>"[Name of police database] is the place where the data is collected on which the predictions are based." (Matt to intelligence officers in an email) | No further interaction | "Well, we let it go now. The [intelligence officers at] police stations know best about crime details." (Data scientist Dennis) |
| *Police managers' responses to translation* | Insist that they need a meaningful overview of crime predictions | "Let's set priorities. Look, we cannot handle everything, but let's at least make a choice and set a priority for this. Like, we [police and intelligence] will in any case tackle this [crime prediction], because we now find this important." (Police manager Rudy)<br>"We [police managers] need concrete action points." (Head of police department George) | Start to act on the intelligence officers' suggestions | "I think that people who are knowledgeable about CAS [intelligence officers] have thought about this [the recommendation]. So then I expect that it has added value too. And then I think, yes, we should just do this [use CAS in operational decision-making]." (Police manager Harry)<br>"Now, police managers ask us to report it. It used to be 'this is CAS, there's an increased chance of burglary,' and that was it. And then you'd wish that officers would do a bit of driving around there. Now we need to report at the end of our shift, like, 'yes, we've been there and we didn't see anything.'" (Police officer Jay) | Suggestions are relevant for operational decision-making | "Based on the home and car burglary predictions, we have decided to place the [specialized team] in that area for the upcoming two weeks." (Email of police managers)<br>"Well, CAS helps to give direction to police work. You're not uselessly driving around in circles. If you really do things based on information, then you're useful." (Police manager Harry) |

Consequently, the first step was to find out if the causes of predictions could be made transparent and they asked the data scientists to create a tool that would make the decision logic of crime predictions visible. The assumption was that such a tool would make it possible for the intelligence officers to trace how a crime prediction was calculated. However, the data scientists insisted that "the algorithm did not easily display why something was predicted" (manager of the data science team Jules) and that generating the best possible predictions required complex techniques for pattern recognition in vast amounts of data, which made the learning algorithm opaque. As a consequence of these beliefs, the team of data scientists claimed that pattern recognition through machine learning, which combines many different variables and theories, required "such complex mathematical reasoning that it probably extends beyond human reasoning."[13] Data scientist Dennis further explained this belief as follows:

> "If you want to have the perfect set of selection rules, it means that you have to study a lot of variances for a long time. And this is the reason why [data scientists] don't do it in a commonsense way [using human reasoning] because there are too many possible variations. You have to do it by computer [using machine learning]."

To help the intelligence officers, the data scientists did explain the basic techniques they used for developing CAS. For example, they showed the variables that were included in the learning algorithm. Such a list of variables still, however, did not give insight into which variable was considered most important for a given prediction and for what reason. These explanations therefore did not satisfy the intelligence officers' need to understand how the crime predictions were generated and gradually they gave up on their quest to gain deep insights into the learning algorithm. Dedicated to fulfilling their tasks as brokers, they decided to leave the data scientist aside and started to examine the predictions by inspecting the source they had direct access to: the police data. As intelligence officer Eva reflected:

> "How predictions come about technically might be a guess but you can have a look at the police data of past years and find quite some reasons."

[13] https://www.politieacademie.nl/kennisenonderzoek/kennis/mediatheek/pdf/89539.pdf

For example, to understand why burglaries were often predicted in the morning, insight into how the timeframe of crime predictions was calculated was needed, which triggered the intelligence officers to dig into the police database and look for timestamps in burglary reports. It appeared that, if a burglary occurred in a period when people were away from home, the report included a timeframe (e.g., 08:00 to 18:00) instead of one timestamp (e.g., 08:30 a.m.). So, they reasoned that the time the data scientists decided to use was the so-called 'starting time' of an incident (in this case 08:00 a.m.) instead of including the full timeframe for calculating predictions.

Taking their assignment to create connections between the world of algorithms and the police occupational world seriously, the intelligence officers unsuccessfully tried to share their findings from the police data with the data scientists. For example, when they suggested a different method for calculating timeframes, the data scientists maintained their belief in the machine learning techniques they had applied and said that this was the "only scientifically proven method" for calculating time predictions (data scientists Dennis and Mary). In another instance, when one of the intelligence officers emailed the data scientists to share that CAS generated predictions for car burglaries in areas where cars were not permitted, data scientist Dennis continued to believe in the CAS predictions and answered that "it really was a parking area."

These interactions with the data scientists made the intelligence officers realize there was a serious boundary between the machine learning knowledge and their interpretations, which blocked a mutual understanding between them and the data scientists. According to the intelligence officers, the data scientists were "trying to develop better tools" (intelligence officer Fred) but "did not understand what they [intelligence officers] wanted" (intelligence officer Bart). They grew more and more skeptical of how machine learning knowledge was developed. As intelligence officer Wendy remarked: "Data scientists don't have a clue about police work. CAS is just a tool with some kind of science behind it. Well, if you reason like that, you don't get our reasoning." Moreover, no matter how much effort they put into examining the data to better understand where machine learning knowledge came from, "sometimes [they] just could not deduce from the data why a prediction appeared" (intelligence officer Joey), which was considered to be a serious bottleneck in performing their work as knowledge brokers. As intelligence officer Fred explained:

> "Understanding CAS is especially important for getting to the final step, for putting the predictions in the context of the police. If I know that the reason behind a prediction is just that a lot of crimes happened there in the past, then I can suggest that the police officers drive around in that area so that they can prevent the predicted crimes from coming true. If the prediction appears because of demographic data, indicating that there's a lot of money over there or something like that, then police officers have to take another approach. Then they have to warn the residents and make them prevent these crimes from happening [e.g., by improving their locks]."

The inability to fully comprehend the decision logic of CAS had fundamental consequences for translating predictions from the learning algorithm to the police domain. To better understand how this was so influential, we first turn to how the intelligence officers also put efforts into better understanding the police domain.

*Learning about the target domain.* Initially, the intelligence officers also struggled with translating the crime predictions to the police domain. To solve this issue, they started to interact more directly with the police to gain a better understanding of the occupational world. By printing a crime prediction, sitting down with police officers, and asking them to make sense of that prediction from their occupational perspective (see Figure 3.4), they learned that "more concrete" (police manager Rudy) or contextualized predictions included specific details of the area or of potential suspects. For example, the police managers told the intelligence officers that algorithmic predictions would start to make sense to them if the intelligence officers "dared to add suspects" (Rudy). To create these more contextualized predictions, the intelligence officers relied on police data; navigating the police databases and reading police reports (e.g., DNA matches, burglary reports that included descriptions of burglars, pictures of crimes or criminals sent to the police via community WhatsApp groups).

**Figure 3.4 Intelligence officer and police officer together making sense of a prediction**

They also learned from interacting with police managers that short and action-oriented descriptions best fit the police occupational world. “We gave the police managers a couple of options and asked for their opinion,” intelligence officer Wendy reflected, “and eventually they said ‘give us as little as possible.’” Using their improved understanding of police work, the intelligence officers changed the way they handled crime predictions and started deleting, editing, and interpreting them. The request for a concise document triggered the intelligence officers to limit the number of predictions they presented to five timeframes (from on average 28) and two locations (from on average 56) and to delete all predictions they thought did not make sense. For example, they removed burglary predictions when no burglaries happened the week before. Moreover, even though they could not comprehend the decision logic of the crime predictions, the intelligence officers tried to increase the meaning by including details that they could link to the predictions without knowing the exact causes, such as area characteristics (e.g., “rehabilitation center for ex-convicts in the vicinity”), housing conditions (e.g., “mainly student houses” or “outdated locks”), or even adding potential suspects who had been criminally active in the area before. Intelligence officer Ben summarized their knowledge brokerage work as follows:

> “We add an interpretation to the algorithmic predictions so police managers can do something with them. In other words: ‘It is like this for these reasons.’ You can also give police managers advice, like: ‘I would focus on this or that person,’ or ‘I wouldn't do anything about that type of crime because it's way too unpredictable.’”

The police managers appreciated the new way of domesticating algorithmic predictions and perceived the brokerage work as more relevant and valuable. They expressed, for example, that thanks to the intelligence officers' interpretations the algorithmic predictions gave more "direction to their decision-making work" (police manager Harry) and also recognized the increased value of intelligence officers' work for "coordinating police work" (police manager Rudy). Moreover, during the time that the intelligence officers became more knowledgeable of police work and the police managers started using the crime predictions to inform their operational decisions, the police managers observed an overall decline in the number of high-impact crimes (e.g., burglary and car theft). The decrease in the number of burglaries was even so spectacular that the police station won a national award called "Harm Alarm" for the largest reduction in burglaries (minus 47 percent compared to the year before). In their internal communication, the police managers attributed this achievement largely to the learning algorithm that offered them "new ways of gathering and analyzing data." Even though the declining crime numbers could have reasons unrelated to the use of algorithmic predictions (e.g., criminals being less interested in doing 'laborious' burglaries and moving towards cybercrime instead), the police managers felt they had reasons to believe that the use of algorithmic predictions was paying off. Happy with the work of the intelligence officers, the police managers decided to give more weight to the brokering activities of the intelligence officers. They appointed them as key figures for informing their operational and strategic decisions by inviting them into regular management meetings. To "make crime predictions more central" (police manager Harry), management scheduled about 20 minutes at the beginning of these meetings for intelligence officers to present their advice.

In sum, to translate machine learning knowledge to the police domain, the intelligence officers realized they themselves first had to better understand how machine learning knowledge was generated and how police work was performed. In their efforts to find out more about the decision logic of crime predictions, they encountered the opaque nature of learning algorithms in the complex, embedded, and implicit nature of machine learning knowledge, which solidified a knowledge boundary between the machine learning domain and the intelligence officers. On the other hand, due to the consistent interactions with the police, the access to the police data, and the police managers' increased belief in the value of crime predictions, the knowledge differences between the intelligence officers and the police managers was slowly fading. This allowed the intelligence officers to contextualize the algorithmic predictions in such a way that they made sense to the police managers (see Table 3.2). As such their knowledge brokerage role can best be described as an "interpreter". However, even though their contextualizing efforts seemed to work for the police managers, the intelligence officers continued to struggle with passing the machine learning knowledge boundary.

### 3.5.3 Algorithmic knowledge broker as curator

Now that the intelligence officers became more used to their ascribed expertise as algorithmic knowledge brokers, they searched for ways to deal with the opaque machine learning knowledge and discussed this with the head of their department. He suggested that, maybe, the difference between how machine learning knowledge was generated and their human interpretation was so large that it could not be overcome at all and that they should therefore use their own expertise:

> "Intelligence work is not only about CAS. You can include your input there as well. Human intelligence is by definition smarter than algorithmic systems." (Head of intelligence department Rick)

By now, the intelligence officers were so knowledgeable of the police domain that they felt confident enough to leave CAS aside and focus only on helping police managers to not be disturbed by "useless" issues and emphasize the "really important" ones (intelligence officer Richard). Moreover, a side-effect from their efforts to deduce details about machine learning techniques from police data was that they realized that they used many more data sources in their knowledge brokerage work than those included in CAS. "To be honest, I trust CAS less than I trust the information I can gather from the police databases," intelligence officer Joey expressed the shared sentiment. They also became increasingly vocal amongst each other about the centrality of their work for guiding police managers. For example, in one of their department meetings, they agreed that intelligence work should not be about "figuring out how systems work, but making meaningful data combinations for police managers."

The data scientists believed that the intelligence officers made the crime predictions meaningful to the police and helped police managers to make their operational processes "smarter and better" (head of data science Jules). In the meantime, the intelligence officers substituted CAS with more explainable solutions that supported their human judgments. For example, the intelligence officers requested their local IT desk to develop an archival and analysis tool. This tool operated on Excel and used all data sources the intelligence officers worked with previously to make sense of algorithmic predictions. It did not include a learning algorithm but was merely there to help the intelligence officers to store and add codes to police reports, which facilitated quick and easy information retrieval and analysis. Since the tool did not use a learning algorithm, it was possible to scrutinize the calculated patterns, which facilitated their knowledge brokerage work. For example, they requested that the tool included a new method for calculating crime timeframes, i.e., by using and visualizing a weighted average of the time windows of past crimes. When the intelligence officers compared the times calculated with the times predicted by CAS, they considered their "own" times "more explainable" (intelligence officer Louisa). Their new tool only gave the intelligence officers insights into past crime patterns and had no predictive capacity (see Appendix 3 for an example of CAS predictions compared to outcomes of their new tool). However, the transparent and explainable nature of their new tool helped them in making predictions that they thought would best fit the police domain. As intelligence officer Wendy reflected:

> "We already see the problem and then we go and double-check it with CAS and say: oh, well, it supports our judgment, we can point police managers' attention there. The problem is already clear, it's already evident, so we don't need CAS that much anymore."

Interestingly, while they pushed the learning algorithm to the background and constructed explainable alternatives that aligned with their human judgments, only the intelligence officers themselves were aware of this shift. Driven by police management's pushback to being disturbed by the complex technology and pushed by their encouragement s to come up with "concise" predictions, e.g., to "give them as little as possible" (police manager Rudy), the intelligence officers shielded the police managers from the process through which they generated the substitutes. "We should keep these choices away from police management," said the head of intelligence Rick during one of their department meetings, "they just need a clear recommendation, we shouldn't bother them with what kind of tools we used for it." This was also reinforced by the intelligence officers' experiences during their presentations at management meetings. During these presentations, police managers did not pay attention to slide handouts or explanations and were instead checking their phones. Yet, they plainly followed the intelligence officers' recommendations. "We give our advice," intelligence officer Wendy reflected, "and most of the time the police managers allocate police resources accordingly." These occurrences during meetings made them believe that the police managers took their advice seriously without the need for any references. They thus decided to just offer the substitutes without the need to "back up their suggestions to police managers with numbers" (intelligence officer Aileen). Wendy explained:

> "In the beginning, we had this whole document with a long interpretation [of the algorithmic predictions]. Now, I only present the problem and our advice. Police managers just don't care at all what the numbers look like."

In the end, the intelligence officers presented their recommendations using just one slide, which only included a direct and short piece of advice without its source, such as: "Due to incidents with disorderly conduct because of alcohol/narcotics use, the intelligence department advises police management to conduct alcohol/narcotics tests on traffic participants during the nightly hours over the weekend. Mainly at locations [anonymized]." Being able to substitute the crime predictions with their own alternatives that were willingly accepted by the police managers, the intelligence officers felt they had grown more equal to them:

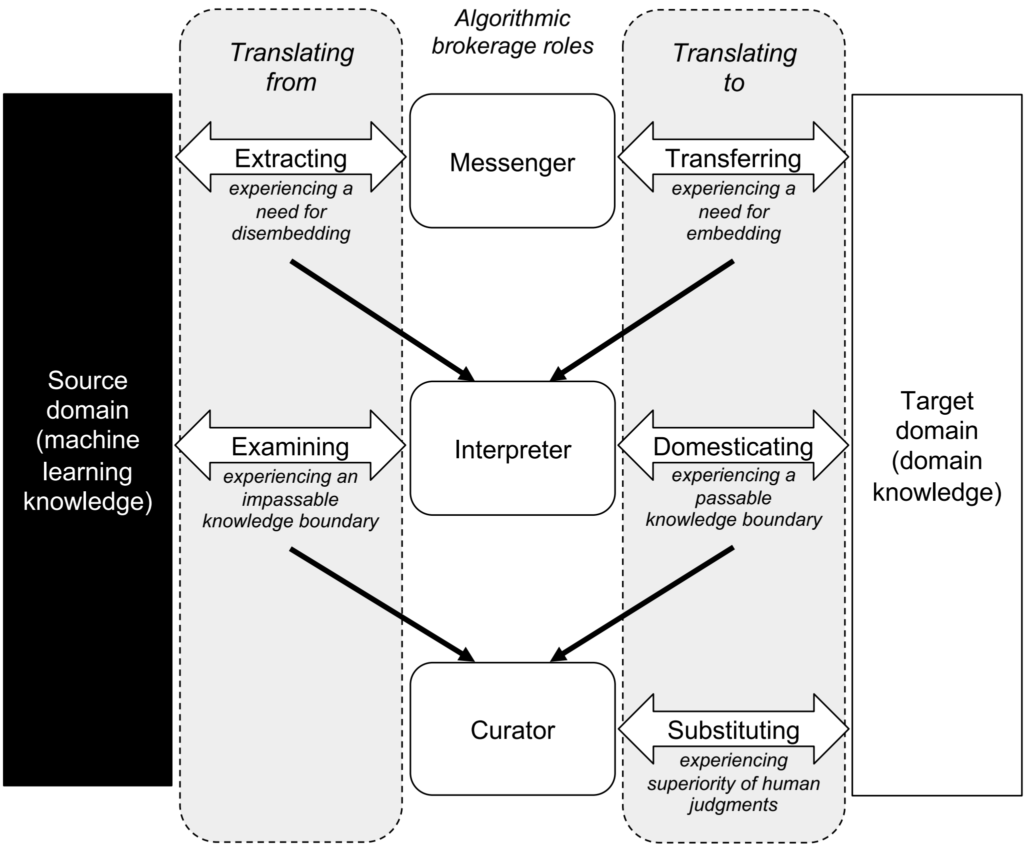
> "We are now considered more as a partner of police managers. Before, we would usually wait for police managers to give us a task. Now, it's just: we are a department and we have something to say too. And we have good suggestions. That's the difference. We changed into an intelligence department having a seat at the table." (Intelligence officer Wendy)

In sum, the intelligence officers eventually realized that the boundary between machine learning knowledge and their human interpretation of crime predictions was impassable. As a consequence, they pushed back the learning algorithm and substituted it with explainable alternatives that aligned with their human judgments and that they considered most suitable for the police managers (see Table 3.2). As such, their knowledge brokerage role can be described as a "curator", in which they grew to become more influential and were eventually even considered more as a partner. As curators, the intelligence officers stopped translating the knowledge from the machine learning domain and substituted the knowledge to the police domain instead, without police managers ever noticing it.

## 3.6 Discussion

Building on the findings of our case, we offer a general explanation of how algorithmic knowledge brokers translate machine learning knowledge from the source domain to the target domain (see Figure 3.5). In particular, we observed how brokers enact translation practices that afford them to perform increasingly influential algorithmic brokerage roles. These brokerage roles change over time, because when they attempt to translate machine learning knowledge, knowledge differences emerge between the brokers and the source and target domains. At the start of the brokerage work, brokers lack sufficient understanding of machine learning and of the target domain and cannot do more than act as messengers. They do so by extracting and transferring knowledge which leads to failed attempts to de-contextualize the machine learning knowledge from the source domain and to contextualize it to the target domain. To solve this, realization sets in that translation requires deeper insights into both domains. This means a move away from merely acting as a messenger to an interpreter role, aiming to examine the machine learning knowledge and domesticating it in the target domain. While it is possible for the brokers to reach a deeper understanding of the target domain, the opaque nature of learning algorithms prevents them from understanding how algorithmic predictions are generated. Because of this, the brokers experience an impassable knowledge boundary between them and the source domain, which triggers them to act as curators and substitute the machine learning knowledge with their own human judgments

**Figure 3.5 Theoretical model of brokering machine learning knowledge**




Bringing together the fields of emerging technologies and organizational theory allows for the emergence of a new phenomenon, that of the algorithmic knowledge broker with its dynamic and influential nature. More specifically, the current divide between the two fields has resulted in an academic understanding of knowledge brokerage in which the need to understand the knowledge source to be able to translate has been taken more or less for granted. The recent rise of learning algorithms as technologies that generate opaque knowledge brings to the fore the need for uniting the two fields. Particularly, our case of knowledge brokers in the age of learning algorithms highlights the complex and important practice of translating *from* the source domain for knowledge brokerage.

Studying the translation practices of opaque machine learning knowledge reveals that knowledge brokers can become increasingly influential, even to the extent that brokers can eventually substitute the original knowledge sources, and gives us a better understanding of how and why this growth in influence happens. Below, we offer the key contributions of our study.

### 3.6.1 Algorithmic brokerage work as translating from and translating to

One of the core findings of the research presented in this paper is that algorithmic knowledge brokers enact different translation practices over time in their efforts to translate machine learning knowledge to practice. This dynamic perspective on brokerage work offers new insights into the literature on knowledge brokers and to translation theory.

Previous studies argued that knowledge brokerage tasks emerge when a semantic boundary hinders two groups from sharing knowledge (Boari & Riboldazzi, 2014; Carlile, 2004; Dougherty, 1992) and reasoned that knowledge brokers could resolve boundaries and align perspectives by enacting translation practices (Barley, 1996; Grady & Pratt, 2000; Kellogg et al., 2020; Paul & Whittam, 2010; Tushman & Katz, 1980; Wenger, 1999). We contribute to the knowledge brokerage literature by providing a more fine-grained and dynamic perspective on how knowledge brokers enact translation practices over time and in relation to opaque machine learning knowledge. Building on Røvik (2016) and based on our empirical findings, we consider 'extracting' and 'examining' as practices to translate *from* machine learning knowledge, and 'transferring', 'domesticating', and 'substituting' as practices to translate *to* domain knowledge, which offers a more refined insight into the complexity of brokerage work.

For brokers to resolve a semantic boundary and to translate knowledge, prior research has emphasized the need to understand the source domain and the target domain (Brown & Duguid, 1998; Carlile, 2004; Gal et al., 2020; Shulman, 1987; Sturdy & Wright, 2011). Our research reveals that, in the case of learning algorithms, such "contextual bilingualism" (Røvik, 2016, p. 299) cannot be obtained because gaining a deep understanding of the source domain is impossible. Through the brokers' failed translation practices, which are caused by a lack of understanding of how machine knowledge is generated, a knowledge boundary solidified between the machine learning domain and the brokers. As we mentioned above, most research on knowledge brokers mainly focuses on the semantic boundary that brokers should be able to resolve (Boari & Riboldazzi, 2014; Carlile, 2004; Dougherty, 1992). Our case shows that, in the efforts to resolve a semantic boundary between the source domain and the target domain through translation practices, knowledge boundaries can solidify between knowledge brokers and the groups they intend to connect. This added complexity regarding knowledge boundaries uncovers an additional understanding of knowledge brokers; by translating knowledge, they can create their own boundaries.

By unpacking the practices through which brokers translate knowledge from the source and to the target domain, this study also contributes to translation theory (Callon, 1986; Czarniawska & Sevón, 2005; Latour 1986, 2005; Law, 2002; Røvik, 2016) by emphasizing the dynamic and changing nature of translation practices. Moreover, while translation theory scholars have paid extensive attention to how ideas are translated to specific fields and organizations (e.g., Bergström, 2007; Ciuk & James, 2014; Mueller & Whittle, 2011; Nielsen et al., 2014; Saka, 2004; Waldorff, 2013), only a few studies have focused on how knowledge is translated from its original source (Furusten, 1999; Heusinkveld & Benders, 2005; Suddaby & Greenwood, 2001). These studies, so far, did not address what translation entails if knowledge boundaries are impassable, such as in the case of learning algorithms. Our case offers an extreme example in which the knowledge that needs to be translated is highly complex, embedded, and implicit (Røvik, 2016) and brings to the fore the importance of the first 'translating from' phase for the process of translation.

### 3.6.2 Algorithmic knowledge brokers as influential curators

Another core finding of this study are the knowledge brokerage roles that change to become more influential over time. Especially the emergence of algorithmic knowledge brokers as curators, acting as 'kings in the land of the blind' adds to our understanding of the role of knowledge brokers as influential and consequential.

Research on knowledge brokers has largely regarded these actors to be neutral intermediaries who deal with the knowledge of others but have no recognizable knowledge of their own (Barley, 1996; Barley & Bechky, 1994). To better understand the influential nature of algorithmic brokerage work, the analogy of art curators provides a useful lens. Around the 16th Century, with the materialization of 'cabinets of curiosity', art curators emerged and became responsible for taking care of works of art and valuable objects. In that time, they were leveraging the direct connection between artists and collectors. The cabinets were closed to the public and housed the private art collections of wealthy citizens. Stemming from the Latin word *cura*, the art curators' work at that time was to take care of art objects behind closed doors and was not considered to have a recognizable status. Interestingly, with the rise of public museums, the caretaking efforts triggered the public to consider art curators as experts of art objects (Balzer, 2014; Teather, 1990). Over time, art progressed into "too many artists, too many movements, too many artworks in too many shows, too much discussion" (Balzer, 2014, p. 65). The direct connection between an artist and a collector thus was vanishing and knowledge about art became increasingly abstract and difficult to understand. Given their knowledge of art sources, art curators stepped in as key figures in the translation of art towards the wider public and were usually blindly trusted by collectors.[14] The story of art curators is particularly helpful because it reveals the change from hidden caretakers to a highly influential and independent occupation. The historical journey of curators helps us to understand that, in contrast to our previous understanding of knowledge brokers as neutral intermediaries, the algorithmic brokers in our study become so influential that they may move away from the knowledge source and substitute it with their human judgments.

It is interesting to note that the development of the art curator role departs from the current interest in "data curators" who are mainly considered to act as content creators,

[14] Examples of currently well-known art curators are Hans Ulrich Obrist, Carolyn Christov-Bakargiev, and Okwui Enwezor.

data cleaners, or data editors (e.g., Carah, 2014; Karasti et al., 2006; Kellogg et al., 2020; Muller et al., 2009; Parmiggiani & Miria, 2020). Some studies describe how such curator activities happen 'behind the scenes' of technology development and are therefore usually invisible (Sachs, 2020). For example, Gray and Suri (2019) described how "ghost workers" emerged because of the need to review the content and quality of the data that is used for training learning algorithms. As the current focus of curation is mainly on the input of technology, our case of algorithmic knowledge brokers as curators shifts this perspective towards the output of learning algorithms, just like the output of art. This study therefore emphasizes the need to acknowledge that algorithmic knowledge brokers acting as curators can occupy a much more influential role than what was previously assumed in the invisible 'ghost work' of data curators and to unpack the consequences of curation for how machine learning knowledge is (re)presented to users.

### 3.6.3 Practical implications and future research

This study offers practical implications for domain experts, managers, and technology developers engaged in the development and implementation of emerging technologies in organizations. In various fields and parts of organizations, dealing with issues around explainability of technology is becoming an important topic. As we have seen so far, on the side of technology developers and regulatory bodies these issues are mainly assumed to reside in the 'translating from' side and technical solutions are offered (e.g., Barredo et al., 2020; Doran et al., 2017; Kirsch, 2017; Lipton, 2018; Miller, 2019; Mittelstadt et al., 2019; Preece et al., 2018; Robbins, 2019). On the other hand, organizations are generally interested in the 'translating to' side when confronted with issues of algorithmic (in)transparency and push for more contextualization towards the target domain without recognizing the need for explaining how machine learning knowledge is generated (Henke et al., 2018; Kellogg et al., 2020). Our study emphasizes, however, that one cannot exist without the other, which requires involving both the technology developers and domain experts, for example, through mutual reflection and adaptation already during the development and implementation process (Van den Broek et al., 2021; Zhang et al., 2020).

Involvement in terms of understanding each other's thought worlds requires more long-term investments and new skills (Waardenburg et al., 2021). For example, developers need social skills to understand the domain needs, domain experts need technical skills to understand the reasoning behind and limits of these technologies. Developing such skills will provide a first step to overcome the knowledge boundary between machine learning knowledge and the user domain.

This study also shows that algorithmic knowledge brokers are not neutral intermediaries that can objectively represent algorithmic predictions, but are likely to include their own interpretations. While brokerage work can be crucial for using learning algorithms in practice, it needs clear demarcations through, for example, regulation and close monitoring to prevent the work from going beyond translating into substituting. As Røvik (2016) emphasized: "the more the transfer process is regulated by authorities, the less transformable the transferred construct is for the translator." (p. 300). Also, to be able to perform brokerage work, our case highlights data access as an important resource for brokers to be able to translate algorithmic predictions to the expert domain. Yet, while data access can offer transparency, this study shows that unguided data access can also trigger brokers to trust their own interpretations more than algorithmic predictions and set aside the learning algorithm.

It is worth noting several boundary conditions of our study, which also open up opportunities for further research. Our case shows that occupational values matter for how desirable access to explanations may be from the perspective of the user. In our study, the users (i.e., police managers) did not feel the need for an explanation of machine learning knowledge and blindly left the responsibilities of translating the knowledge with the intelligence officers. While brevity and action orientation are virtues in the police occupational culture, this might be different in other occupational groups, such as radiology, where the decision-making practices of the users might require as much evidence as possible (e.g., Rezazade Mehrizi et al., 2020). We encourage future studies to look at other occupational domains to further understand the differences in explanations required and to provide further insights into who or what is accountable in the age of learning algorithms. Also, we presented a case of the use of a learning algorithm within a highly hierarchical and siloed organizational structure which hindered the interaction between the different groups. It would be interesting for advancing our knowledge on algorithmic knowledge brokering, to also include more innovative or flat research settings, in which different relationships exist between developers and users (such as co-creation or agile technology development). Finally, our study focused on a relatively basic and simple version of a learning algorithm, which nevertheless had a fundamental consequence for work and organizing. With the emergence of more advanced and even more opaque learning algorithms and computational techniques such as artificial intelligence tools based on deep learning, these consequences can be further enlarged. We thus encourage future research to continue to unpack algorithmic brokerage work to provide deep insights into the organizational consequences of emerging technologies that are increasingly opaque.

## 3.7 Conclusion

Learning algorithms, because of their highly complex, embedded, and implicit nature, offer an extreme case for understanding how knowledge brokers translate knowledge in practice. In this study, we provided a case of knowledge brokers who aimed to translate machine learning knowledge to a target domain. Translation has always been the core of knowledge brokerage work, yet so far has been mainly taken for granted. It is now, in the age of learning algorithms, of significant importance to question how knowledge brokers are able to translate from a source domain, since these domains have become increasingly difficult to understand. As this study shows, when the source domain is opaque to all actors involved, brokers can become 'kings in the land of the blind' and decide to substitute machine learning knowledge with their own judgments. The case of learning algorithms therefore highlights that knowledge brokers should not be considered as merely instrumental in solving knowledge boundaries but even more so as highly influential curators of knowledge.

## References


Ajunwa, I. (2020). The “black box” at work. *Big Data & Society, 7*(2), 1–6.

Allen, T. (1977). *Managing the flow of technology*. Cambridge, MA: MIT Press.

Ananny, M. (2016). Toward an ethics of algorithms: Convening, observation, probability, and timeliness. *Science, Technology & Human Values, 41*(1), 93–117.

Annany, M., & Crawford, K. (2016). Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. *New Media & Society, 20*(3), 973–989.

Ancona, D. G., & Caldwell, D. F. (1992). Bridging the boundary: External activity and performance in organizational teams. *Administrative Science Quarterly*, 37(4), 634–665.

Anteby, M., Chan, C. K., & DiBenigno, J. (2016). Three lenses on occupations and professions in organizations: Becoming, doing, and relating. *Academy of Management Annals, 10*(1), 183–244.

Anthony, C. (2021). When knowledge work and analytical technologies collide: The practices and consequences of black boxing algorithmic technologies. *Administrative Science Quarterly*. doi:00018392211016755.

Appelbaum, E., & Batt, R. (2014). *Private equity at work: When wall street manages main street.* New York, NY: Russell Sage Foundation.

Bader, V., & Kaiser, S. (2019). Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence. *Organization, 26*(5), 655–672.

Bailey, D. E., & Barley, S.R. (2020). Beyond design and use: How scholars should study intelligent technologies. *Information & Organization, 30*(2). doi:10.1016/j.infoandorg.2019.100286

Balasubramanian, N., Ye, Y., v& Xu, M. (2020). Substituting human decision-making with machine learning: Implications for organizational learning. *Academy of Management Review.* doi:10.5465/amr.2019.0470

Balzer, D. (2014). *Curationism: How curating took over the art world and everything else.* Toronto: Coach House Books.

Barley, S. R. (1996). Technicians in the workplace: Ethnographic evidence for bringing work into organizational studies. *Administrative Science Quarterly, 41*(3), 404–441.

Barley, S. R., & Bechky, B. A. (1994). In the backrooms of science: The work of technicians in science labs. *Work & Occupations, 21*(1), 85–126.

Barocas, S., & Selbst, A. D. (2016). Big data’s disparate impact. *California Law Review, 104*, 671–732.

Barredo, A. A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., et al. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information. Fusion, 58*, 82–115.

Bergström, O. (2007). Translating socially responsible workforce reduction—A longitudinal study of workforce reduction in a Swedish company. *Scandinavian Journal of Management, 23*(4), 384–405.

Boari, C., & Riboldazzi, F. (2014). How knowledge brokers emerge and evolve: The role of actors' behaviour. *Research Policy, 43*, 683–695.

Bolin, G., & Andersson Schwarz, J. (2015). Heuristics of the algorithm: Big Data, user interpretation and institutional translation. *Big Data & Society*, 2(2). doi:10.1177/2053951715608406

Brayne, S. (2020). *Predict and surveil: Data, discretion, and the future of policing.* Oxford: Oxford University Press.

Brown, J. S., & Duguid, P. (1998). Organizing knowledge. *California Management Review, 40*(3), 90–111.

Brown, J. S., & Duguid, P. (2001). Knowledge and organization: A social- practice perspective. *Organization Science, 12*:198–213.

Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review.*

Bucher, E. L., Schou, P. K., Waldkirch, M. (2020). Pacifying the algorithm – Anticipatory compliance in the face of algorithmic management in the gig economy. *Organization.* doi:10.1177/1350508420961531

Burgess, N., & Currie, G. (2013). The knowledge brokering role of the hybrid middle level manager: The case of healthcare. *British Journal of Management, 24*, S132–S142.

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, 3(1), 1–12.

Burt, R. S. (1992). *Structural holes: The social structure of competition.* Cambridge, MA: Harvard University Press, Cambridge, MA.

Callon, M. (1986). Some elements of a sociology of translation: Domestication of the scallops and the fishermen of Saint Brieuc Bay. In Journal of Law (Ed) *Power, action and belief: A new sociology of knowledge* (Routledge, London).

Campolo, A., & Crawford, K. (2020). Enchanted determinism: Power without responsibility in artificial intelligence. *Science, Technology, & Society, 6*, 1–19.

Canales, R. (2010). Rule bending, sociological citizenship, and organizational contestation in microfinance. *Regulation & Governance, 5*(1), 90–117.

Carah, N. (2014). Curators of databases: Circulating images, managing attention and making value on social media. *Media International Australia, 150*(1), 137–142.

Carlile, P. R. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization Science, 15*(5), 55–68.

Carrizosa, E., & Morales, D. R. (2013). Supervised classification and mathematical optimization. *Computers & Operational Research, 40*(1), 150–165.

Chiambaretto, P., Massé, D., & Mirc, N. (2019). "All for One and One for All?" - Knowledge broker roles in managing tensions of internal coopetition: The Ubisoft case. *Research Policy, 48*(3), 584–600.

Christin, A. (2017). Algorithms in practice: Comparing web journalism and criminal justice. *Big Data & Society, 4*(2). doi:10.1177/2053951717718855

Christin, A. (2020). The ethnographer and the algorithm: Beyond the black box. *Theory & Society.* doi:10.1007/s11186-020-09411-3

Christin, A., & Brayne, S. (2020). Technologies of crime prediction: The reception of algorithms in policing and criminal courts. *Social Problems.* doi.:10.1093/socpro/spaa004

Ciuk, S., & James, P. (2015). Interlingual translation and the transfer of value-infused practices: an in-depth qualitative exploration. *Management Learning, 46*(5), 565–581.

Czarniawska, B., & Sevón, G. (2005). Translation is a vehicle, imitation its motor, and fashion sits at the wheel. In Czarniawska B, Sevón G (eds) *Global Ideas: How Ideas, Objects and Practices Travel in the Global Economy*. Malmø: Liber & Copenhagen Business School Press.

Davenport, T. (2018). *The AI advantage: How to put the artificial intelligence revolution to work.* Cambridge, MA: MIT Press.

DiMaggio, P. (1993). Nadel's paradox revisited: Relational and cultural aspects of organizational structures. Nohria N, Eccles R, eds. *Networks and organization.* Boston, MA: Harvard Business School Press

Doran, D., Schulz, S., & Besold, T. R. (2017). What does explainable AI really mean? A new conceptualization of perspectives. *arXiv:1710.00794.*

Dougherty, D. (1992). Interpretive barriers to successful product innovation in large firms. *Organization Science*, 3(2), 179–202.

Dourish, P. (2016). Algorithms and their others: Algorithmic culture in context. *Big Data & Society, 3*(2). doi:10.1177/2053951716665128

Durán, J. M., & Jongsma, K. R. (2021). Who is afraid of black box algorithms? on the epistemological and ethical basis of trust in medical AI. *Journal of Medical Ethics, 47*(5), 329–335.

Edacott, C. G., & Leonardi, P. M. (2020). Keep them apart or join them together? How identification processes shape orientations to network brokerage. *Communication Research.* doi:10.1177/0093650220947316

Eubanks, V. (2017). *Automating inequality: How high-tech tools profile, police, and punish the poor.* New York, NY: St. Martin's Press.

Evers H. D., & Menkhoff, T. (2004). Expert knowledge and the role of consultants in an emerging knowledge-based economy. *Human Systems Management, 23*(2), 123–135.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information & Organization, 28*(1), 62–70.

Fernandez-Mateo, I. (2007). Who pays the price of brokerage? Transferring constraint through price setting in the staffing sector. *American Sociological Review, 72*(2), 291–317.

Fernandez, R.M., & Gould, R. V. (1994). A dilemma of state power: Brokerage and influence in the National Health Policy domain. *American Journal of Sociology, 99*(6), 1455–1491.

Fisher, G., & Aguinis, H. (2017). Using theory elaboration to make theoretical advancements. *Organization Research Methods, 20*(3), 438–464.

Fleming, L., & Waguespack, D. M. (2007). Brokerage, boundary spanning, and leadership in open innovation communities. *Organization Science, 18*(2), 165–180.

Forsythe, D. E. (1993). The construction of work in artificial intelligence. *Science, Technology & Human Values, 18*(4), 460–479.

Furusten, S. (1999). *Popular management books: How they are made and what they mean for organizations*. London: Routledge

Gal, U., Jensen, T. B., & Stein, M. K. (2020). Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. *Information & Organization,* 30(2). doi:10.1016/j.infoandorg.2020.100301

Glaser, V. L., Pollock, N., & D'Adderio, L. (2020). The biography of an algorithm: Performing algorithmic technologies in organizations. *Organization Theory*. doi: 10.1177/26317877211004609

Glikson, E., & Woolley, A. W. (2020). Human trust in Artificial Intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660.

Gould, R. V., & Fernandez, R. M. (1989). Structures of mediation: A formal approach to brokerage in transaction networks. *Sociological Methodologies, 19,* 89–126.

Grady, R., & Pratt, J. (2000). The UK technology transfer system: calls for stronger links between higher education and industry. *Journal of Technology Transfer, 25,* 205–211.

Gray, M. L., & Suri, S. (2019). *Ghost work: How to stop Silicon Valley from building a new global underclass*. Boston, MA: HMH Books.

Grimmelmann, J., & Westreich, D. (2017). Incomprehensible discrimination. *California Law Review, 7*, 164–177.

Haas, A. (2015). Crowding at the frontier: boundary spanners, gatekeepers and knowledge brokers. *Journal of Knowledge Management, 19*(5), 1029–1047.

Hafermalz, E., & Huysman, M. (2019). Please explain: Looking under the hood of explainable AI. *Paper presented at PROS* (Crete, Greece).

Hargadon, A., & Bechky, B. A. (2006). When collections of creatives become creative collectives: A field study of problem solving at work. *Organization Science, 17*(4), 484–500.

Hargadon, A., & Sutton, R. I. (1997). Technology brokering and innovation in a product development firm. *Administrative Science Quarterly, 42*(4), 716–749.

Heaphy, E. D. (2013). Repairing breaches with rules: Maintaining institutions in the face of everyday disruptions. *Organization Science, 24*(5), 1291–1315.

Heimer, C. A., & Stevens, M. L. (1997). Caring for the organization: Social workers as frontline risk managers in neonatal intensive care units. *Work & Occupations*, *24*(2), 133–163.

Henke, N., Levine, K., & McInerney, P. (2018). You don't have to be a data scientist to fill this must-have analytics role. *Harvard Business Review.*

Heusinkveld, S., & Benders, J. (2005). Contested commodification: Consultancies and their struggle with new concept development. *Human Relations, 58*(3), 283–310.

Hoffer Gittell, J. (2002). Coordinating mechanisms in care provider groups: Relational coordination as a mediator and input uncertainty as a moderator of performance effects. *Management Science, 48*(11), 1408–1426.

Howells, J. (2006). Intermediation and the role of intermediaries in innovation. *Research Policy, 35*, 715–728.

Huising, R., & Silbey, S. S. (2011). Governing the gap: Forging safe science through relational regulation. *Regulation & Governance, 5*(1), 14–42.

Huysman, M. (2020). Information systems research on artificial intelligence and work: A commentary on "Robo-Apocalypse cancelled? Reframing the automation and future of work debate". *Journal of Information Technology*. doi.:10.1177/0268396220926511

Introna, L. D. (2016). Algorithms, governance, and governmentality: On governing academic writing. *Science, Technology & Human Values, 41*(1), 17–49.

Johri, A. (2008). Boundary spanning knowledge broker: An emerging role in global engineering firms. *38th Annual Frontiers in Education Conference* (Ieee).

Karasti, H., Baker, K. S., & Halkola, E. (2006). Enriching the notion of data curation in e-science: data managing and information infrastructuring in the long term ecological research (LTER) network. *Computer Supported Cooperative Work, 15*(4), 321–358.

Kellogg, K. C. (2014). Brokerage professions and implementing reform in an age of experts. *American Sociological Review, 79*(5), 912–941.

Kellogg, K. C., Valentine, M., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.

Kim, B., Koopmanschap, I., Mehrizi, M. H. R., Huysman, M., & Ranschaert, E. (2021). How does the radiology community discuss the benefits and limitations of artificial intelligence for their work? A systematic discourse analysis. *European Journal of Radiology*. doi:136:109566.

Kirsch, A. (2017). Explain to whom? Putting the user in the center of explainable AI. *Proc. 1st Workshop on Comprehensibility and Explanation in AI and ML* (AI*IA, Bari, Italy).

Kissling-Naf, I. (2009). From a learned society to a 21st-century broker: The Swiss Academy of Sciences as a partner in the dialogue with society. *International Journal of Technology Management, 46*(1-2), 120–131.

Langley, A., Lindberg, K., Mørk, B. E., Nicolini, D., Raviola, E., & Walter, L. (2019). Boundary work among groups, occupations, and organizations: From cartography to process. *Academy of Management Annals, 13*(2), 704–736.

Latour, B. (1986). The powers of associations. In Law J (ed.) *Power, Action and Belief: A New Sociology of Knowledge?* London: Routledge & Kegan Paul

Latour, B. (2005). *Reassembling the social: An introduction to actor-network-theory* Oxford: Oxford University Press.

Law, J. (2002). *Aircraft stories. Decentring the object in technoscience.* Durham, NC: Duke University Press

Leavitt, K., Schrabram, K., Hariharan, P., & Barnes, C. M. (2020). Ghost in the machine: On organizational theory in the age of machine learning. *Academy of Management Review In Press.*

Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2019). *Doubting the diagnosis: How artificial intelligence increases ambiguity during professional decision making.* New York, NY: New York University

Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2021). Is AI ground truth really "true"? The dangers of training and evaluation AI tools based on experts' know-what. *MIS Quarterly, Forthcoming.*

Leonardi, P. M., & Bailey, D. E. (2017). Recognizing and selling good ideas: Network articulation and the making of an offshore innovation hub. *Academy of Management Discoveries, 3*(2), 116–144.

Levina, N., & Vaast, E. (2005). The emergency of boundary spanning competence in practice: Implications for implementation and use of information systems. *MIS Quarterly, 29*(2), 335–363.

Lingo, E. L., & O'Mahony, S. (2010). Nexus work: Brokerage on creative projects. *Administrative Science Quarterly, 55*(1), 47–81.

Lipton, Z. C. (2018). The mythos of model interpretability. *Queue, 16*(3), 31–57.

Lomas, J. (2007). The in-between world of knowledge brokering. *Bmj, 334*(7585), 129–132.

Mehra, A., Kilduff, M., & Brass, D. J. (2001). The social networks of high and low self-monitors: Implications for workplace performance. *Administrative Science Quarterly, 46*, 121–146.

Meyer, M. (2010). The rise of the knowledge broker. *Science Communication, 32*(1), 118–127.

Michalski, R. S., Carbonell, J. G., & Mitchell, T. M. (2013). *Machine learning: An artificial intelligence approach.* Cham: Springer.

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence, 267*, 1–38.

Mittelstadt, B., Russell, C., & Wachter, S. (2019). Explaining explanations in AI. *FAT.* Atlanta, GA: ACM, Atlanta, GA (pp. 279–288).

Mueller, F., & Whittle, A. (2011). Translating management ideas: A discursive devices analysis. *Organization Studies, 32*(2), 187–210.

Muller, M. J., Milien, D. R., & Feinberg, J. (2009). Information curators in an enterprise file-sharing service. Wagner I, Tellio!lu H, Balke E, Simone S, Ciolfi L, eds. *ECSCW 2009*. London: Springer.

Newell, S. (2015). Managing knowledge and managing knowledge work: What we know and what the future holds. *Journal of Information Technology, 30*(1), 1–17.

Nielsen, J. A., Mathiassen, L., & Newell, S. (2014). Theorization and translation in information technology institutionalization: Evidence from Danish home care. *MIS Quarterly, 38*(1), 165–186.

Obstfeld, D. (2005). Social networks, the tertius iungens and orientation involvement in innovation. *Administrative Science Quarterly, 50*(1), 100–130.

Obstfeld, D.S., Borgatti, P., & Davis, J. P. (2014). Brokerage as a process: Decoupling third party action from social network structure. Brass DJ, Labianca G, Mehra A, Halgin DS, Borgatti SP, eds. *Research in the Sociology of Organizations.* Bingley: Emerald Books.

O'Mahony, S., & Bechky, B. A. (2008). Boundary organizations: Enabling collaboration among unexpected allies. *Administrative Science Quarterly, 53*(3), 422–459.

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy.* New York, NY: Broadway Books.

Pachidi, S., Berends, H., Faraj, S., & Huysman, M. (2020). Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organization Science.* doi:10.1287/orsc.2020.1377

Parmiggiani, E., & Grisot, M. (2020). Data Curation as Governance Practice. *Scandinavian Journal of Information Systems, 32*(1), 3––38

Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information.* Cambridge, MA: Harvard University Press.

Paul, S., & Whittam, G. (2010). Business angel syndicates: An exploratory study of gatekeepers. *Venture Capitalism, 12*, 241–256.

Pawlowski, S. D., & Robey, D. (2004). Bridging user organizations: Knowledge brokering and the work of information technology professionals. *MIS Quarterly, 28*(4), 645–672.

Preece, A., Harborne, D., Braines, D., Tomsett, R., & Chakraborty, S. (2018). Stakeholders in explainable AI. *arXiv:1810.00184*.

Raisch, S., & Krakowski, S. (2020). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Annals*. doi:10.5465/2018.0072

Reagans, R., & McEvily, B. (2003). Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly, 48*(2), 240–267.

Reay, T., Golden-Biddle, K., & Germann, K. (2006). Legitimizing a new role: Small wins and microprocesses of change. *Academy of Management Journal, 49*(5), 977–998.

Rezazade Mehrizi, M. H., van Ooijen, P., & Homan, M. (2020). Applications of artificial intelligence (AI) in diagnostic radiology: A technography study. *European Journal of Radiology*. doi:10.1007/s00330-020-07230-9

Robbins, S. (2019). A misdirected principle with a catch: Explicability for AI. *Mind & Machine, 13*(1), 1–20.

Røvik, K. A. (2016). Knowledge transfer as translation: Review and elements of an instrumental theory. *International Journal of Management Reviews, 18*(3), 290–310.

Sachs, S. E. (2020). The algorithm at work? Explanation and repair in the enactment of similarity in art data. *Information, Communication & Society, 23*(11), 1689–1705.

Saka, A. (2004). The cross-national diffusion of work systems: Translation of Japanese operations in the UK. *Organization Studies, 25*(2), 209–228.

Selbst, A. D., Boyd, D., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and Abstraction in Sociotechnical Systems. *Proceedings of the Conference on Fairness, Accountability, and Transparency*: 59–68.

Sele, K., & Grand, S. (2016). Unpacking the dynamics of ecologies of routines: Mediators and their generative effects in routine interactions. *Organization Science, 27*(3), 722–738.

Shestakofsky, B., & Kelkar, S. (2020). Making platforms work: relationship labor and the management of publics. *Theory & Society, 49*(5), 863–896.

Shulman, L. (1987). Knowledge and teaching: Foundations of the new reform. *Harvard Educational Review, 57*(1), 1–23.

Soundarajan, V., Khan, Z., & Tarba, S. Y. (2018). Beyond brokering: Sourcing agents, boundary work and working conditions in global supply chains. *Human Relations, 71*(4), 481–509.

Stovel, K., & Shaw, L. (2012) Brokerage. *Annual Review of Sociology, 38*(1), 139–158.

Sturdy, A., & Wright, C. (2011). The active client: The boundary-spanning roles of internal consultants as gatekeepers, brokers and partners of their external counterparts. *Management Learn*ing, *42*(5), 485–503.

Strauss, A., & Corbin, J. (1990). *Basics of qualitative research*. Thousand Oaks, CA: Sage Publications.

Suddaby, R., & Greenwood, R. (2001). Colonizing knowledge: Commodification as a dynamic of jurisdictional expansion in professional service firms. *Human Relations, 54*(7), 933–953.

Teather, J. L. (1990). The museum keepers: The Museums Association and the growth of museum professionalism. *Museum Management & Curatorship, 9*(1), 25–41.

Tshitoyan, V., Dagdelen, J., Weston, L., Dunn, A., Rong, Z., Kononova, O., Persson, K. A., Ceder, G., & Jain, A. (2019). Unsupervised word embeddings capture latent knowledge from materials science literature. *Nature, 571*(7763), 95–98.

Tushman, M. L., & Katz, R. (1980). External communication and project performance: An investigation into the role of gatekeepers. *Management Science, 26*, 1071–1085.

Van Den Broek, E., Sergeeva, A., Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. *MIS Quarterly Forthcoming.*

Van Maanen, J. (1973). Observations on the making of policemen. *Human Organization, 32*, 407–418.

Van Zoonen, W., & Sivunen, A. (2020). Knowledge brokering in an era of communication visibility. *International Journal of Business Communication*. doi: 10.1177/2329488420937348.

Vogel, A., & Kaghan, W. N. (2001). Bureaucrats, brokers, and the entrepreneurial university. *Organization, 8*(2), 358–364.

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries, 4*(4), 404–409.

Waardenburg, L., Huysman, M., & Agterberg, M. (2021). *Managing AI wisely: From development to organizational change in practice.* Edward Elgar, In Press.

Waldorff, S. B. (2013). Accounting for organizational innovations: Mobilizing institutional logics in translation. *Scandinavian Journal of Management, 29*(3), 219–234.

Wenger, E. (1999). *Communities of practice: Learning, meaning and identity.* Cambridge: Cambridge University Press.

Zarsky, T. (2015). The trouble with algorithmic decisions. *Science, Technology & Human Values. 41*(1), 118–132.

Zhang, Z., Nandhakumar, J., Hummel, J. T., & Waardenburg, L. (2020). Addressing the key challenges of developing machine learning AI systems for knowledge-intensive work. *MIS Quarterly Executive, 19*(4), 221–238.

# Appendix 1

*Simplified examples of the dataset used in CAS*

**Table A1. Simplified visualization of the dataset used for developing CAS**

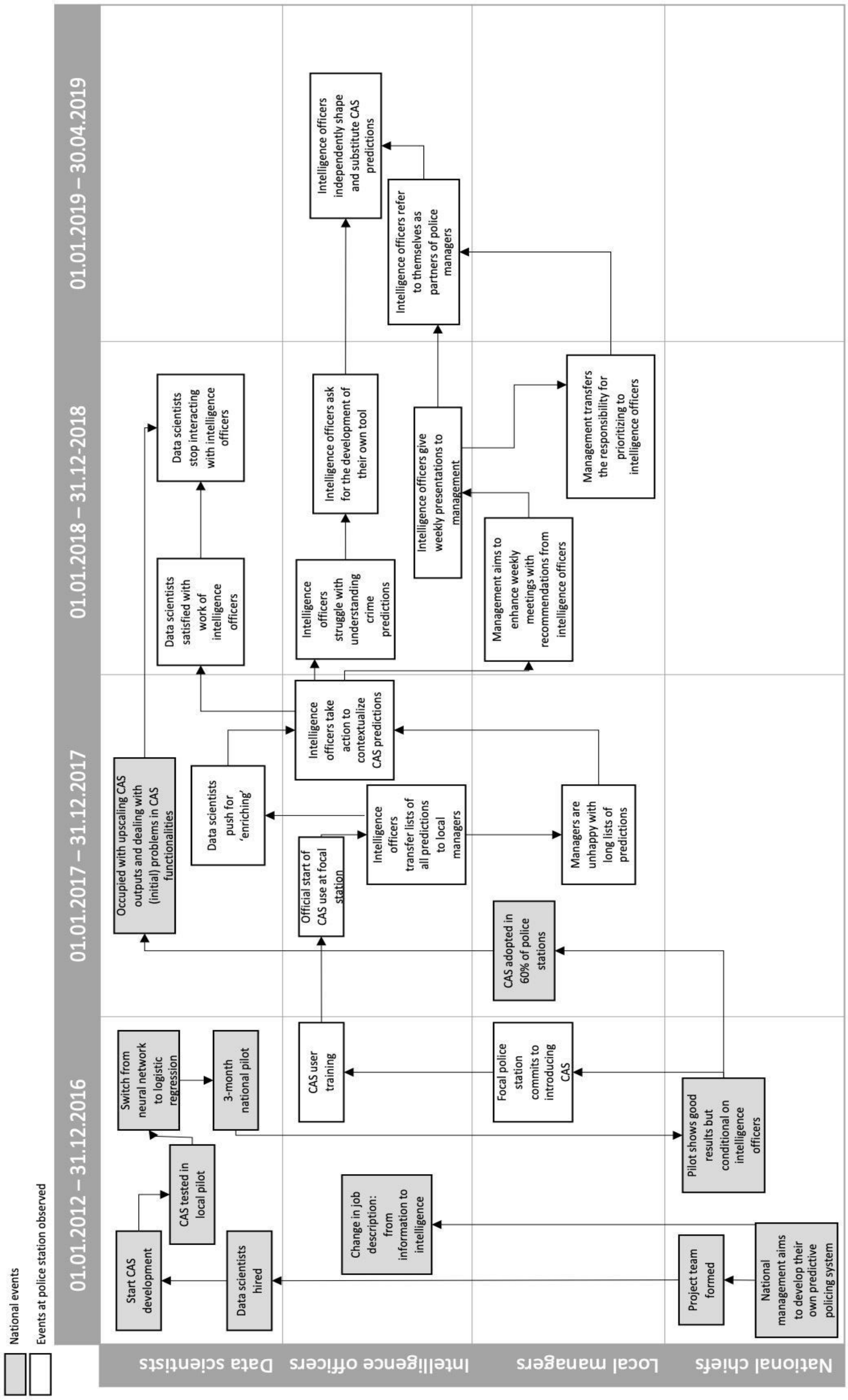
| Line | Square ID | No. of one-parent households | Avg. house price (€) | Avg. age of inhabitants (years) | Time since last burglary (days) | No. of burglaries in last 2 weeks | Burglary happened in last 2 weeks |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 10 | 150,000 | 25 | 5 | 11 | 1 (Yes) |
| 2 | 1 | 10 | 150,000 | 25 | 12 | 7 | 1 (Yes) |
| 77 | 2 | 4 | 450,000 | 40 | 2 | 25 | 1 (Yes) |
| 153 | 3 | 11 | 250,000 | 65 | 30 | 0 | 0 (No) |

**Table A2. Simulated and simplified example of predicted crime probabilities**

| Square ID | No. of one-parent households | Avg. house price (€) | Avg. age of inhabitants (years) | Time since last burglary (days) | No. of burglaries in last 2 weeks | Burglary happened in last 2 weeks | Predicted burglary |
|---|---|---|---|---|---|---|---|
| 4 | 12 | 170,000 | 28 | 6 | 13 | 1 (Yes) | 0.81 |
| 5 | 3 | 480,000 | 38 | 2 | 21 | 1 (Yes) | 0.95 |
| 6 | 9 | 220,000 | 68 | 41 | 0 | 0 (No) | 0.13 |

# Appendix 2

***Visual map of main events***



# Appendix 3

***Example of CAS time predictions compared to intelligence officers' own outputs***

| Type of crime | CAS (algorithmic predictions) | | Intelligence officers' explainable tool (historic patterns) | |
|---|---|---|---|---|
| *Home burglary* | Monday | 12:00 - 16:00 | Monday | - |
| | Tuesday | - | Tuesday | 13:00 - 14:00 |
| | Wednesday | - | Wednesday | - |
| | Thursday | 12:00 - 16:00 | Thursday | 11:00 - 12:00 |
| | | - | | 17:00 - 18:00 |
| | Friday | - | Friday | - |
| | Saturday | - | Saturday | - |
| | **Sunday** | **00:00 - 04:00** | **Sunday** | **00:00 - 01:00** |
| *Car theft* | Monday | - | Monday | 08:00 - 11:00 |
| | Tuesday | 00:00 - 04:00 | Tuesday | 14:00 - 15:00 |
| | **Wednesday** | **00:00 - 04:00** | **Wednesday** | **00:00 - 02:00** |
| | | - | | 14:00 - 15:00 |
| | | - | | 17:00 - 18:00 |
| | | - | | 20:00 - 22:00 |
| | Thursday | 00:00 - 04:00 | Thursday | - |
| | Friday | 00:00 - 04:00 | Friday | - |
| | Saturday | 00:00 - 04:00 | Saturday | - |
| | Sunday | 00:00 - 04:00 | Sunday | - |
| *Public nuisance* | Monday | - | Monday | - |
| | Tuesday | - | Tuesday | - |
| | Wednesday | - | Wednesday | - |
| | Thursday | - | Thursday | 22:00 - 00:00 |
| | Friday | - | Friday | 22:00 - 00:00 |
| | Saturday | 00:00 - 04:00 | Saturday | - |
| | Sunday | 00:00 - 04:00 | Sunday | - |

Source: Observation notes

# 4. Organizing for AI at work

Towards a holistic perspective on AI system implementation

## Abstract

Artificial intelligence (AI) systems are intended to accomplish tasks that are normally performed by humans. Their unique features – the dependence on large amounts of data, the ability to self-learn which limits explainability, and the capability to generate alternative, pattern-based insights – make them fundamentally different from the technologies that organizations have previously implemented. However, because of the strong divide in management scholarship between either a focus on technology development or on organizational change, the features of AI are generally left out when studying its influence in organizations. Using examples from five large organizations that implemented AI in their organizational processes, we unpack how organizations need to "cross the implementation line" between technology development and organizational change to organize for data, organize for explainability, and organize for alternative insights. These AI implementation practices require developers and organizational actors to engage in continuous and reflective "collaborative learning", which has socio-technical consequences for both technology development and organizing. Taking a holistic perspective on AI system implementation offers new insights to the current understanding of the relationship between AI and organizing, including a plea for slow system development.

**Keywords:** Artificial intelligence, data, technology and organizing, technology implementation

## 4.1 Introduction

Artificial intelligence (AI) refers to a field in computer science that is concerned with creating systems that can accomplish tasks that normally require human intelligence (Nilsson, 1971; Pesapane, Codari, & Sardanelli, 2018). By using learning algorithms, AI systems can generate decisions, classifications, or predictions that "resemble those of a knowledge worker" (Faraj, Pachidi, & Sayegh, 2018, p. 62). Recent technological developments – i.e., increasing datafication and computing power – have made mainstream AI implementation possible in organizations. Workers are therefore increasingly confronted with systems that are able to perform tasks previously left to humans. Accordingly, a number of scholars have turned their attention towards the potential organizational impacts of AI systems (e.g., Faraj et al., 2018; Gal, Jensen, & Stein, 2020; Glaser, Valadao, & Hannigan, 2021; Kellogg, Valentine, & Christin, 2020; Raisch & Krakowski, 2021; Von Krogh, 2018). However, as AI systems have the potential to learn and adjust unlimitedly, merely looking at the 'organizational side' is not enough to fully understand its consequences. Instead, studying AI systems requires a holistic perspective that "crosses the implementation line" (Leonardi, 2009) to include both organizational and technological change (Bailey & Barley, 2020).

In line with earlier calls for including the specific characteristics of technology for gaining a deeper understanding of organizational change (Faraj & Pachidi, 2021; Zammuto et al., 2007) and to consider "technological and organizational change as mutually constitutive in nature" (Leonardi, 2009, p. 295), we examine AI-specific features, how organizations cope with these features upon implementing AI systems, and how this triggers further technological change. We use empirical examples from data collected in organizations in a variety of fields (i.e., healthcare, law enforcement, finance, insurance, and recruitment) that have introduced AI systems in their existing work processes. In the balance of this paper, we combine existing research with the illustrations from our cases to understand how the implementation line can be crossed in the case of AI. By doing this, we emphasize a blind spot in current research on AI systems and organizational change:

organizing for AI systems calls for a continued intertwinement of organizational actors and technology developers, from the technology's initiation all the way to its deployment in practice.

## 4.2 Defining the specific features of ai systems

AI is certainly not a new phenomenon, as computer scientists have been occupied with whether machines can think since Alan Turing first asked this question in 1950 (Wooldridge, 2020). Yet, it has only been in recent years that AI systems have been increasingly developed for, and implemented in organizations. For example, AI systems can now help radiologists detect tumors that are sometimes invisible to the human eye (Aerts, 2018; Kim et al., 2021), or they can provide legal support by, within seconds, digging through lengthy documents and pinpointing where specific information can be found (Zhang et al., 2020). AI systems can reach these new application areas because they are said to have three unique features that make them fundamentally different from previous 'intelligent technologies' (e.g., knowledge management systems): (1) they depend on large amounts of data, (2) they are self-learning which limits their explainability, and (3) they offer alternative, pattern-based insights.

### 4.2.1 The data-driven nature of AI systems

For algorithms to recognize patterns and 'learn' from them requires comprehensive data sets, which makes data the central building block of AI systems. Data has been the topic of much scholarly attention over the past years and many scholars have written about the extensive digitization and datafication of organizational processes (e.g., Agostinho, 2019; Chen, Chiang, & Storey, 2012; Davenport et al., 2012; Flyverbom & Murray, 2018; Jones, 2019; McAfee et al., 2012; Newell & Marabelli, 2015; Von Krogh, 2018; Zuboff, 2019). The emergence of these studies reflects the rise of a 'data-driven logic' in organizations and management, which implies an increasing belief in the potential of data to provide better insights into, for example, internal organizational practices, market opportunities, or trends (Brynjolfsson & McAfee, 2014; Davenport & Harris, 2017; Lycett, 2017). Moreover, since "information technology has become increasingly efficient at capturing and storing task-related data across the organization" (Von Krogh, 2018, p. 404), the datafication and digitization practices of organizations have become more comprehensive (Brayne, 2017; Newell & Marabelli, 2015). Collecting data is now considered necessary for organizations to, for example, gain or maintain a competitive advantage (Gregory et al., 2020; Günther et al., 2017) or as a "strategic resource" (Hartmann & Henkel, 2020).

As data sets have become 'bigger' over time, they have grown to become so comprehensive that organizational actors cannot derive meaningful insights from just inspecting their content any longer. The need or wish to generate data-driven insights for organizing purposes therefore triggered the development and use of machine learning algorithms; a series of coded instructions aimed at solving an arithmetic problem, which can improve through experience and thus have a capacity to learn (Tegmark, 2017). In order to learn, these algorithms are programmed to automatically identify patterns in the data provided. It is generally assumed that the larger the amount of data, the bigger the opportunities for uncovering new patterns or relations between existing phenomena, and the faster the machine learning algorithm is able to develop. As such, data is the foundation for AI systems' unique capacity to learn (Brynjolfsson & McAfee, 2014; Davenport & Harris, 2017).

### 4.2.2 The self-learning and unexplainable nature of AI systems

What differentiates learning algorithms from other 'intelligent technologies,' such as knowledge management systems, is that machine learning does not follow pre-programmed, rule-based patterns (e.g., by following a decision tree), but can autonomously find these patterns by combining large data sets with advanced computational methods (Brynjolfsson & McAfee, 2017; Burrell, 2016; Davenport, 2018). This is also referred to as 'machine reasoning' (Burrell, 2016). There are several techniques through which machine learning algorithms can be programmed to learn (i.e., supervised learning, unsupervised learning, reinforcement learning). For example, in the case of so-called 'supervised learning', a machine learning algorithm autonomously derives patterns from labeled data (data sets in which each data point has its own tag) through which it learns to recognize new data points. If such a system uses a data set with images of forks (data points) all labeled as 'fork' (tags), then the algorithm will learn to connect these data points with their tags and thereafter be able to distinguish 'forks' from 'not forks'.

Because of this self-learning nature, an AI system can autonomously create connections or find patterns between data points (Balasubramanian et al., 2020; Dourish, 2016). However, this autonomy of AI systems also creates new problems, for it becomes increasingly difficult for humans to understand how these systems arrive at insights (Anthony, 2021; Burrell, 2016; Christin, 2020a; Zhang et al., 2021). Machine learning algorithms are therefore often described as "black boxes" which are closed-off or "opaque" to their users (e.g., Ajunwa, 2020; Burrell, 2016; Introna, 2016; Pasquale, 2015). Various organizational scholars have argued that this black-boxed nature of AI systems is problematic in practice, for it creates difficulties for users to trust and use these algorithms in their decision-making processes (Bader & Kaiser, 2019; Christin, 2017; Gal et al., 2020; Glikson & Wooley, 2020). Moreover, the more advanced machine learning algorithms (such as neural networks) not only leave users but even AI developers in the dark about how learning algorithms arrive at insights (Faraj et al., 2018; Lindebaum & Ashraf, 2021; O'Neil, 2016; Zhang et al., 2021). This poses new organizational challenges regarding how to implement a system that cannot be explained.

### 4.2.3 Offering alternative, pattern-based insights

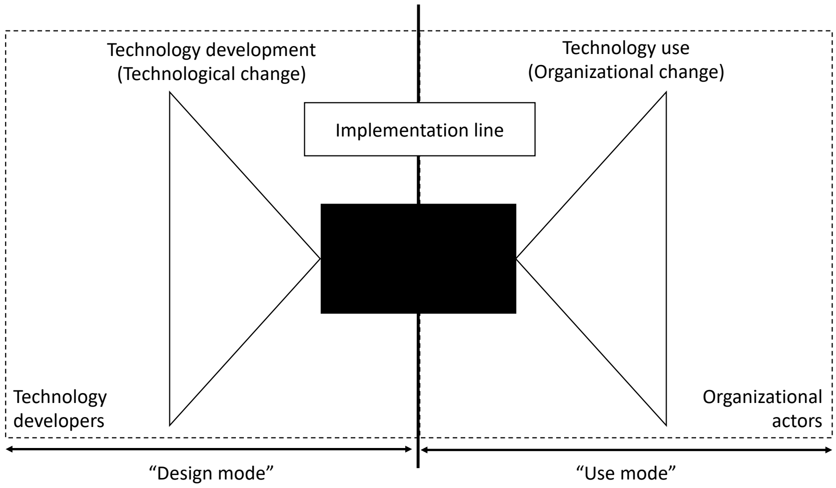
The ability of learning algorithms to autonomously create connections and find patterns between data points results in another unique characteristic to AI systems, which is that this makes them able to arrive at alternative, pattern-based insights with the potential to transcend human knowledge (Agarwal & Dhar, 2014; Agrawal, Gans, & Goldfarb, 2018; Davenport & Kirby, 2016; Domingos, 2015; Ford, 2018; Leavitt et al., 2020; Tshitoyan et al., 2019). Especially the more advanced techniques, such as reinforcement learning, add to this potential. With reinforcement learning, computer scientists aim to approach and resemble how children learn, by 'handing over' a data set to a learning algorithm and having it figure out by itself which combinations lead to a good outcome (Gollapudi, 2016). For example, when trying to teach an algorithm to play various Atari games, computer scientists used reinforcement learning. Without receiving any specific instructions, the algorithm learned by itself to play a number of different games but was especially exceptional in playing 'Pong' (a game where you have to remove a brick wall by using a ball and a bat). Looking back at the playing history, the learning algorithm started off badly, missing the ball nearly every time. Yet, slowly the system became better and eventually developed new strategies for optimally playing the game, obtaining the highest number of points with the least hits (Wooldridge, 2020).

In general, according to computer scientists, the alternative, pattern-based insights promise to be more objective, efficient, and new (Cukier & Mayer-Schönberger, 2013). They are argued to be more *objective* because the data that is used for training learning algorithms is supposed to be 'raw' which, compared to human experts, represents reality more holistically and objectively (Agrawal et al., 2018; Cukier & Mayer-Schönberger, 2013; Jones, 2019; Kitchin, 2014; Siegel, 2016; Van den Broek et al., 2021). For example, for tasks such as employee selection or crime judgement, scholars have argued that human biases or irrational decisions can be avoided by using AI systems that can automatically derive patterns from large amounts of data (Kleinberg et al., 2017; Kuncel et al., 2013). Because of the speed with which AI systems can analyze data and uncover underlying patterns, AI-based insights are expected to be more *efficient* (Domingos, 2015; Schildt, 2017). For example, Zhang et al. (2020) described how lawyers engaged in the development of an AI system that could analyze court files containing hundreds of pages and could suggest where to find a specific data source in only seconds, something that would normally take lawyers weeks to achieve. Finally, because learning algorithms can not only find patterns or connections that have been prepared by humans, but generate their own 'ground up' rules, AI-based insights are promised to be *new* or different from what was known before (Bonde Thylstrup, Flyverbom, & Helles, 2019; Henriksen & Bechmann, 2020; Kitchin, 2014; Leavitt et al., 2020). For example, Beck et al. (2011) have described how, in the field of radiology, a machine learning algorithm for analyzing breast tissue to predict breast cancer discovered new markers that could indicate breast cancer which were previously unknown to radiologists.

## 4.3 The role of technology for understanding organizing

The unique features of AI systems bring to the fore questions about how these features are implicated when machine learning algorithms are implemented and deployed in an organizational context. The question of whether and how technology influences organizing is not new to organizational literature. In their recent work, Faraj and Pachidi (2021) date such questions as far back as Marx's work in 1847 and Schumpeter's in 1942. Interestingly, organizational scholars have only recently pointed out that, while questions around technology and organizing might have been around for nearly two centuries, many organizational scholars have refrained from taking into account how specific features of technology and forms of organizing are intertwined (Bailey & Barley, 2020; Faraj & Pachidi, 2021; Faraj et al., 2018; Kellogg et al., 2020; Leonardi & Barley, 2010; Orlikowski, 1992). In the past, some organizational scholars have specifically called for the inclusion of technological features to understand organizational form and change (Zammuto et al., 2007). To understand why this still did not happen, Leonardi (2009) provided a useful model in which he emphasized the tendency for organizational scholars to maintain a fixed (yet artificial) line between technology development and technology use (see Figure 4.1). Leonardi (2009) argued for the need to "cross the implementation line" to understand how technological and organizational change are inherently intertwined. In addition, some recent scholars have started to unpack specific technological features (e.g., Brayne, 2017; Faraj et al., 2018; Gal et al., 2020; Van den Broek et al., 2021). For example, in her quest to understand "what data can do," Christin (2020b) attempted to break down the umbrella concept "data" into smaller types (e.g., metadata, biometrics, indicators) and used this to unpack how mechanisms such as "tracking" or "nudging" can emerge. Yet, the perspective in which the specific features and thus the agency of technology is taken into account for understanding organizational phenomena, is still largely neglected or put aside in the field of organizational research (Faraj & Pachidi, 2021; Leonardi & Barley, 2010).

**Figure 4.1 The "implementation line" Leonardi (2009, p. 294)**




As we discussed above, the unique features of AI systems make them fundamentally different from, and potentially much more consequential than any other technology that organizations have previously implemented. This makes having a deep understanding of the relationship between technology development and organizational deployment even more pressing. As AI systems depend on large amounts of data, this requires bringing together organizational processes (to gather data) and technology development (to learn from that data). Because AI systems are self-learning, organizational involvement is required to validate the system and decide whether it is 'good enough'. And because AI systems can generate alternative, pattern-based insights, technology developers have to remain involved when the system is deployed in the organization to make sure the insights continue to 'make sense' (Waardenburg, Huysman, & Agterberg, 2021). Accordingly, the plea for a more holistic perspective on studying technology implementation (Bailey & Barley, 2020; Leonardi, 2009; Leonardi & Barley, 2010) is more urgent than ever. Yet, despite attempts at unpacking specific features of technology (e.g., Brayne, 2017; Christin, 2020b; Faraj et al., 2018; Gal et al., 2020; Van den Broek et al., 2021) and studies regarding the potential organizational consequences of emerging technologies, such as AI systems (e.g., Faraj et al., 2018; Gal et al., 2020; Glaser et al., 2021; Kellogg et al., 2020; Raisch &

Krakowski, 2021; Von Krogh. 2018), what is still left to be studied is how the “implementation line” can be crossed in the case of AI, in which technology development and organizational deployment are often worlds apart.

## 4.4 Implementing ai systems in practice

In this section, we present five illustrative cases that offer deep insights into the relationship between the AI-specific features and organizational implementation. The examples are derived from a collective research effort and for every illustration at least one of the authors was involved in the data collection. By bringing together the various cases of AI implementation, we saw strong overlaps between them and decided to further explore this. We constructed case narratives, between 10 and 14 pages each, in which we provided detailed information about the AI system and the implementation process. We then zoomed in on the practices enacted by the organizations in the implementation of the AI systems and found three overlapping “AI implementation practices” that linked to the technology’s key features: (1) organizing for data, (2) organizing for explainability, and (3) organizing for alternative insights. We went back to the literature related to AI implementation and found that our cases further substantiated or offered alternative perspectives to the current understanding of AI implementation in organizations. Below, we first give a brief summary of the five cases, after which we take a closer look at the three AI implementation practices that we identified, which we embed in the literature on data-driven work and organizing, black-boxed or opaque technologies, and the changing nature of work.

### 4.4.1 Introduction of illustrations

***Predictive policing.*** Since 2008, police departments across the world have turned their attention to developing and using AI systems to predict where and when a crime is most likely to occur. The main aim of implementing these systems is not to “catch thieves” but to more efficiently and effectively schedule and deploy police officers. One of the most well-known examples is PredPol, developed by the Los Angeles Police Department, but there are many more examples across the world. In 2012, the Dutch police set up a project group to develop their own “predictive policing” AI system. These systems are not undisputed. For example, mainstream media regularly claim that learning algorithms can create ‘self-fulfilling prophecies’ of crime. By carrying out targeted actions at predicted locations, police officers automatically register more crimes at those locations. Since these crimes count as data points, to be used for training learning algorithms, a location can become labeled as a ‘high crime area’ through a vicious cycle of algorithmic predictions. Another common argument is that such systems reinforce profiling (e.g., targeting people with a specific ethnic background), as these systems contain prejudices that have been ingrained in police work for decades. Partially due to these warnings, the Dutch police hired a group of data scientists in 2012 to create an AI system that would be less sensitive to these criticisms. The team eventually built a supervised learning algorithm using a relatively simple logistic regression analysis and called it the “Crime Anticipation System” (CAS). To predict a week in advance where and when a crime will happen, the variable “incident versus no incident” is related to approximately 55 predictors, such as previous crimes, average household income, and household size. To reduce chances of profiling, no individual-related variables are included. Based on the existing data, the algorithm is trained to learn a mapping between the predictive variables and whether an incident did or did not occur. To this day, CAS predicts a week in advance where (per 125m$^2$ block) and when (per 4-hour timeframe) the chances of pattern-based crimes (e.g., burglary, car theft, robbery) are highest. CAS is used across almost all 168 Dutch police stations (Waardenburg et al., 2021).

***Predictive tumor modeling.*** In recent years, the healthcare industry has faced a shift towards “value-based healthcare” (VHBC) aimed at both maximizing the quality of patient care as well as reducing the costs of providing care. This has major consequences for many areas of medical expertise but especially for radiologists. After all, radiologists are often frontrunners when it comes to technological innovation (e.g., the x-ray innovation was the trigger for the profession to emerge in the first place). In the past ten years, the images developed and used by radiologists have become digitized; in other words, they are digitally produced, reported, and archived. The increased amount of digital imaging available has led to a corresponding demand for quantitative analysis of these images. Accordingly, many hospitals are now implementing AI systems to automate tasks that previously belonged to the work of radiologists, such as image review and image processing support. This is also the case at a large Dutch hospital, where members of the radiology department are involved in the development and deployment of a learning algorithm focused on recognizing and predicting the growth pattern of a vestibular schwannoma (VS). A VS is a benign tumor that grows slowly within the ear and skull. Despite being benign, the slow but continued growth of a VS can put pressure on the nerves and brainstem, causing symptoms such as hearing loss, dizziness, balance problems, and facial paralysis. The supervised learning algorithm for modeling VS tumors serves two purposes. First, it can automatically process MRI scans, segment the VS tumors, and calculate the volume of tumors. Second, based on scans and clinical information from the Ear, Nose, and Throat (ENT) department, a predictive model estimated the development of the VS tumors. This way, scans can be scheduled and performed more efficiently, taking time-consuming tasks off the hands of radiologists, and making follow-up treatments for patients faster and more personalized (Kim et al., 2021).

***Predictive people analytics.*** Many organizations around the world face a growing number of applicants. MultiCo[15], one of the world's largest Fast-Moving Consumer Goods organizations, faces more than 10,000 applicants every year for their European talent programs. To cope with the large number of applicants and to improve the efficiency and objectivity of the hiring process, MultiCo asked and external technology developer (NeuroYou[16]) to create an AI system for recruitment purposes. NeuroYou developed an AI system to be used in the first round of the talent program selection process. In this round, applicants are asked to play fifteen online neuroscientific games, which assess traits such as concentration, emotional intelligence, and leadership qualities. The supervised learning

[15] Pseudonym
[16] Pseudonym

algorithm used in the AI system is trained on the profiles of successful MultiCo employees. Having learned a mapping between character traits and employee 'success,' the system predicts whether applicants are likely to be successful employees within MultiCo (and should therefore continue to the next round of interviews). The learning algorithm was first implemented at the Sales department of MultiCo Europe but, since it has been evaluated as a success by the organization, is now also in use at the IT department and at MultiCo's global headquarters in the United States. Recently, new discussions have started with NeuroYou about extending the use of AI beyond the first selection round and also using automatic video analysis software. The use of AI systems at MultiCo is thus still also in constant development (Van den Broek et al., 2021).

***Fraud prediction.*** Over the last years, the financial sector has increasingly been confronted with the need for societal engagement. For example, banks play an important role in the fight against financial crime. Across the world, around 2,400 billion euros a year account for criminal transactions, including money laundering and financial terrorism. Detecting suspicious transactions is much like looking for a needle in a haystack; it takes a lot of time and requires very precise work. Banks around the world are therefore trying to find technological solutions to increase the effectiveness of detecting suspicious transactions to fulfill their responsibilities. Specifically focusing on money laundering, BankCo[17], a large bank operating in the European market, developed the so-called 'Anti-Money Laundering' (AML) system; an AI system for generating targeted, potential laundering alerts. The system uses both supervised and unsupervised models. The supervised model is trained on existing alerts, finding a mapping between an alert and the predictive variables. This way, the supervised model can improve the quality and efficiency of the alerts already known to BankCo. In addition, the unsupervised model is a type of "anomaly detection model;" a model aimed at detecting outliers or rare actions. The unsupervised model can discover new, unknown money laundering patterns and has the potential to generate alerts previously unknown to BankCo. Both the supervised and the

[17] Pseudonym

unsupervised model are implemented in the daily work of the human money laundering analysts.

***Helpdesk chatbot.*** The insurance industry faces customer expectations around 24/7 service and immediate support. In response to these expectations, insurance companies are implementing chatbots that have the benefits of 24/7 availability. While chatbots are in use for a number of years already, most have not proven to be very useful because they had to be pre-programmed and could only answer a very limited number of questions. For example, the earlier chatbots required pre-composed scripts that resembled question-answer conversations typically performed by helpdesk employees (e.g., questions about the coverage of certain policies or how to make adjustments to insurance contracts). Because these scripts provide a fixed sequence of steps that a chatbot could follow, these tools are called “linear” chatbots. InsureCo[18], a large international insurance company, also started with a pre-programmed linear chatbot but has continued to work on the tool and has developed it into a supervised learning algorithm using natural language processing. This so-called “nonlinear” chatbot can solve a much wider variety of queries because the machine learning algorithm is trained to recognize the meaning a particular phrase can have in a particular situation. For example, the AI system is trained to recognize all possible words that represent the subject or the direct object; in the sentence ‘there is damage to my car’, the learning algorithm is trained to recognize the subject (‘damage’) and the direct object (‘car’). In this way, the learning algorithm can find the connections between the different words and learn to unpack the intention behind a large number of questions, which helps to provide the right information to the customer.

Table 4.1 provides an overview of the details related to the above-mentioned five illustrative cases. Below, we use these examples and discuss them in further detail to unpack the organizing efforts of implementing AI systems in practice.

[18] Pseudonym

**Table 4.1 Overview of illustrations**

| Case | AI system | Algorithm | Development | Reasons for development | Current status |
|---|---|---|---|---|---|
| Police | Predictive policing 'CAS' | Supervised learning (logistic regression) | Internal | - Growing capacity problems<br>- More objective decisions<br>- Part of a broader strategic initiative | Fully implemented |
| Radiology | Predictive tumor modeling | Supervised learning (image recognition) | Internal | - Increasing efficiency<br>- More consistent diagnoses<br>- Part of a broader strategic initiative | Being implemented |
| MultiCo | Predictive people analytics | Supervised learning (with neuro-scientific games) | External | - More objective decisions<br>- Better overview of applicants<br>- Part of a broader strategic initiative | Fully implemented |
| BankCo | Anti-money laundering (AML) system | - Supervised learning for known alerts<br>- Unsupervised learning for new alerts | Internal | - Greater institutional pressure to find solutions to, e.g., track money laundering practices<br>- Labor intensive existing methods | Fully implemented |
| InsureCo | Helpdesk chatbot | Supervised learning (natural language processing) | Internal | - Reduce workload of helpdesk workers<br>- Increase efficiency of helpdesk workers<br>- Part of a broader strategic initiative | Fully implemented |

### 4.4.2 Organizing for data

As we have discussed above, data is the fundamental building block of AI systems. Big data is a 'big' topic, which obtained a lot of scholarly attention (e.g., (e.g., Agostinho, 2019; Chen, Chiang, & Storey, 2012; Flyverbom & Murray, 2018; Gregory et al., 2020; Jones, 2019; Lycett, 2017; Newell & Marabelli, 2015). Yet, what data should be about ('the content') when developing AI systems for organizing purposes, and how data is constructed in a way that fits AI system development is often overlooked or put aside in organizational literature (Parmiggiani, Østerlie, & Almklov, 2021). This is specifically problematic because data is used to train learning algorithms, which means that how data is gathered, produced, and constructed can have fundamental consequences for the functioning of AI systems (Pachidi et al., 2020). Our case examples show that to develop AI systems that fit within organizational processes, data gathering is not just a 'technical' activity on the side of AI developers. Instead, to cope with the data-driven nature of AI systems requires active organizational involvement around *organizing for data*; a collaborative process between AI developers and organizational actors to generate the right data set, which often requires new data-related tasks, roles, and expertise within an organization.

Making AI systems fit well with organizational processes preferably requires data that is derived from within the organization, which means that to ensure that sufficient data is available to train a learning algorithm, organizational activities around data gathering and data construction have to be performed. For example, for the development of the recruitment AI system at MultiCo, the developers asked MultiCo's HR-professionals to provide data about the organization's own employees. The developers were convinced that, if they trained the learning algorithm using data that included characteristics, such as personal traits and skills, of MultiCo's own employees, the AI system would be better able to make accurate and organization-specific predictions. However, this data was not yet available and required MultiCo's HR-professionals to approach 300 employees and ask them to play online neuroscientific games made available by the AI developers. These games measured, for example, employees' ability to concentrate, their emotional intelligence, and their leadership qualities. In addition, the developers also asked the HR-professionals to provide performance data (i.e., data about how well each employee performed in the organization) for each of the 300 employees. This way, the scores of the online games could be linked to the overall performance of employees, which helped to train the learning algorithm to detect which game scores belonged to 'successful' employees. These were used to predict the suitability of new applicants (Van den Broek et al., 2021).

Organizing for data is thus a key practice already during the development phase of a learning algorithm and can include organizational activities like adding new tasks to existing roles, which can have implications for existing work practices, such as in the example of the HR-professionals at MultiCo described above. In more extreme cases, it can also lead to completely new roles for data production and construction. In various organizations we now see so-called "data engineers" who are responsible for gathering, cleaning, and preparing datasets for developing and training AI systems (DalleMule & Davenport, 2017; Ross, 2019). Such a new role was observable at the radiology department of a large hospital, where its members were developing an AI system to predict the growth rate of an ear tumor. To train the learning algorithm, the department already had a large data set available with existing ear tumor scans. However, just having these images available was not enough. Each tumor had to be outlined in the scans, so that the algorithm could learn to recognize and distinguish images of tumors from 'not-tumors'. Since the members of the radiology department were planning to develop more AI systems than just the one for predicting ear tumor growth, and because analyzing and manually drawing contours around the tumors in the scans required a considerable time investment, the hospital decided to create a new department dedicated to this data work. They hired non-radiologists for a so-called "Imaging Services Group" who became solely responsible for data preparation (Kim et al., 2021).

Of course, there are ethical considerations organizations have to be aware of when organizing for data. Datafication is widely scrutinized in recent literature (e.g., Crawford & Schultz, 2014; Lyon, 2014; Mai, 2016; Tene & Polonetsky, 2013; Van Dijck, 2014) and organizations are increasingly criticized regarding their motives for data collection (e.g., boyd & Crawford, 2012; Zuboff, 2019). Studies question the objectivity of data by emphasizing that categorization is dependent on human judgment (e.g., Barocas & Selbst, 2016; Elish & boyd, 2018; Gitelman, 2013; O'Neil, 2016) and some empirical studies also maintain that collected data will never represent reality (e.g., Pine & Liboiron, 2015; Vad Karsten, 2020). For example, journalists tactically upload "quick-and-dirty" articles to increase their publication score (Christin, 2017) and employees often consider management expectations when reporting their work activities (Cunha & Carugati, 2018; Pachidi et al., 2020). Also, AI developers speak a "computer language" that is required for coding learning algorithms that is often unfamiliar to organizational actors (Pachidi et al., 2020; Slota et al., 2020; Van den Broek et al., 2021). This can lead to confusion, miscommunication, or failures when organizing for data. Returning to the example of the recruitment AI system at MultiCo, the organization faced the need of the HR-professionals to acquire data-related knowledge to collect data in a responsible manner that would not be detrimental to the existing employees. MultiCo therefore facilitated training courses to help the HR-professionals obtain data-related knowledge about, for example, sample selection, data quantity and quality, and understanding data legislation, such as the General Data Protection Regulation (GDPR). At the same time, MultiCo also facilitated the interaction between the developers and the HR-professionals, so that the developers could find out how to best communicate their needs and wishes for data collection to the HR-professionals but also for them to understand the potential pitfalls and shortcomings of the data (Van den Broek et al., 2021). To cope with the potential issues related to organizing for data, organizational actors thus need to acquire statistical and data-related knowledge and technology developers need to obtain the more 'social skills' related to organizing.

In sum, the data-driven nature of AI systems requires organizing for data, which has socio-technical consequences for organizational actors and for technology developers. On the organizational side, it requires new data-related tasks, roles, and expertise. On the side of the technology developers, it needs a deeper understanding of datafied work processes as well as new, organization-related social skills.

### 4.4.3 Organizing for explainability

How AI systems learn and whether they work are questions generally dealt with by computer scientists or AI developers (e.g., Hand & Khan, 2020; Menzies & Pecheur, 2005; Xie et al., 2011). These are often technical questions regarding the measurability of outcomes (e.g., predictions must be accurate in at least 90% of the cases), which methods lead to the best results, and whether outcomes make sense mathematically (e.g., how are data patterns modeled). This is also why technical "explainability" is now often considered an important condition for AI systems (e.g., Arrieta et al., 2020; Doran, Schultz, & Besolt, 2017; Miller, 2019; Robbins, 2019).[19] Less attention is paid to whether and how AI systems work in an organizational context, which is a challenging question given learning algorithms' black-boxed nature (Ajunwa, 2020; Burrell, 2016; Christin, 2020a; Introna, 2016; Pasquale, 2015). However, our cases show that implementing AI systems in an organizational context requires activities that go beyond looking at technical questions and conditions and include whether predictions make sense in practice. In other words, it requires *organizing for explainability*. For example, when the Dutch police implemented their predictive policing AI system, the organizational requirement was not only whether crime predictions were technically correct but also if the predictions made sense in relation to the existing police operations they had to be included in.

Organizing for explainability is a cumbersome and challenging task, especially because there is a large difference between the mathematical reasoning used in AI systems and human reasoning based on often years of domain knowledge (Burrell, 2016; Christin, 2020a). For example, by means of calculations, an AI system might be able to predict whether a convicted criminal will reoffend. However, a judge generally builds on years of expertise (instead of complex calculations) to make a decision. This difference in reasoning makes it difficult for judges to fully trust and accept AI-based predictions (Christin, 2017). In line with these struggles, some studies refer to the need to interpret or translate insights produced by learning algorithms to make them resonate with human reasoning (Gal et al., 2020; Henke, Levine, & McInerney, 2018; Waardenburg, Sergeeva, & Huysman, 2018). According to these organizational scholars, this requires new roles such as "algorithmic brokers" who dedicate their time and work to translating, interpreting, or explaining algorithmic outcomes and to "sell" these to their users (Gal et al., 2020; Kellogg et al., 2020). At BankCo, where they implemented the AI system to detect money laundering, management appointed a number of experienced analysts to act as algorithmic brokers to guide other analysts and help them work with the AI-based insights. To support the new tasks of the brokers, the AI developers created a "translation machine;" a technical solution

[19] E.g., High Level Expert Group on AI Ethics and Guidelines for Trustworthy AI (2019); UNESCO ad hoc expert group for recommendations on the ethics of artificial intelligence; GDPR legislation in Europe has even included this as an explicit condition when validating and testing AI.

that, for example, produced a list of the top three indicators of an alert or a top 20 of the most suspicious transactions. Indicators like unusually large cash withdrawals or money exchange transactions of a noteworthy large amount were used by the broker analysts to put fraud predictions in context and to support their colleagues in trusting and using these predictions for their fraud investigations.

While the role of an algorithmic broker seems to be the ideal solution at first, creating new roles for algorithmic brokerage has important implications for the nature of AI. One of the general assumptions regarding AI systems is that, because they generate their own rules and connections based on large amounts of data, they can produce more objective insights compared to human analyses (Davenport & Kirby, 2016; Mayer-Schönberger & Cukier, 2013). However, a consequence of algorithmic brokerage is that AI-based insights are almost never directly transferred to users but first interpreted or translated. As any human decision-making involves subjective influences – such as short-term memory, personal preferences, and cultural backgrounds – when algorithmic brokerage activities are used to close the gap between AI systems and their users, objectivity of results cannot be taken for granted (e.g., Waardenburg et al., 2018). When the Dutch police started using an AI system for predicting crime, they also appointed algorithmic brokers to translate the predictions towards the police. To make the predictions more relevant, the brokers added information such as pictures of potential suspects of the predicted crimes, even though this was not included in the AI system. Algorithmic brokers therefore do not perform a neutral "translator" role (Henke et al., 2018), maintaining the supposed objectivity of algorithmic predictions, but they can actively shape insights by including their own interpretations.

To keep grip on how predictions are transformed in practice, organizing for explainability means ensuring transparency in brokerage work by creating feedback loops between algorithmic brokers, AI developers, and users (see Figure 4.2). In the case of the recruitment AI system at MultiCo, the organization designated a so-called "people analytics" (PA) team to perform the work of algorithmic brokers. This team made sure that predictions about applicants were usable for managers who handled the applications by, for example, helping managers visualize the scores of applicants compared to high and low performing employees. In addition, the team was also responsible for providing feedback to the AI developers regarding the usability of predictions in practice and potential areas of improvement. One of the results of this feedback was that the AI developers integrated a spider chart function into how the output of the AI system was presented. By including feedback loops, algorithmic brokers not only translate and interpret the AI system's outputs toward users, they can also translate the user domain towards AI developers.

**Figure 4.2 Feedback loops in algorithmic brokerage**


In sum, the self-learning nature of AI systems requires organizing for explainability. This means that new roles for algorithmic brokering emerge, in which maintaining transparency and interaction between users, brokers, and developers is of central importance. Organizing for explainability also has socio-technical consequences for developers, as this means that they should go beyond finding technical solutions to explain AI systems and require deeper knowledge about how AI-based insights resonate in the workplace.

### 4.4.4 Organizing for alternative insights

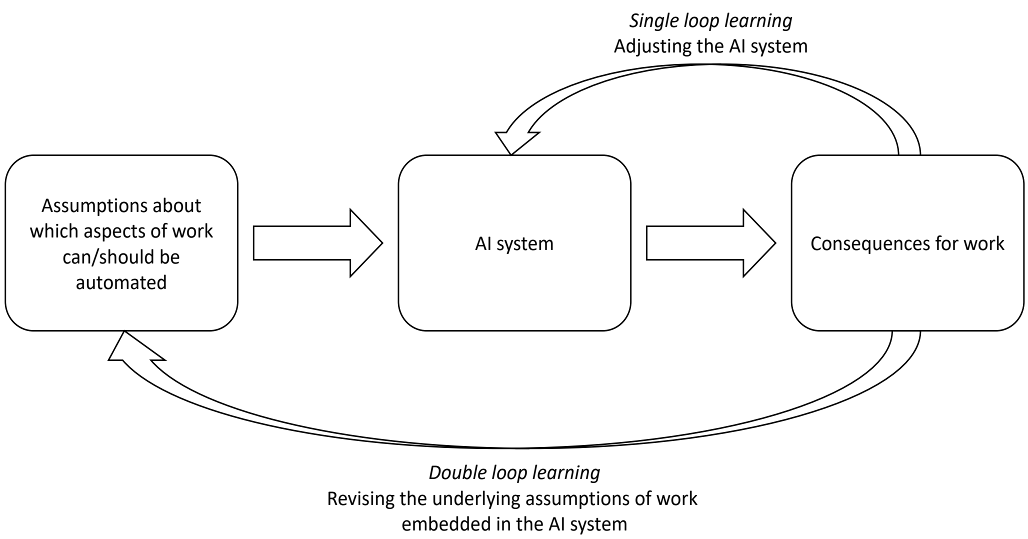
The third unique feature of AI systems is their ability to offer alternative pattern-based insights. One of the central aims of implementing AI systems is to automate or augment knowledge work but the alternative insights are not an automatic recipe for success, as they are sometimes regarded with distrust which might even lead to disuse of the system (e.g., Bader & Kaiser, 2019; Christin, 2017; Christin & Brayne, 2020; Glikson & Woolley, 2020; Jussupow, et al., 2021; Pachidi et al., 2020). To go beyond distrust and disuse to automate and augment knowledge work (Raisch & Krakowski, 2021) requires *organizing for alternative insights*, which involves anticipating wider impacts and ripple effects, balancing automation and augmentation of work, and organizing for reflection to trigger the ability for organizational learning from these insights.

AI systems are implemented not only at the level of "factory workers," as the alternative insights are specifically targeted at knowledge workers. This means that the consequences of these systems for work will be different than what we have seen with previous technologies. Prior research on knowledge work has shown that knowledge consists of more than just knowing how to perform individual tasks and includes collaboration between experts who collectively contribute to and share it (e.g., Brown & Duguid, 2001; Carlile, 2004; Wasko & Faraj, 2005). This means that the expertise included in, for example, making a decision is usually derived from a network or "community" of actors (Brown & Duguid, 2001). For example, to write a headline piece, journalists not just depend on their own knowledge of writing articles, but also on the expertise of others on the topic they have selected. Developing and implementing AI-based insights is therefore likely to have consequences that go beyond the targeted professionals and create so-called "ripple effects" in work processes with often unexpected consequences (Baptista et al., 2020; Orlikowski & Scott, 2016). For example, as discussed above, generating AI-based insights about the growth-rate of ear tumors had consequences beyond the day-to-day work of radiologists and included the emergence of a new "Imaging Services Department" with expertise in tagging tumor scans (Kim et al., 2021). Similarly, the introduction of an AI system for predicting crime at the Dutch police was aimed to support police managers in their decisions about the allocation of work and resources, but it also impacted the work of patrol officers in unanticipated ways. Since the learning algorithm largely depended on new data for learning, data production became a key task for patrol officers who, as a consequence, spent an increasing amount of time behind their computers to report crime instead of "catching thieves" (Waardenburg, Sergeeva, & Huysman, 2021).

There is also a lot of debate about how workers may or may not fall victim to AI systems' ability to take over repetitive and routine tasks (e.g., Jussupow et al., 2021; Manyika et al., 2017). For example, in the case of radiology, some computer scientists argue that we should "stop training radiologists now" (Mukherjee, 2017, p. 12) because learning algorithms are starting to recognize malignancies with greater accuracy than human radiologists. Yet, practice shows that radiologists embed AI systems in their work practices in such a way that they are able to spend more of their valuable time on complex diagnoses (Kim et al., 2021). Work can be augmented by automating routine processes, leaving room for more meaningful work, such as personal contact with clients or more intellectually challenging and knowledge-intensive tasks (Huysman, 2020; Raisch & Krakowski, 2021). Effectively organizing for alternative insights is therefore not a matter of choosing between automating or augmenting work (e.g., Daugherty & Wilson, 2018; Davenport & Kirby, 2016), but requires finding a healthy balance between the two (Raisch & Krakowski, 2021). However, there is also a downside to this. For example, in the case of the implementation of the helpdesk chatbot, the chatbot covered simple, straightforward questions which were normally taken up by human helpdesk workers. At first, automating the simple tasks seemed to give helpdesk workers more agency and to result in more challenging and fulfilling tasks. However, the helpdesk workers were required to constantly take on emotionally heavy cases with no possibility to 'breathe' in-between (e.g., by taking up one of the simpler requests). While emphasis is placed on collaboration between workers and AI systems in new forms of "hybrid intelligence" (Ebel et al., 2021; Gal et al., 2020; Glaser et al., 2020; Graef et al., 2020; Mirbabaie, Stieglitz, & Frick, 2021) and between AI developers and organizations for automation to contribute to the augmentation of work (Pasquale, 2020; Raisch & Krakowski, 2021), understanding the unintended consequences of AI implementation with the aim to augment work requires deep involvement in the targeted work processes.

Finally, to make use of the potentially increased objectivity, efficiency, and novelty of AI-based insights means for organizations to reflect on and learn from them. This links to what has been widely discussed in organization literature as "double loop learning" (Argyris & Schön, 1997). By reflecting on the insights generated through machine learning, organizations can uncover (and thus change) existing assumptions or prejudices about which aspects of work could or should be automated (see Figure 4.3). For example, at MultiCo, in the development of an AI system for recruitment, the first tests of the learning algorithm made visible that the organization almost always recruited “extraverted” people (Van den Broek et al., 2021). This form of double loop learning requires organizational actors and AI developers to collaborate closely to progress in both machine learning and organizational learning, as reflecting on underlying biases in human decision-making and assumptions about work can lead to changes in existing work practices and forms of organizing.

**Figure 4.3 Single and double loop learning in the case of AI systems**




In sum, the alternative, pattern-based insights that AI systems can offer requires organizing for these insights in practice. For organizations, this means anticipating the wider impacts and ripple effects that implementing alternative insights can have, balancing automation and augmentation of existing work practices, and organizing for reflection to learn from these alternative insights. For developers, this means that “keeping the human in the loop” remains of central importance across the development and implementation of AI systems. Moreover, developers are also required to have a deeper understanding of how machine learning and organizational learning relate, to arrive at new forms of “hybrid intelligence” (see Table 4.2 for an overview of the three AI implementation practices).

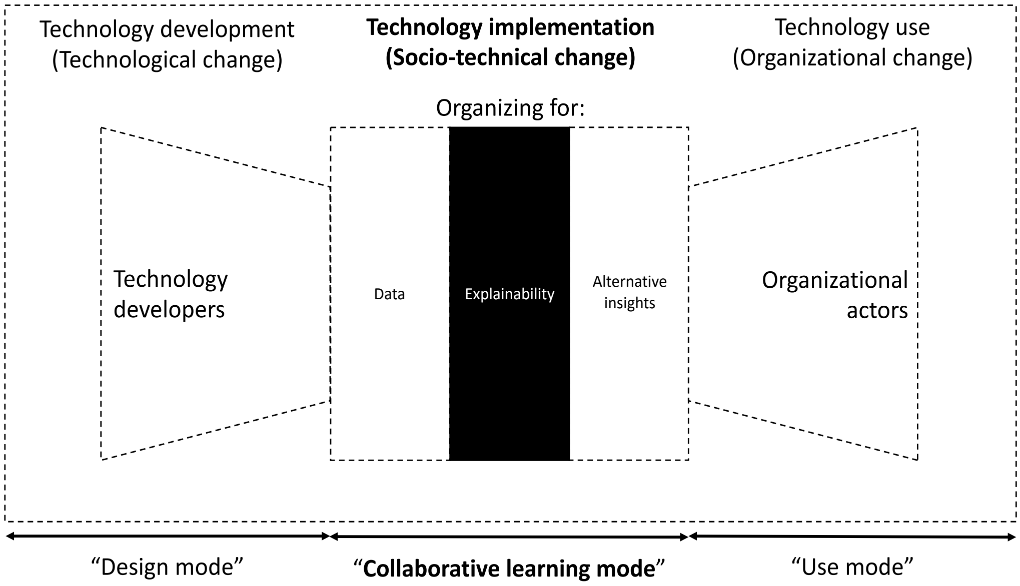
**Table 4.2 Features of AI systems and new implementation practices**

| Features of AI system | AI implementation practices | Socio-technical consequences for organizational actors | Socio-technical consequences for technology developers | Examples |
|---|---|---|---|---|
| **Crossing the implementation line** | | | | |
| Data-driven nature | Organizing for data | - New data-related tasks<br>- New data-related roles<br>- New data-related expertise | - Deeper understanding of datafied work processes and how to use the data for training learning algorithms<br>- New, organization-related 'social skills' | - 300 employees making data for a recruitment algorithm<br>- New department at a hospital for 'data engineering' work<br>- HR professionals learning about data and statistics |
| Self-learning and unexplainable nature | Organizing for explainability | - New roles for algorithmic brokering<br>- Maintaining transparency and interaction in brokerage work (e.g., through feedback loops) | - Deeper knowledge about how AI-based insights resonate in the workplace<br>- New possibilities to adjust how outcomes are presented to users | - Analysts tasked with assisting colleagues in the use of an AI system for fraud prediction<br>- Brokers making crime predictions useful by adding additional information<br>- Brokers providing feedback to AI developers when developing a recruitment AI system |
| Offering alternative, pattern- based insights | Organizing for alternative insights | - Anticipating wider impacts and ripple effects<br>- Balancing automation and augmentation of work<br>- Organizing for reflection | - "Keeping the human in the loop" and a focus on "hybrid intelligence"<br>- Deeper understanding of how machine learning and organizational learning relate | - New types of work at the radiology department and the Dutch police<br>- Changing work of helpdesk workers<br>- Reflecting on biased decision-making in recruitment |

## 4.5 Contributions

In this study, we addressed the question of how technology developers and organizational actors can "cross the implementation line" (Leonardi, 2009) in the case of AI systems by unpacking the relationship between the specific features of the technology and organizing. We discussed how crossing the implementation line in the case of AI systems means enacting AI implementation practices to organize for data, explainability, and alternative insights, in which both technology developers and organizational actors have to be involved for successful AI implementation. As such, crossing the AI system implementation line means technology developers stepping out of the "design mode" and organizational actors leaving the "use mode" to meet each other in the middle, which we call the "collaborative learning mode," where actions have socio-technical consequences for both technology development and organizing (see Figure 4.4).

**Figure 4.4 Crossing the implementation line re-interpreted**




Bringing to the fore the relationship between technological change and organizational change offers contributions to existing scholarship on technology and organizing and calls for new methods for future research, which we discuss below.

### 4.5.1 Technology and organizing

The role of technology and its features has for a long time been downplayed in studies on changing work and organizing (e.g., Leonardi & Barley, 2010; Orlikowski, 2007). Organizational scholars have often feared falling back to "technological determinism" and have given premacy to the social over the material (or technological) in understanding organizational change (Leonardi, 2009; Faraj & Pachidi, 2021; Zammuto et al., 2007). Yet, organizational scholars increasingly emphasize the need "to pay attention to what a technology lets users do, to what it does not let them do, and to the workarounds that users develop to address the latter" (Leonardi & Barley, 2010, p. 35). This paper offers a contribution to this urgent call by paying specific attention to the features that are involved in organizing for AI implementation, which we substantiate with empirical examples. We unpack what is unique about AI systems – i.e., it depends on large amounts of data, it is self-learning, and it offers alternative, pattern-based insights – and emphasize the AI implementation practices that can be enacted to cope with the features of AI systems.

This paper also offers an alternative perspective to the divide between technology design and use – or the "design mode" and "use mode" (Orlikowski, 1992, p. 408) that dominated studies on technology implementation (Bailey & Barley, 2020; Leonardi, 2009; Van den Broek et al., 2021). While it has long been acknowledged that social construction of technology happens by both developers and users (e.g., Boudreau & Robey, 2005; Orlikowski, 1992; Weick, 1990; Zammuto et al., 2007), prior research has generally considered the design phase to belong to technology developers and the use phase to organizational actors (e.g., Forsythe, 1993; Slota et al., 2020). By asking how organizations cope with the unique features of AI systems, this study unpacks the mutual dependence of technology developers and organizational actors in the implementation of AI, which we call the "collaborative learning mode" (see Figure 4.4). For example, coping with the data-driven nature of AI systems through organizing for data requires organizational actors to acquire new data-related skills to actively gather and construct data sets which aids the further development of learning algorithms. However, to develop a system that is useful in practice requires developers to understand what the user domain looks like, which therefore also requires developers to be invested in the organizational side of the AI system. Unpacking the mutual dependence of technology developers and organizational actors in the "collaborative learning mode" therefore allows us to see how "crossing the implementation line" is performed in the case of AI.

### 4.5.2 Studying AI in practice

The focus on "crossing the implementation line" (Leonardi, 2009) and including the unique features of technology as well as the organizing efforts in relation to AI systems also offers insights into how to study "intelligent technologies" (Bailey & Barley, 2020; Glaser et al., 2020). We emphasize the need for organizational scholars to take a holistic perspective when studying technology, which involves closely following the activities of key groups in the development, implementation, and use of technology to understand their consequences for work and organizing. We relate to recent studies calling for a deeper accounting of technology and its role in triggering organizational change, without falling prey to technological determinism (Faraj & Pachidi, 2021; Pachidi et al., 2020; Sergeeva et al., 2020; Van den Broek et al., 2021) and to "bring technology back in" to organizational research (Orlikowski & Scott, 2016; Zammuto et al., 2007).

This implies the importance of studying both the side of the technology, as well as the organizational side and requires the specific inclusion of technology developers and their decisions regarding the construction of learning algorithms and to trace how these decisions lead to opportunities and challenges in using AI systems in practice. Including technology developers will help future studies to unpack the technical reasoning behind, and included in, learning algorithms – the "design intentions" (Bailey & Barley, 2020; Orlikowski, 1992) – as well as the organizational reasoning regarding their deployment. This will support further research on the unexpected organizational changes with regards to the use of AI systems.

Organizational scholars thus need to take the specifics of the development of technology into account, which means not only a true socio-technical analysis, but also that the researchers themselves need to be socio-technically engaged and trained to have the absorptive capacity to understand that decisions in the design process matter for the implementation and use of technology. We show that such a holistic, socio-technical approach is particularly important in the case of AI systems, with their promise to generate more objective, efficient, and new insights. Finally, we also emphasize that paying attention to technology development – in addition to organizations implementing and using the technology – and unpacking the decisions embedded in and the features of the AI system calls for getting comprehensive access to the case at hand. Often, technology developers are disconnected from the domain where the AI system is put into use. This means that developing a holistic perspective on AI system implementation requires access to the network of actors and organizations through which an AI system is developed and ultimately deployed.

### 4.5.3 Practical implications

Our study also offers practical implications to technology developers and organizational actors. First, our analysis of the "collaborative learning" mode required for AI implementation indicates the need for technology developers and organizations to go beyond the traditional "silos" that exist between development and use. This also means that buying AI systems "off the shelf" is likely not a recipe for long-term success. Instead, successful AI development and implementation requires close collaboration between developers and organizational actors already from the start. To achieve this requires new responsibilities for all actors involved, which also means that these actors need to acquire new skills. For technology developers, these skills are focused on the more "social" domains, so that they can successfully interact with organizations. For organizational actors, the new skills will be mainly related to data and statistics, to better understand the possibilities and limits of implementing and using AI systems in practice. Our story, therefore, implies the need for technology developers as well as organizations to engage in continuous development of skills related to emerging technologies.

Second, we have shown that the implementation of AI systems in practice requires much interaction and reflection of all the actors involved. Our study therefore calls for a new perspective on "slow" technology development and implementation in organizations. Especially since technologies such as AI systems have the ability to learn and adjust indefinitely, "quick prototyping" and handing over is no longer desired. This perspective, at first, seems to be in contrast with the recent trend towards agile methods, in which one of the core aspects is a quick turnaround between a technology prototype and its use. However, "slow development" can actually be combined with agile methods, if only the developers continue to be involved with the technology over time. As such, quick turnarounds of prototypes need to be combined with continuous interaction, reflection, and adjustment for both developers and organizational actors to stay "in the loop" when the machine learns on its own.

## References

Aerts, H. J. (2018). Data science in radiology: A path forward. *Clinical Cancer Research, 24*(3), 532–534.

Agarwal, R., & Dhar, V. (2014). Big data, data science, and analytics: The opportunity and challenge for IS research. *Information Systems Research, 25*(3), 443–448.

Agostinho, D. (2019). The optical unconscious of Big Data: Datafication of vision and care for unknown futures. *Big Data & Society, 6*(1). doi:10.1177/2053951719826859

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence.* Harvard Business Press.

Ajunwa, I. (2020). The "black box" at work. *Big Data & Society, 7*(2), 1–6.

Anthony, C. (2021). When knowledge work and analytical technologies collide: The practices and consequences of black boxing algorithmic technologies. *Administrative Science Quarterly*. doi:00018392211016755.

Argyris, C., & Schön, D. A. (1997). Organizational learning: A theory of action perspective. *Reis,* (77/78), 345-348.

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115.

Bader, V., & Kaiser, S. (2019). Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence. *Organization, 26*(5), 655–672.

Bailey, D. E., & Barley, S. R. (2020). Beyond design and use: How scholars should study intelligent technologies. *Information and Organization, 30*(2). doi:10.1016/j.infoandorg.2019.100286

Balasubramanian, N., Ye, Y., & Xu, M. (2020). Substituting human decision-making with machine learning: Implications for organizational learning. *Academy of Management Review.* doi:10.5465/amr.2019.0470

Baptista, J., Stein, M. K., Klein, S., Watson-Manheim, M. B., & Lee, J. (2020). Digital work and organisational transformation: Emergent digital/human work configurations in modern organisations. T*he Journal of Strategic Information Systems, 29*(2).

Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review, 104*, 671–732.

Beck, A. H., Sangoi, A. R., Leung, S., Marinelli, R. J., Nielsen, T. O., Van De Vijver, M. J., ... & Koller, D. (2011). Systematic analysis of breast cancer morphology uncovers stromal features associated with survival. *Science Translational Medicine, 3*(108), 108ra113-108ra113.

Bonde Thylstrup, N., Flyverbom, M., and Helles, R. (2019) Datafied knowledge production: Introduction to the special theme. *Big Data & Society, 6*(2), 1–5.
Boudreau, M. C., & Robey, D. (2005). Enacting integrated information technology: A human agency perspective. *Organization Science, 16*(1), 3–18.
boyd, d., & Crawford, K. (2012). Critical questions for big data. *Information, Communication & Society, 15*(5), 662–679.
Brayne, S. (2017). Big data surveillance: The case of policing. *American Sociological Review, 82*(5), 977–1008.
Brown, J. S., & Duguid, P. (2001). Knowledge and organization: A social-practice perspective. *Organization science, 12*(2), 198–213.
Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* New York: W.W. Norton & Company.
Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society, 3*(1). doi:10.1177/2053951715622512
Carlile, P. R. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization science, 15*(5), 555–568.
Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS quarterly, 36*(4), 1165–1188.
Christin, A. (2017). Algorithms in practice: Comparing web journalism and criminal justice. *Big Data & Society, 4*(2). doi:10.1177/2053951717718855
Christin, A. (2020a). The ethnographer and the algorithm: beyond the black box. *Theory and Society.* doi:10.1007/s11186-020-09411-3
Christin, A. (2020b). What data can do: A typology of mechanisms. *International Journal of Communication, 14*, 1115–1134.
Christin, A., & Brayne, S. (2020). Technologies of crime prediction: The reception of algorithms in policing and criminal courts. *Social Problems.* doi:10.1093/socpro/spaa004
Crawford, K., & Schultz, J. (2014). Big data and due process: Toward a framework to redress predictive privacy harms. *Boston College Law Review, 55*(1), 93–128.
Cukier, K., & Mayer-Schönberger, V. (2013). The rise of big data: How it's changing the way we think about the world. *Foreign Affairs, 92*(3), 28–40.
Cunha, J., & Carugati, A. (2018). Transfiguration work and the system of transfiguration: How employees represent and misrepresent their work. *MIS Quarterly, 42*(3), 873–894.
DalleMule, L., & Davenport, T. H. (2017). What's your data strategy. *Harvard Business Review, 95*(3), 112–121.
Daugherty, P. R., & Wilson, H. J. (2018). *Human+ machine: Reimagining work in the age of AI.* Harvard Business Press.

Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics, 1*(2), 73–80.

Davenport, T., & Harris, J. (2017). *Competing on analytics: Updated, with a new introduction: The new science of winning.* Harvard Business Press.

Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines.* New York, NY: Harper Business.

Davenport, T. H., Barth, P., & Bean, R. (2012). How "Big Data" is different. *MIT Sloan Management Review, 54*(1), 22–24.

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering, 61*, 637–643.

Domingos, P. (2015). *The master algorithm: How the quest for the ultimate learning machine will remake our world.* Basic Books.

Doran, D., Schulz, S., & Besold, T. R. (2017). What does explainable AI really mean? A new conceptualization of perspectives. arXiv preprint arXiv:1710.00794.

Dourish, P. (2016). Algorithms and their others: Algorithmic culture in context. *Big Data & Society, 3*(2). doi:10.1177/2053951716665128

Ebel, P., Söllner, M., Leimeister, J. M., Crowston, K., & de Vreede, G.-J. (2021). Hybrid intelligence in business networks. *Electronic Markets.* doi:10.1007/s12525-021-00481-4

Elish, M.C., & boyd, d. (2018). Situating methods in the magic of Big Data and AI. *Communication Monographs, 85*(1), 57–80.

Faraj, S., & Pachidi, S. (2021). Beyond Uberization: The co-constitution of technology and organizing. *Organization Theory, 2*(1). doi:10.1177/2631787721995205

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70.

Flyverbom, M., & Murray, J. (2018). Datastructuring—Organizing and curating digital traces into action. *Big Data & Society, 5*(2). doi:10.1177/2053951718799114

Ford, M. (2018). *Architects of intelligence: The truth about AI from the people building it.* Birmingham, UK: Packt Publishig Ltd.

Forsythe, D. E. (1993). The construction of work in artificial intelligence. *Science, technology, & human values, 18*(4), 460-479.

Gal, U., Jensen, T. B., & Stein, M.-K. (2020). Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. *Information and Organization, 30*(2). doi: 10.1016/j.infoandorg.2020.100301

Gitelman, L. (2013). *Raw data is an oxymoron.* Cambridge, MA: MIT press.

Glaser, V. L., Pollock, N., & D'Adderio, L. (2020). The biography of an algorithm: Performing algorithmic technologies in organizations. *Organization Theory, 2*(2). doi:10.1177/26317877211004609

Glaser, V. L., Valadao, R., & Hannigan, T. R. (2021). Algorithms and routine dynamics. In M. S. Feldman, B. T. Pentland, L. D'Adderio, K. Dittrich, C. Rerup, & D. Seidl (Eds.), *Cambridge Handbook of Routine Dynamics.* Cambridge: Cambridge University Press.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660.

Gollapudi, S. (2016). *Practical machine learning*. Birmingham, UK: Packt Publishing Ltd.

Graef, R., Klier, M., Kluge, K., & Zolitschka, J. F. (2020). Human-machine collaboration in online customer service – a long-term feedback-based approach. *Electronic Markets.* doi:10.1007/s12525-020-00420-9

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2020). The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review.* doi:10.5465/amr.2019.0178

Hand, D. J., & Khan, S. (2020). Validating and verifying ai systems. *Patterns, 1*(3). doi:10.1016/j.patter.2020.100037

Hartmann, P., & Henkel, J. (2020). The rise of corporate science in AI: Data as a strategic resource. *Academy of Management Discoveries.* doi:10.5465/amd.2019.0043

Henke, N., Levine, J., & McInerney, P. (2018). You don't have to be a data scientist to fill this must-have analytics role. Harvard Business Review. Via: https://hbr.org/2018/02/you-dont-have-to-be-a-data-scientist-to-fill-this-must-have-analytics-role.

Henriksen, A., & Bechmann, A. (2020). Building truths in AI: Making predictive algorithms doable in healthcare. *Information, Communication & Society*, *3*(6), 802–816.

Huysman, M. (2020). Information systems research on artificial intelligence and work: A commentary on "Robo-Apocalypse cancelled? Reframing the automation and future of work debate". *Journal of Information Technology, 35*(4), 307-309.

Introna, L.D. (2016). Algorithms, governance, and governmentality: On governing academic writing. *Science, Technology, and Human Values, 41*(1), 17–49.

Jones, M. (2019). What we talk about when we talk about (big) data. *The Journal of Strategic Information Systems, 28*(1), 3–16.

Jussupow, E., Spohrer, K., Heinzl, A., & Gawlitza, J. (2021). Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence. *Information Systems Research.* doi: 10.1287/isre.2020.0980.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.

Kim, B., Koopmanschap, I., Mehrizi, M. H. R., Huysman, M., & Ranschaert, E. (2021). How does the radiology community discuss the benefits and limitations of artificial intelligence for their work? A systematic discourse analysis. *European Journal of Radiology.* doi:136:109566.

Kitchin, R. (2014). Big Data, new epistemologies and paradigm shifts. *Big Data & Society, 1*(1), 1–12.

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2017). Human decisions and machine predictions. *The Quarterly Journal of Economics, 133*(1), 237–293.

Kuncel, N. R., Klieger, D. M., Connelly, B. S., & Ones, D. S. (2013). Mechanical versus clinical data combination in selection and admissions decisions: A meta-analysis. *Journal of Applied Psychology, 98*(6), 1060.

Leavitt, K., Schrabram, K., Hariharan, P., & Barnes, C. M. (2020). Ghost in the machine: On organizational theory in the age of machine learning. *Academy of Management Review.*

Leonardi, P. M. (2009). Crossing the implementation line: The mutual constitution of technology and organizing across development and use activities. *Communication Theory, 19*(3), 278–310.

Leonardi, P. M., & Barley, S. R. (2010). What's under construction here? Social action, materiality, and power in constructivist studies of technology and organizing. *The Academy of Management Annals, 4*(1), 1–51.

Lindebaum, D., & Ashraf, M. (2021). Ghost in the machine, or ghost in organizational theory? A complementary view on the use of machine learning. *Academy of Management Review.* doi:10.5465/amr.2019.0247

Lycett, M. (2017). 'Datafication': Making sense of (big) data in a complex world. *European Journal of Information Systems, 22*(4), 381–386.

Lyon, D. (2014). Surveillance, Snowden, and big data: Capacities, consequences, critique. *Big data & Society, 1*(2). doi:10.1177/2053951714541861

Mai, J.E. (2016). Big data privacy: The datafication of personal information. *Information Society, 32*(3), 192–199.

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., & Ko, R. (2017). *Jobs lost, jobs gained: Workforce transitions in a time of automation.* McKinsey Global Institute.

Mayer-Schönberger, V., & Cukier, K. (2013). *Big Data: A revolution that will trans- form how we live, work, and think.* New York: Houghton Mifflin Harcourt.

McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J., & Barton, D. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10), 60–68.

Menzies, T., & Pecheur, C. (2005). Verification and validation and artificial intelligence. *Advances in Computers, 65*, 153-201.

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence, 267*, 1–38.

Mirbabaie, M., Stieglitz, S., & Frick, N. R. J. (2021). Hybrid intelligence in hospitals: Towards a research agenda for collaboration. *Electronic Markets.* doi:10.1007/s12525-021-00457-4

Mukherjee, S. (2017). AI v. MD. *New Yorker.*

Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'. *Journal of Strategic Information Systems, 24*(1), 3–14.

O'neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy.* Crown.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science, 3*(3), 398–427.

Orlikowski, W. J., & Scott, S. V. (2016). *Digital work: A research agenda. In A Research Agenda for Management and Organization Studies.* Edward Elgar Publishing.

Pachidi, S., Berends, H., Faraj, S., & Huysman, M. (2020). Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organization Science.* doi:10.1287/orsc.2020.1377

Parmiggiani, E., Østerlie, T., & Almkov, P. (2021). In the backrooms of data science. *Journal of the Association of Information Systems, Forthcoming.*

Pasquale, F. (2015). *The black box society.* Cambridge, MA: Harvard University Press.

Pasquale, F. (2020). *New laws of robotics: Defending human expertise in the age of AI.* Belknap Press.

Pine, K. H., & Liboiron, M. (2015). *The politics of measurement and action.* Paper presented at the Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210.

Robbins, S. (2019). A misdirected principle with a catch: Explicability for AI. *Minds and Machines, 13*(1), 1–20.

Ross, A. (2019). Data engineer: The 'real' sexiest job of the 21st century. Last accessed April 23, 2021, via: https://www.information-age.com/data-engineer-sexiest-job-21st-century-123480578/

Schildt, H. (2017). Big data and organizational design – the brave new world of algorithmic management and computer augmented transparency. *Innovation, 19*(1), 23–30.

Siegel, E. (2013). *Predictive analytics: The power to predict who will click, buy, lie, or die.* New Jersey: John Wiley & Sons.

Slota, S. C., Hoffman, A. S., Ribes, D., & Bowker, G. C. (2020). Prospecting (in) the data sciences. *Big Data & Society, 7*(1). doi:10.1177/2053951720906849

Sturm, T., Gerlach, J. P., Pumplun, L., Mesbah, N., Peters, F., Tauchert, C., Nan, N., & Buxmann, P. (2021). Coordinating human and machine learning for effective organizational learning. *Accepted for publication in MIS Quarterly.*

Tegmark, M. (2017). *Life 3.0: Being human in the age of artificial intelligence.* Knopf.
Tene, O., & Polonetsky, J. (2013). A theory of creepy: technology, privacy and shifting social norms. *Yale Journal of Law & Technology, 16*, 59–102.
Tshitoyan, V., Dagdelen, J., Weston, L., Dunn, A., Rong, Z., Kononova, O., ... Jain, A. (2019). Unsupervised word embeddings capture latent knowledge from materials science literature. *Nature, 571*(7763), 95–98.
Vad Karsten, M. M. (2020). Dislocated dialogue: An anthropological investigation of digitisation among professionals in fire safety. *Organization.* doi:10.1177/1350508420961527
Van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. *Accepted for publication at MIS Quarterly.*
Van Dijck, J. (2014). Datafication, dataism and dataveillance: Big Data between scientific paradigm and ideology. *Surveillance & society, 12*(2), 197–208.
Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries, 4*(4), 404–409.
Waardenburg, L., Huysman, M., & Agterberg, M. (2021). *Managing AI wisely: From development to organizational change in practice.* Edward Elgar Publishing.
Waardenburg, L., Sergeeva, A., & Huysman, M. (2018). Hotspots and blind Spots. In *Working Conference on Information Systems and Organizations* (pp. 96–109). Springer, Cham.
Waardenburg, L., Sergeeva, A., & Huysman, M. (2021). The burden of data production: How anticipating data work shapes police practices. *Paper presented at EGOS 2021.*
Wasko, M. M., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*, *29*(1), 35–57.
Weick, K. E. (1990). Technology as equivoque: Sensemaking in new technologies. P. S. Goodman, L. S. Sproull, (eds.) *Technology and Organizations.* Jossey-Bass, San Francisco, CA, 1–44.
West, R. B., Van De Rijn, M. & Koller, D. (2011). Systematic analysis of breast cancer morphology uncovers stromal features associated with survival. *Science Translational Medicine, 3*(108), 1–11.
Wooldridge, M. (2020). *The road to conscious machines: The story of AI.* Penguin UK.
Xie, X., Ho, J. W., Murphy, C., Kaiser, G., Xu, B., & Chen, T. Y. (2011). Testing and validating machine learning classifiers by metamorphic testing. *Journal of Systems and Software, 84*(4), 544–558.
Zammuto, R. F., Griffith, T. L., Majchrzak, A., Dougherty, D. J., & Faraj, S. (2007). Information technology and the changing fabric of organization. *Organization Science, 18*(5), 749–762.

Zhang, Z., Lindberg, A., Lyytinen, K., & Yoo, Y. (2021). The unknowability of autonomous tools and the liminal experience of their use. *Information Systems Research, in press.*

Zhang, Z., Nandhakumar, J., Hummel, J. T., & Waardenburg, L. (2020). Addressing the key challenges of developing machine learning AI systems for knowledge-intensive work. *MIS Quarterly Executive, 19*(4), 221–238.

Zuboff, S. (2019). *The age of surveillance capitalism: The fight for a human future at the new frontier of power.* London: Profile Books.

# 5. Discussion

## The road ahead when studying AI at work

## 5.1 Summary of findings and contributions

In the preceding chapters, I presented the findings of three studies that together offer insights to *how organizations cope with the production and use of machine learning knowledge in practice.* In the sections below, I summarize the key findings, main contributions, and boundary conditions and directions for future research of each study separately (see also Table 5.1). After these summaries, I bring the findings of the studies together to address the overarching research question of this dissertation, where I also discuss the broader theoretical and practical implications. I end this discussion with a methodological reflection.

**Table 5.1 Summary of studies**

| | **Chapter 2** | **Chapter 3** | **Chapter 4** |
|---|---|---|---|
| **Title** | The burden of data production: How anticipating data work shapes police practices | In the land of the blind, the one-eyed man is king: Knowledge brokerage in the age of learning algorithms | Organizing for AI at work: Towards a holistic perspective on AI system implementation |
| **RQ** | How do workers cope with data work in their situated practices? | How do knowledge brokers translate machine learning knowledge when they cannot understand how this knowledge is generated? | How can the "implementation line" be crossed in the case of AI systems? |
| **Findings** | - Three tensions between the experience of data work and situated work.<br>- Three strategies to cope with anticipated data work in situated practices. | - Three different brokerage roles with associated translation practices.<br>- Different knowledge boundaries between the brokers and the developers and users. | - Three core features of AI systems<br>- Three different AI implementation practices.<br>- Socio-technical consequences of the AI implementation practices for both technology development and organizing. |
| **Response to overarching RQ** | Producing machine learning knowledge in practice requires workers to engage more in data work. Yet, data work as a practice is often different from situated work, which can create tensions that can be highly consequential for situated work. | Using machine learning knowledge in practice requires translation, which can be done by algorithmic brokers. However, to translate requires brokers to understand how machine learning knowledge is generated. This is problematic in the case of AI and can trigger brokers to become curators instead. | Producing and using machine learning knowledge in practice requires organizations to enact AI implementation practices that bring together developers and organizational actors in a "collaborative learning" mode. |

| | | | |
|---|---|---|---|
| **Contributions** | - Provides insights into the influences of data work on situated work.<br>- Argues that data construction starts at the situated practices, even before data work is performed.<br>- Shows the important role of anticipation in how data work and situated work is performed. | - Offers an integrative perspective on organizational theory and emerging technologies.<br>- Reveals the emergence of a new phenomenon: algorithmic knowledge brokers who can become increasingly influential.<br>- Emphasizes how knowledge brokers can create new knowledge boundaries.<br>- Stresses the importance of unpacking how knowledge is translated from its original source. | - Shows the relationship between the specific features of AI and organizing.<br>- Highlights the importance of collaborative learning between developers and users for AI implementation.<br>- Stresses the need to unpack the specifics of technology and take a holistic perspective when studying AI in practice. |
| **Future research** | Future research may:<br>- Look at contexts where data production is largely automated.<br>- Further explore the role of the body and emotions in data production.<br>- Look at less extreme contexts for understanding tensions between the experience of data work and situated work and the associated responses. | Future research may:<br>- Look at other occupational domains to further understand the differences in explanations required.<br>- Use insights from other domains to provide further insights into who is accountable in the age of learning algorithms.<br>- Look at settings in which relationships exist between developers and users.<br>- Include even more complex and opaque tools, such as those based on deep learning. | Future research may:<br>- Examine how the "collaborative learning mode" changes over time in the further development and deployment of AI systems.<br>- Unpack the design intentions of developers and how these relate to the organizational reasoning for implementing AI.<br>- Explore other features of "intelligent technologies" and how these features influence technology implementation. |

### 5.1.1 The burden of data production

In Chapter 2, I asked how workers cope with data work in their situated practices. To answer this question, I built on my ethnographic fieldwork of the Dutch police, specifically eight months of full-time research at the emergency response department. I spent over 100 shifts (day, evening, and night) following how police officers went about their situated work and performed the associated data work practices.

***Key findings***. In this study, I found that, in contrast to what is generally expected regarding data work (Cunha & Carugati, 2018; Pachidi et al., 2020; Pine & Liboiron, 2015), police officers are not 'misrepresenting' their situated activities in their reports. Instead, they adjusted their situated work to fit the practice of data work. To explain this outcome, I found three tensions the police officers experienced between data work and their situated performances. They experienced the practice of data work as bodily constrained, materially rigid, and ethereal, while their experience of their situated work was deeply embodied, contextual, and lived. I discovered that to cope with these tensions, the police officers enacted three coping strategies in their situated work: avoiding work, deviating from protocol, and capturing experiences. Interestingly, by using these coping strategies, they adjusted the situated activities that they subsequently had to record, thereby aligning their situated performances to reflect the practice of data work. As a consequence, the police officers thus *ex-ante* enacted data work in their situated activities.

***Theoretical contributions.*** The findings of this study offer contributions to existing research on data production and specifically data work (Bossen et al., 2016; Cunha & Carugati, 2018; Pachidi et al., 2020; Pine & Bossen, 2020; Pine & Liboiron, 2015; Truelove, 2019) by emphasizing that, in contrast to how data work has previously been understood, data construction is not a stand-alone activity but instead is inherently entwined with situated work. I argue that data work practices go beyond "impression management" (Cunha & Carugati, 2018) and emphasize the importance of including situated work to understand how data work is performed and with what intentions and consequences. In addition, by taking a more holistic approach to the experience of data work in practice, I offer new insights into the role of the body in data work (e.g., by emphasizing the bodily exhausting nature of data work). Finally, I also contribute to studies on anticipation and anticipatory work (Barley, 2015; Bucher, Schou, & Waldkirch, 2020; Flyverbom & Garsten, 2021) by showing that anticipation not only builds upon existing data but is highly consequential for how data is constructed.

***Boundary conditions and future research.*** In this study, the data work performed is largely 'manual,' which means that data production is not yet automated. There are also contexts in which datafication is already a largely automated process, which might lead to different or new tensions between the situated work and the data that is being produced. Future research could therefore look into cases in which "self-reporting" (Cunha & Carugati, 2018) is no longer an option to expand our understanding of how situated work changes. In addition, while I provide a first attempt at exploring the role of the body in data work, future research can further expand this by looking deeper into the specific role of the body in data work, as well as including the part that emotions play in data production. Finally, with my research at the emergency response department, I offer an extreme case in which the tensions between situated work and data work are particularly prevalent. There are other contexts in which the difference between the two practice worlds is less severe, such as cases where situated work and data work are performed in the same environment. Studying less extreme cases might lead to more nuanced changes in situated work, which may be even more difficult to observe yet just as important to understand.

### 5.1.2 In the land of the blind, the one-eyed man is king

In Chapter 3, I set out to understand how knowledge brokers translate machine learning knowledge when they cannot understand how this knowledge is generated. For this, I again built on my ethnographic work of the Dutch police, yet this time I used 2 years of research at the intelligence department where I studied the implementation and deployment of a learning algorithm to predict where and when crimes were most likely to occur.

***Key findings.*** I analyzed the implementation process of the learning algorithm over an extended period of time and found that a group of so-called "intelligence officers" – who were tasked with translating abstract crime predictions for police managers – enacted different translation practices that afforded them to perform increasingly influential knowledge brokerage roles over time (i.e., messenger, interpreter, and curator). The changes in roles are explained by the knowledge differences that emerged when the intelligence officers attempted to translate machine learning knowledge into practice. At first, the translation practices of the intelligence officers were informed by their unfamiliarity with both the learning algorithm and the police occupational world, yet their attempts to simply list and transfer the crime predictions towards the police were unsuccessful. The intelligence officers realized that to perform knowledge brokerage work, they had to better understand the technical details and domain details. Their efforts to better understand the police domain were successful, through which the knowledge differences between the intelligence officers and the police domain dissolved. However, no matter how much they tried they could not understand the inner workings of the learning algorithm which made the intelligence officers realize that the boundary between machine learning knowledge and their human interpretations was impassable. While their brokerage work increasingly fitted the police requirements, the intelligence officers remained unable to open the black-boxed learning algorithm. As a consequence, they eventually substituted machine learning knowledge with their own judgments.

***Theoretical contributions.*** The study offers an integrative perspective on organizational theory and emerging technologies, such as AI systems, and reveals the emergence of algorithmic knowledge brokers as a new, dynamic, and influential organizational phenomenon. I provide new insights into the literature on knowledge brokers (e.g., Brown & Duguid, 1998; Burgess & Currie, 2013; Meyer, 2010; Pawlowski & Robey, 2004) by taking a process perspective on knowledge brokerage work. I show that the translation practices that knowledge brokers enact over time afford them a unique position through which they can grow and become increasingly influential. Also, I emphasize that knowledge brokerage work is more complex than merely resolving a knowledge boundary between groups, as when they attempt to resolve these boundaries, knowledge brokers can create new boundaries between themselves and the groups they intend to connect. In addition, by showing what happens to translation in the case of opaque machine learning knowledge, the findings contribute to translation theory (e.g., Czarniawska & Sevón, 2005; Mueller & Whittle, 2011; Nielsen et al., 2014; Røvik, 2016). Since these studies mainly focus on how knowledge is translated *to* specific recipients, I show the importance of unraveling how knowledge is translated *from* its original source in the first place.

***Boundary conditions and future research.*** This study shows that occupational values matter for how desirable access to explanations may be for users. Future studies might look at other occupational domains to deeper understand the occupational differences regarding required explanations. Unpacking the different occupational values also might provide further insights into who or what is accountable in the age of learning algorithms. Furthermore, the case presented in this study is highly hierarchical, with a largely siloed organizational structure. This prevented the different groups from interacting with each other. To further advance our understanding of algorithmic knowledge brokering, it would be interesting to include more innovative or "flat" research settings, where relationships between developers and users can exist. Finally, the learning algorithm presented in this study is relatively basic, with nevertheless fundamental consequences for work and organizing. I encourage future research to continue to unpack algorithmic brokerage work in relation to increasingly advanced and complex learning algorithms (such as those using deep learning) to provide further insights into the organizational consequences of increasingly opaque "intelligent technologies."

### 5.1.3 Organizing for AI at work

In Chapter 4 I aimed to understand how the "implementation line" between technology development and organizational change can be crossed in the case of AI systems. To this end, I used empirical examples of five large organizations that implemented AI in their organizational processes, combined with a review of current organizational and information systems literature on AI systems and technology implementation.

***Key findings.*** In this study, I first unpack the three key features of AI systems: they depend on large amounts of data, they are self-learning which limits their explainability, and they offer alternative, pattern-based insights. I then unpack how organizations cross the implementation line between technology development and organizational change by accounting for the unique features of AI in their organizational processes. Specifically, organizations engage in three AI implementation practices: organizing for data, organizing for explainability, and organizing for alternative insights. By unpacking these practices, I uncover the close relationship required between technology developers and organizational actors, a process I define as continuous and reflective "collaborative learning." Because of the close connection between developers and organizational actors, enacting the AI implementation practices has socio-technical consequences for both technology development and organizing.

***Theoretical contributions.*** The findings of this study contribute to the literature on the relationship between technology and organizing (Faraj & Pachidi, 2021; Leonardi. 2009; Leonardi & Barley, 2010; Orlikowski, 1992; Zammuto et al., 2007). First, by paying specific attention to the unique features of AI systems, I emphasize the relationship between the specific features of AI and organizational change, which I substantiate with specific empirical examples. Moreover, by emphasizing the importance of collaborative learning between technology developers and organizational actors, this study offers an alternative perspective to the divide between technology design and use that has dominated studies on technology implementation (Leonardi, 2009; Orlikowski, 1992). Finally, this study builds on and expands recent calls for bringing technology into organizational research (Bailey & Barley, 2020; Orlikowski & Scott, 2016; Van den Broek, Sergeeva, & Huysman, 2021; Zammuto et al., 2007) by stressing the need to unpack the specifics of technology and take a holistic perspective, including a variety of actors, when studying AI in practice.

***Boundary conditions and future research.*** This study offers insights into the need to better understand the "collaborative learning mode" between technology developers and organizational actors. Future research may further expand on this by examining how this collaborative learning changes over time, with the further development and deployment of (increasingly advanced) AI systems. Moreover, I encourage future research to pay specific attention to studying both the side of the technology and the organizational side, as this will help to unpack the technical reasoning included in learning algorithms and to compare this to the organizational reasoning regarding their deployment. This will support further understanding of the unexpected organizational changes with regard to the use of AI in practice. Finally, as the current "intelligent technologies" continue to develop quickly, over time, new features may emerge that are important to include in our understanding of technology and organizing. I encourage future research to keep a close eye on technology development and to frequently reconsider its unique features.

## 5.2 Response to overarching research question and implications

In Chapter 1 of this dissertation, I introduced AI systems as an emerging organizational phenomenon. I discussed that organizations increasingly believe in the promise of objective, efficient, and new "machine learning knowledge." I also explained that not all scholars agree with this perspective and that it is increasingly argued that augmenting work with AI systems requires bringing together machine learning knowledge and human knowledge. I discussed that this leads to a problem that is commonly overlooked in existing research, namely that the fundamental difference between the procedures used for creating machine learning knowledge and how human knowledge is produced creates a knowledge boundary between the two. My goal of this dissertation was therefore to examine: *How do organizations cope with the production and use of machine learning in practice?*

The findings of this dissertation indicate the distributed, effortful, and consequential nature of producing and using machine learning knowledge in practice. In Chapters 2 and 3, I zoomed in on the micro-practices of producing and using machine learning knowledge in practice. In Chapter 2, I described the work that is required to make the data to be used for developing and training learning algorithms, and thus for producing machine learning knowledge that fits the organizational needs. In Chapter 3, I presented the work of algorithmic knowledge brokers that is needed to translate machine learning knowledge into practice so that it can ultimately be used. I showed how performing translation work cannot be taken for granted, but demands one to understand how machine learning knowledge is produced, a requirement that is highly problematic in the case of AI systems. Finally, in Chapter 4, I took a broader perspective on the organizing practices required to implement AI and I discussed that the production and use of machine learning knowledge require new ways of collaboration between technology developers and organizational actors.

Based on the findings presented in this dissertation, I argue that organizational hopes and dreams about machine learning knowledge being objective and efficient give a distorted picture of the reality of organizing for machine learning in practice. Moreover, while AI systems – using large amounts of data and advanced computational techniques – might offer organizations new insights, the findings of this dissertation emphasize that leveraging this new knowledge in forms of "hybrid intelligence" and thereby augmenting work is not merely a matter of bringing together humans and AI systems. Instead, producing and using machine learning in practice requires deep involvement and efforts from a wide range of actors, understanding of what AI systems can and cannot produce, and careful organizing to keep track of unintended consequences.

With this dissertation, I emphasize the need for organizational and information systems scholars to go beyond the "AI hype" to instead look "behind the scenes of AI." I showed that studying AI behind the scenes means taking a holistic perspective on AI development, implementation, and use, including a variety of stakeholders, to uncover and understand unexpected patterns of action. This holistic perspective means, for example, unpacking the technical details of the AI system as well as the domain details of the intended users, and understanding the intentions of AI developers as well as the needs of organizations. This is specifically important since AI systems and organizations might seem worlds apart, yet how AI systems learn is often largely dependent on and intertwined with organizational actions. For example, in Chapter 4 I showed the various practices organizations enact that influence how AI systems are developed and trained. Taking a holistic perspective has large consequences for how to study AI in practice, as unpacking the technical and domain details requires the researcher to obtain technical and domain knowledge, uncovering the different organizational actors involved in the development and deployment of AI requires the researcher to be fully embedded in the context for an extended period. To fully uncover both the challenges and the opportunities of using AI systems, I therefore call for a more embedded approach to studying technology in practice.

Building on the insights of this dissertation, I offer three key implications for organizational and information systems scholarship on the consequences of "intelligent technologies" for work and organizing.

### 5.2.1 The need for organizational scholars to understand technological features

Scholars may gain from this dissertation, that fully understanding the consequences of technology for work and organizing requires a deep comprehension of what makes these technologies so unique and consequential in the first place. In all previous chapters of this dissertation, I have questioned and unpacked the specific features of AI systems to understand their relationship with organizational practices. For example, in Chapter 2, I have paid specific attention to the data-driven nature of "intelligent technologies" and the associated need to produce large amounts of work-related data. By questioning how such data comes about, I have uncovered that this includes many "data work" efforts (Pachidi et al., 2020; Pine & Bossen, 2020; Sachs, 2020), and in my case specifically around "self-reporting" one's work (Cunha & Carugati, 2018). Moreover, I showed that, due to the specific features of data and the tools involved in data production, the practice of data work can create tensions with the existing situated work. By digging deeper into how workers cope with these tensions, I was able to move beyond the current understanding of data work as "impression management" (Cunha & Carugati, 2018; Pachidi et al., 2020), which offers new insights into the relationship between data and situated work.

Similarly, in Chapter 3, I dug into the promise of learning algorithms to produce new knowledge and discussed how this comes with the challenge of such technologies being increasingly opaque or "black-boxed." As recently scholars suggested that new occupations such as "algorithmic brokers" (Kellogg, Valentine, & Christin, 2020) or "algorithmists" (Gal, Jensen, & Stein, 2020) may emerge to translate such new knowledge into practice, I asked how these "algorithmic knowledge brokers" are able to translate machine learning knowledge when the opacity of the learning algorithm prevents them from understanding how such knowledge is generated. This helped me to uncover how algorithmic knowledge brokers attempted to unpack the learning algorithm but found that they could never fully understand how the system generated its new insights. Closely tracing how the brokers struggled with translating knowledge without understanding how it was generated allowed me to see how our understanding of translation changes in the case of opaque technologies. As it is commonly assumed that translation is facilitated by means of technology (Røvik, 2016), I showed in this study that this is highly dependent on the specific features of that technology. In other words, if the technology is opaque, translation is hindered instead of facilitated.

In sum, with this dissertation, I join scholars currently pointing at the potentially large consequences of AI systems for work and organizing (e.g., Faraj, Pachidi, & Sayegh, 2018; Glaser, Valadao, & Hannigan, 2021; Raisch & Krakowski, 2021; Von Krogh, 2018). Yet, as the computational methods become more complex and the number of data points increases to generate better insights or new knowledge for organizations (e.g., Kellogg et al., 2020; Van den Broek et al., 2021), I emphasize that understanding, for example, *what* is required for AI systems to learn and *how* these technologies generate new knowledge is crucial to gain insights into the reach of their influence on work and organizing. As knowledge is never a stand-alone object in organizations but resides in an ecology of actors (Brown & Duguid, 2000), we should consider AI systems as one of these actors and unpack their specific 'skills' accordingly, as well as their relationship to other organizational actors. This requires scholars to deeply engage with and question the features of AI systems, how these relate to specific organizational practices, and how the features might change over time to become more or less salient in the process of generating new knowledge.

### 5.2.2 Let go of the divide between technology and organizing

Related to the above-mentioned need to unpack the features of technology, scholars may also learn from this dissertation that studying technology (and specifically AI systems) in practice requires one to let go of the classic divide in organizational scholarship between technology development and organizational change (Faraj & Pachidi, 2021; Leonardi, 2009; Leonardi & Barley 2010; Orlikowski, 1992). This goes beyond understanding the features of technology, to look at technology implementation as a holistic process that includes a variety of actors. This means at least developers and users, but often this includes more than those two types of actors. For example, in Chapter 4, I provided examples of different organizations that implemented AI systems in their work processes. Stepping away from the “design mode” and “use mode” (Orlikowski, 1992) that is common in organizational and information systems scholarship helped me to identify how deeply entwined a technology such as an AI system is with the work processes in which it is deployed. As these technologies learn and adjust over time, there is no more such a thing as an “end” to technology development.

Letting go of the divide between technology and organizing also helps to uncover unexpected role changes or the emergence of new roles. In Chapter 4 I discussed some examples of this (such as new departments for data production), but Chapter 3 is specifically exemplary to this point. In Chapter 3, I traced how a group of algorithmic knowledge brokers emerged between the technology developers and the intended users to facilitate the implementation and use of a learning algorithm. I found that, as the brokers became increasingly familiar with the user domain, they became more influential for operational decision-making, even to the point where they were fully trusted and could let go of the black-boxed learning algorithm altogether. The findings of this study therefore allowed me to go beyond the current understanding of brokers as “neutral intermediaries” (Anteby, Chan, & DiBeningo, 2016), towards conceptualizing algorithmic knowledge brokers as influential and consequential.

Thus, this dissertation shows that because of the ability of learning algorithms to learn and adjust indefinitely, studying AI systems in practice requires organizational and information systems scholars to go beyond a focus on either technology development or organizational change (Faraj & Pachidi, 2021). Surpassing this traditional divide gives researchers the opportunity to deeper understand the socio-technical relationships between AI systems and organizing, and to unpack how machine learning and organizational learning are intertwined. Specifically, this allows researchers to see how AI systems change and learn through the actions of its users, and to look beyond the roles of developers and users to find new emerging occupations, such as algorithmic knowledge brokers, to be largely consequential for both the development and use of AI in practice.

### 5.2.3 Towards a holistic perspective on technology in practice

Finally, scholars may gain from this dissertation that taking a practice perspective on studying technology goes beyond the role of human and material agency. For this, I link to recent calls for a more holistic perspective on how technology is perceived and used, specifically taking into account how technology is embedded and interrelated with core elements of a practice that are often overlooked, such as bodily strains and emotions (Hindmarsh, Hyland, & Banerjee, 2014; Oborn, Barrett, & Davidson, 2011; Sergeeva, Faraj, & Huysman, 2020; Vertesi, 2012). In Chapter 2, I described how new data work practices can create tensions with existing, more situated work. Beyond human and material agency, these tensions are also related to how the body was experienced in doing the work. For example, data work was experienced as bodily constrained, which resulted in a tension with the deeply embodied and often adrenaline-driven situated work. It was this bodily tension that triggered the police officers to avoid some of the more "exciting" work altogether. Including the experience of the body in understanding technology in practice therefore gave me deeper insights into the how and why the technology was consequential for work.

Finally, scholars may also be inspired to look at the relationship vice versa; the role of AI systems for the body at work. As the body is becoming increasingly important in organizational scholarship (e.g., Best & Hindmarsh, 2019; Cunliffe & Coupland, 2012; de Rond, Holeman, & Howard-Grenville, 2019) it is surprising to notice that not so much is written about how the use of technology changes bodily practices (Sergeeva et al., 2020 provides an exception). Again, in Chapter 2, I described how police officers started to use bodycams to enhance their vision and memory and capture their experiences in their data work. Yet, this also came with a cost, as this resulted in detailed but one-dimensional insights into the situated and lived experiences of police officers. As technologies for capturing data and experiences are becoming more prevalent in everyday organizational life, one could ask what such increased surveillance means for the body at work.

In sum, the case of AI systems and the need to capture and produce data for these technologies to learn provides an excellent opportunity for taking a more holistic perspective on technology-in-practice to also include, for example, bodily or emotional experiences. As this dissertation shows, the body at work can be largely consequential for how and what data is produced. Yet, so far studies on data production have focused on accounts *of* the body, analyzing which medical procedures are and are not reported (e.g., Mol, 2003; Pine & Liboiron, 2015) and not *from* the body, exploring what data production "feels like" (de Rond et al., 2019; Wacquant, 2005). Taking into account the experience of the body in the development and deployment of AI systems will allow researchers to go beyond the social and technical consequences of these technologies for work and organizing to observe the ramifications that are commonly overlooked or misunderstood.

## 5.3 Practical implications

Besides the theoretical implications, the findings presented in this dissertation also provide insights for practitioners involved in the development, implementation, and deployment of AI in practice.

### 5.3.1 Understand what AI can and cannot do

As AI systems are becoming increasingly prevalent in organizations, with the promise to generate more objective, efficient, and new insights, to avoid falling into the trap of the "AI hype," it is important for practitioners to understand what these systems can and cannot do. First of all, this means that on the organizational side, managers and the users of AI systems need to obtain new skills to understand the potential of AI and to be able to critically reflect on the outputs that are presented to them. These could be data-related skills, for example, to understand the consequences of certain sampling decisions for how a learning algorithm is trained, but it also includes statistical skills, to understand the limits of the mathematical reasoning embedded in AI systems.

To obtain such skills, organizations could facilitate (external) training programs and encourage employees to become more knowledgeable about the technologies that will become an important part of their organizational life, at least for the near future. Another solution could be to facilitate better interactions between the organizational actors involved in the implementation and use of the AI system and the technology developers. This way, the organization can learn more about the specifics of the learning algorithm, while the developers can learn more about the organization, which can also help them to better fit the AI system to the organizational requirements. In such cases, this does not only require new skills for the organizational actors, it also requires developers to make use of their social skills, move out of their comfort zone and into the organizational domain.

A prerequisite for this closer interaction is transparency, both on the side of developers and users. All through my research, I have heard technology developers say that they usually do not bother sharing details about the technology with organizational users. On the other hand, organizations often do not immediately see the added relevance of giving developers insights into their organizational processes. Moreover, it also means that technology developers have to let go of the veil of "objectivity" that surrounds technologies such as AI systems and share how certain decisions are included and excluded. Organizations, on the other hand, should be willing to show the (often contradictory) actions taken to make AI systems work in practice. The findings of my dissertation show that it is only through such mutual understanding of each other's worlds that fruitful interaction can take place in which one can let go of the "magic" that often surrounds AI systems and move towards a thought-through and trustworthy implementation of a learning algorithm.

### 5.3.2 Engage in collaborative learning

As the divide between technology development and organizational change also persists in practice, it is still often assumed that AI systems can be bought "off the shelf," which means that it should be possible to fully outsource the development of AI (Newlands, 2021). The findings of this dissertation show that, when AI systems are intended to augment existing work processes, such an "off the shelf" idea is a mirage. Instead, every step of the way from development to deployment requires careful consideration and understanding of the situated work practices, which cannot be achieved by merely buying in an external tool.

For producing the data necessary to create and train a learning algorithm, the findings of this dissertation emphasize the need to derive at least parts of the dataset from the organization itself. This means that data production is not a taken-for-granted activity, but requires careful consideration regarding what should and should not be captured and requires practitioners to understand the nature of the work that is being datafied. This leads to new managerial responsibilities related to monitoring the relationship between data work and situated work. At the same time, it also requires new data-related skills for those who make the data. This is especially important for understanding the consequences of the decisions and actions during the data production process and for the learning algorithm that is constructed afterward.

Understanding that data production is not an automated, simplified procedure but requires many efforts and new responsibilities for those involved is also important for maintaining a healthy work environment. As data production is becoming an increasingly central activity in many different occupations, the problems of performing such work are also becoming more visible. Studies are now pointing at the potential of burnouts due to overwhelming, data-related activities (e.g., Gardner et al., 2019; Johnson, Neuss, & Detmer, 2020). Preventing data work from becoming a societal problem thus requires a good alignment between data production activities and situated work.

The findings of this dissertation also emphasize other ways in which one cannot outsource AI. Specifically, since scholars increasingly point to the important role of algorithmic brokers to translate AI outcomes (e.g., Henke et al., 2018, Kellogg et al., 2020), I argue for the importance of both technology developers and users to stay in the loop of such translation work. It is not uncommon for developers to consider their niche to be technology development, while users often maintain in the organizational domain. Yet, this dissertation, and specifically Chapter 3, shows what happens when translation practices are fully outsourced to one dedicated group. It is the responsibility of developers to remain aware of the fit of their tool with the organizational processes, while it is the responsibility of users to remain reflective of whether what is presented to them could even be machine learning knowledge in the first place. While an algorithmic broker can thus be a promising solution for dealing with complex machine learning knowledge, it is not a "one-size-fits-all" solution.

As AI thus often requires the close involvement of all parties through "collaborative learning," managers could use the process of AI development as an opportunity to reflect on (hidden) assumptions about work and organizing, as the procedures of developing AI systems can lead to insights about what has always been taken for granted (Van den Broek et al., 2021). These insights might not always be what organizational actors were expecting or hoping to see as, for example, biases in human judgments can be brought to the fore, yet those insights can help organizations to learn and move forward. This dissertation shows that, when the development of AI systems is approached in a collaborative way, this can help both machines and organizations to learn.

### 5.3.3 Include the work practices in auditing AI

Finally, the findings of this dissertation also provide new insights into and suggestions for the current procedures around auditing and governing AI. Much of the current governmental debates about keeping AI under control revolve around the technical and legal details of AI. For example, there are many discussions about the transparency and responsibility of algorithms. Interestingly, a practice perspective, in which the role of, for example, algorithmic brokers or users is largely missing. I encourage auditors and governmental organizations involved in these debates to go beyond the technical and legal perspectives, as the findings of my dissertation show that much happens to the (outcomes of) AI when it is implemented in an organization.

This is also the case in debates about explainability and so-called "explainable AI." As this is becoming an increasingly important debate in relation to AI development, also in this case the work perspective is missing. Yet, to deeply understand the role of explanations, one has to ask what explanations mean in practice. For example, what is required to make explanations make sense in practice? What kind of explanations are required? And to whom? It is therefore important, even for governments, to step away from the divide between development and use and include both in the process of determining what should be audited and how.

## 5.4 Some methodological reflections

I write this discussion at the end of my four-year Ph.D. trajectory and while the take-aways of this dissertation are presented in a structured fashion, I did not arrive at them in a structured way. Throughout the dissertation process, I had to learn that theorizing about AI and gathering empirics is different than what we have seen before. Moreover, I learned that doing ethnography does not stop when you leave the field, especially not when you experience matters of life and death. I would therefore like to end this dissertation by reflecting on some of my methodological experiences and challenges throughout these four years.

### 5.4.1 Understanding technology to theorize about its implications

One of the key messages of this dissertation is the need for organizational scholars to understand the features of technology to theorize about its implications. I have spent many words in this dissertation to emphasize the importance of unpacking technology, which I will not repeat here. Instead, here I would like to reflect on the lessons learned in the process of becoming knowledgeable and theorizing about this unique technology.

There is a problem with using the term "AI" in organizational scholarship, as well as in mainstream media, as it is becoming a buzzword or umbrella term, which includes many different tools and methods. The term AI has been used in relation to, for example, simple computational methods and Excel spreadsheets, robot arms, and complex predictive models. The danger of this is that the concept becomes so broad that we, as scholars, do not understand anymore how it is and is not consequential in practice. In addition, the term AI evokes associations with "magic," "mysticism," and even "hype" that certainly do not contribute to our understanding of it.

Part of the reasons for the ambiguity regarding what is and is not AI is its long history, in which many computational methods and applications have emerged and have also been replaced. In this dissertation, I was given the opportunity to look into the historic moments of AI development and to unpack how such pivotal points were followed by new developments, more advanced computational methods, and new application areas. This gave me insights into what is currently part of the unique features of AI (i.e., their data-driven nature, their ability to self-learn which makes them black-boxed, and their ability to generate alternative, pattern-based insights), which helped me to identify some areas in which these technologies are currently influential for work and organizing.

What I also learned from looking deeper into the features of AI systems is that we, as organizational and information systems scholars, should not cease to ask "what is AI?" and "why is this AI?" As these technologies continue to learn and develop, their features continue to change. Defining the unique features of AI is therefore not a one-time activity, but an ongoing process of refining and re-defining. Only then will we be able to continue to go beyond the "AI hype" and will AI remain a useful term to understand the specific consequences of this technology for work and organizing.

### 5.4.2 Gaining access, doing ethnography, and experiencing technological reality

As with any type of empirical research, gaining access can be a challenge. In my case, I was lucky enough to meet the right people at the right time who were helpful and knowledgeable to get me into the police. Still, after that, it was up to me. As I described in Chapter 1, from the moment it became clear that I was allowed to do my dissertation research at the police, I knew I wanted to join the emergency response department for an extended period to see how a technology such as an AI system, that at first sight seems so opposite to police work, was used in practice. However, as I described there, this was not an easy thing to get into. It took me multiple years and many negotiations to get what I "wanted" (especially since the risk I was facing in the police car was higher than I would normally face doing my academic work).

Yet, above I described that, as AI systems are aimed to generate knowledge, they are likely embedded in a knowledge ecology (Brown & Duguid, 2000) in organizations. As a researcher, this gives you the opportunity to look beyond "just" the groups of users and developers and also include other organizational actors that are involved in the development and transfer of knowledge in organizations. For me, such a group resided at the intelligence department. I joined the intelligence officers early on in their transition towards "algorithmic brokers" and experienced their highs and lows in relation to the AI system, as well as towards their new role. They shared with me their mental breakdowns, their personal victories, their individual stories, and the roads they took to become "intelligence officers." Even though the intelligence department might not have appeared the most exciting when I entered the police, the access to this department during those early years of AI implementation gave me invaluable insights into the process of translating machine learning knowledge into practice.

It was also this department that taught me everything I had to know about the world of the police (and its endless abbreviations) and about the AI system. By being part of them for two years, I experienced the hopes the intelligence officers had at the start of the implementation of the AI system, the struggles and frustration they encountered in-between when they could not figure out how insights were generated, the energy rush you get when you manually find relationships in police databases between a victim and a potential suspect, and the intelligence officers' final lack of trust and care about the AI-based insights and their increased belief in themselves as knowledgeable actors. Experiencing the "technological reality" of AI systems in practice, and how it changes over time, eventually helped me to find the story of the algorithmic brokers and their increased influence on police occupational decision-making, as I described in Chapter 3.

During my time at the intelligence department, access continued to be something I had to actively seek, not only because I still wanted to join the emergency response department, but also because my research was not just about understanding intelligence work, but about understanding intelligence work in relation to AI systems. This meant that, during those years, I did not only follow the intelligence officers, but I also remained in close contact with the developers of the AI system and the police managers responsible for the AI implementation. Looking behind the scenes of AI by means of ethnography is thus a complex, multi-faceted research project which requires a researcher to maintain relationships with a variety of actors.

Finally, not all data access was as "easy" and unrestricted as my access with the police. Chapter 4 is based on the managerial book I co-authored called "Managing AI wisely." For this book, together with my two co-authors, I used existing cases of the KIN Center for Digital Innovation, but I also performed new small case studies. Here, I had a whole new experience with gaining access to organizations that implemented AI. As organizations appeared to be afraid that I would disclose information that they did not want to be "out there" (e.g., about their use of AI, their decisions regarding AI development, or the kind of data they gathered), many doors remained closed. Other doors were wide open, but when I then entered the organization to interview some of the employees, it appeared that the so-called "AI system" did not include a learning algorithm at all, was at a pilot stage, or, even more extreme, was not even developed yet. Finding a suitable context to study AI implementation, for an extended period, and gaining all technical and organizational details can be extremely time-consuming and challenging. However, once you get in, there is nothing better.

Thus, studying AI in practice comes with its challenges regarding finding a suitable case, gaining access to a wide variety of actors, maintaining these relationships over an extended period, and keeping track of changes in work and organizing, as well as in the technology itself. To get a full understanding of the technological reality, scholars benefit from taking a "traditional" ethnographic approach (e.g., Van Maanen, 1973), spending a large amount of time, even years, in the field to fully understand how it changes over time. However, what is new in the case of AI is that spending this time with one group of organizational actors is not enough. Instead, studying AI in practice requires scholars to bridge between technology and humans, to be a computer scientist and an anthropologist in one.

### 5.4.3 Going through a "lived analysis" – a personal reflection

"*Ethnography is the experience of taking close to the same shit others take day-in and day-out*"

(Van Maanen, 2011, p. 220)

As a final point, I would like to reflect on where doing ethnography starts and ends and with what consequences for us as researchers. With this reflection, I step away from the focus on AI and reflect on what experiencing the field means to us as human beings. With the danger of sounding sentimental: doing ethnography has changed me for life. It has opened up opportunities to experience the world in different ways that would have normally not been accessible to me, but it has also resulted in challenges I did not expect, and in a way also was not prepared for when I faced them.

For this reflection, I build on the second part of my ethnography: the fieldwork at the emergency response department. Of course, this experience enhanced my knowledge of technology and work, but it also changed my life in many other ways. It gave me insight into a world of poverty, sadness, and hopelessness I had never experienced before. It has given me a better understanding of the mental health problems our society faces. It has taught me that our bodies and minds can handle experiences one could never fathom, and even multiple times in a row. I remember vividly how, shortly after leaving the field, I was presenting at a conference and received a compliment about my "cool" research context. "Thanks," I said, "but just to nuance this a bit: the shoes that I'm wearing at the moment have seen more blood and death than one should actually see in a lifetime." I was still in the process of finding a way to deal with all the things I had seen. Interestingly, one of the most surprising aspects of police work, and one that has become a key topic in my dissertation research, was the extreme boredom and the bodily aches I experienced in the long "data work hours" often in the middle of the night or after a long shift. It was through experiencing these long hours that I started to deeply question the consequences of data production.

The experiences I summarized above link to what is generally considered the aim of doing ethnography: to get a "lived experience" of working in a specific context, which is something that is impossible to obtain through a case study and which provides invaluable insights into everyday work and organizing. Some scholars have reflected on what it is like to do fieldwork (e.g., Claus et al., 2019), or the experience of leaving the field (e.g., de Rond, 2012). Yet, what I did not foresee, and what we do not often describe, is that this "lived experience" continues as you analyze your data – the data that reflects what you have seen, sensed, smelled, felt, laughed, and cried over – over and over again.

This is what I would like to call the "lived analysis" and it is something you experience only when you have left the field. For me, this was the part of the ethnography that hit me the hardest. It was not when I was with the police that I reflected on all that I had seen, it was when I had left and I did not have the prospect of a new shift to keep me away from my own thoughts and experiences that they started coming. And here is the interesting thing: to write a meaningful story, we have to relive those moments. We have to go back to those memories and feel again what we felt then. We have to tap into our fear, our adrenaline rush, our confusion, and even our boredom, to keep the lived experiences alive. But doing that is hard, especially if there are stories you would rather forget the details of.

It took me a while to learn how to deal with this experience. It can be quite overwhelming if, as a young researcher, you start doing your data analysis with a lot of enthusiasm, only to feel like someone has hit you with a baseball stick after about an hour. I had to learn how to express my struggles with this, as I was not aware that others were struggling with this too. It takes time to find the right way to deal with these experiences and to learn how to leverage them time and again without falling victim to your own thoughts. Every context has its own stories that we, as researchers, bring with us. It is up to us to study them, to experience and live them, and to relive them.

## References

Anteby, M., Chan, C. K., & DiBenigno, J. (2016). Three lenses on occupations and professions in organizations: Becoming, doing, and relating. *Academy of Management Annals, 10*(1), 183–244.

Bailey, D. E., & Barley, S. R. (2020). Beyond design and use: How scholars should study intelligent technologies. *Information and Organization, 30*(2). doi:10.1016/j.infoandorg.2019.100286

Barley, W. C. (2015). Anticipatory work: How the need to represent knowledge across boundaries shapes work practices within them. *Organization Science, 26*(6), 1612-–1628.

Best, K., & Hindmarsh, J. (2019). Embodied spatial practices and everyday organization: The work of tour guides and their audiences. *Human Relations, 72*(2), 248–271.

Bossen, C., Pine, K., Ellingsen, G., & Cabitza, F. (2016). *Data-work in healthcare: The new work ecologies of healthcare infrastructures.* Paper presented at the Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion - CSCW '16 Companion.

Brown, J. S., & Duguid, P. (1998). Organizing knowledge. *California Management Review, 40*(3), 90–111.

Brown, J. S., & Duguid, P. (2000). *The social life of information.* Cambridge, MA: Harvard Business School Press.

Bucher, E. L., Schou, P. K., & Waldkirch, M. (2020). Pacifying the algorithm – Anticipatory compliance in the face of algorithmic management in the gig economy. *Organization.* doi:10.1177/1350508420961531

Burgess, N., & Currie, G. (2013). The knowledge brokering role of the hybrid middle level manager: The case of healthcare. *British Journal of Management, 24,* S132–S142.

Claus, L., de Rond, M., Howard-Grenville, J., & Lodge, J. (2019). When fieldwork hurts: On the lived experience of conducting research in unsettling contexts. In *The production of managerial knowledge and organizational theory: New approaches to writing, producing and consuming theory.* Emerald Publishing Limited.

Cunha, J., & Carugati, A. (2018). Transfiguration work and the system of transfiguration: How employees represent and misrepresent their work. *MIS Quarterly, 42*(3), 873–894.

Cunliffe, A., & Coupland, C. (2012). From hero to villain to hero: Making experience sensible through embodied narrative sensemaking. *Human Relations, 65*(1), 63–88.

Czarniawska, B., & Sevón, G. (2005). Translation is a vehicle, imitation its motor, and fashion sits at the wheel. In Czarniawska B, Sevón G (eds) *Global Ideas: How Ideas, Objects and Practices Travel in the Global Economy*. Malmø: Liber & Copenhagen Business School Press.

Faraj, S., & Pachidi, S. (2021). Beyond Uberization: The co-constitution of technology and organizing. *Organization Theory, 2*(1). doi:10.1177/2631787721995205

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70.

Flyverbom, M., & Garsten, C. (2021). Anticipation and organization: Seeing, knowing and governing futures. *Organization Theory,* 2(3). doi:10.1177/26317877211020325

Gal, U., Jensen, T. B., & Stein, M.-K. (2020). Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. *Information and Organization, 30*(2). doi:10.1016/j.infoandorg.2020.100301

Gardner, R. L., Cooper, E., Haskell, J., Harris, D. A., Poplau, S., Kroth, P. J., & Linzer, M. (2019). Physician stress and burnout: The impact of health information technology. *Journal of the American Medical Informatics Association, 26*(2), 106–114.

Glaser, V. L., Valadao, R., & Hannigan, T. R. (2021). Algorithms and routine dynamics. In M. S. Feldman, B. T. Pentland, L. D'Adderio, K. Dittrich, C. Rerup, & D. Seidl (Eds.), *Cambridge Handbook of Routine Dynamics.* Cambridge: Cambridge University Press

Henke, N., Levine, K., & McInerney, P. (2018). You don't have to be a data scientist to fill this must-have analytics role. *Harvard Business Review.*

Hindmarsh, J., Hyland, L., & Banerjee, A. (2014). Work to make simulation work: 'Realism', instructional correction and the body in training. *Discourse Studies, 16*(2), 247–269.

Johnson, K. B., Neuss, M. J., & Detmer, D. E. (2020). Electronic health records and clinical burnout: A story of three eras. *Journal of the American Medical Informatics Association.* doi:10.1093/jamia/ocaa274

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.

Leonardi, P. M. (2009). Crossing the implementation line: The mutual constitution of technology and organizing across development and use activities. *Communication Theory, 19*(3), 278–310.

Leonardi, P. M., & Barley, S. R. (2010). What's under construction here? Social action, materiality, and power in constructivist studies of technology and organizing. *The Academy of Management Annals, 4*(1), 1–51.

Meyer, M. (2010). The rise of the knowledge broker. *Science Communication, 32*(1), 118–127.

Mol, A. (2003). *The body multiple.* Duke University Press.

Mueller, F., & Whittle, A. (2011). Translating management ideas: A discursive devices analysis. *Organization Studies, 32*(2), 187–210.

Newlands, G. (2021). Lifting the curtain: Strategic visibility of human labour in AI-as-a-Service. *Big Data & Society, 8*(1). doi: 10.1177/20539517211016026

Nielsen, J. A., Mathiassen, L., & Newell, S. (2014). Theorization and translation in information technology institutionalization: Evidence from Danish home care. *MIS Quarterly, 38*(1), 165–186.

Oborn, E., Barrett, M., & Davidson, E. (2011). Unity in diversity: Electronic patient record use in multidisciplinary practice. *Information Systems Research, 22*(3), 547–564.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science, 3*(3), 398–427.

Orlikowski, W. J., & Scott, S. V. (2016). *Digital work: A research agenda. In A Research Agenda for Management and Organization Studies.* Edward Elgar Publishing.

Pachidi, S., Berends, H., Faraj, S., & Huysman, M. (2020). Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organization Science.* doi:10.1287/orsc.2020.1377

Pawlowski, S. D., & Robey, D. (2004). Bridging user organizations: Knowledge brokering and the work of information technology professionals. *MIS Quarterly, 28*(4), 645–672.

Pine, K. H., & Bossen, C. (2020). Good organizational reasons for better medical records: The data work of clinical documentation integrity specialists. *Big Data & Society, 7*(2). doi:10.1177/2053951720965616

Pine, K. H., & Liboiron, M. (2015). *The politics of measurement and action.* Paper presented at the Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210.

de Rond, M. (2012). Soldier, surgeon, photographer, fly: Fieldwork beyond the comfort zone. *Strategic Organization, 10*(3), 256-262.

de Rond, M., Holeman, I., & Howard-Grenville, J. (2019). Sensemaking from the body: An enactive ethnography of rowing the amazon. *Academy of Management Journal, 62*(6), 1961–1988.

Røvik, K. A. (2016). Knowledge transfer as translation: Review and elements of an instrumental theory. *International Journal of Management Reviews, 18*(3), 290–310.

Sachs, S. E. (2020). The algorithm at work? Explanation and repair in the enactment of similarity in art data. Information, *Communication & Society, 23*(11), 1689–1705.

Sergeeva, A., Faraj, S., & Huysman, M. (2020). Losing touch: An embodiment perspective on coordination in robotic surgery. *Organization Science, 31*(5), 1248–1271.

Truelove, E. (2019). *The changing nature of professional work inside an incumbent firm in the age of social media: examining the challenge of coproduction* (Doctoral dissertation, Massachusetts Institute of Technology).

Van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. *MIS Quarterly, Forthcoming*

Van Maanen, J. (1973). Observations on the making of policemen. *Human Organization, 32*(4), 407–418.

Van Maanen, J. (2011). Ethnography as work: Some rules of engagement. *Journal of management studies, 48*(1), 218–234.

Vertesi, J. (2012). Seeing like a Rover: Visualization, embodiment, and interaction on the Mars exploration Rover mission. *Social Studies of Science, 42*(3), 393–414.

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries, 4*(4), 404–409.

Wacquant, L. (2005). Carnal connections: On embodiment, apprenticeship, and membership. *Qualitative Sociology, 28*(4), 445–474.

Zammuto, R. F., Griffith, T. L., Majchrzak, A., Dougherty, D. J., & Faraj, S. (2007). Information technology and the changing fabric of organization. *Organization Science, 18*(5), 749–762.

# 6. Summary

From recruitment to health care and from law enforcement to education, artificial intelligence (AI) is increasingly implemented in organizations. Using machine learning, these systems produce insights – referred to as "machine learning knowledge" – that potentially go beyond what is humanly possible. Therefore, organizational and information systems scholars increasingly argue that, beyond automation, AI systems can actually augment existing work practices. Such augmentation is said to work in two ways, for when organizational actors work closely with AI systems, they can complement the insights with their unique human capabilities, such as intuition and common-sense reasoning, and AI systems can also complement these actors' domain knowledge by offering previously unknown insights. However, what is commonly overlooked in existing research is that there is a fundamental difference between the procedures used for machine learning and how human knowledge is produced. This difference makes it challenging to find common ground for sharing and collectively producing knowledge in the first place. Even though the expectations about the possibilities of AI systems for organizing are high, organizations thus face new yet unknown challenges when implementing machine learning in practice. Therefore, this dissertation sets out to answer the following research question: *How do organizations cope with the production and use of machine learning in practice?*

The core of this thesis includes three self-contained chapters to answer this question. Chapter 2 relates to the core feature of AI systems: data. As the making of data is becoming increasingly important for organizations in developing and training AI systems, I ask what happens when workers are facing the need to embed "data work" practices in their existing, situated work. In this Chapter, I build on the final year of my ethnographic research at the Dutch police, where I joined the emergency response department full time "in the streets." By comparing the police officers' experience of data work and the characteristics of their situated work, three data work tensions emerge. I show that police officers cope with these tensions by anticipating the data work and adopting three coping strategies in their situated work: avoiding work, deviating from protocol, and capturing experiences. While these strategies help the police officers to alleviate the burden of data production they experience on a daily basis; they have a large influence on how police officers perform their situated work. As a consequence, what and how crimes are reported and data is produced is significantly influenced by their coping strategies.

Chapter 3 builds on my two years of fieldwork at the intelligence department of the Dutch police. In this Chapter, I focus on two more features of AI systems, namely the opaque nature of machine learning and the ability to produce new insights, and offer one of the first empirical accounts of algorithmic brokers. I ask how such brokers can translate machine learning knowledge when they cannot understand how knowledge is generated. I find that as the algorithmic brokers need to translate predictions to the users, they realize that they need to understand how these predictions are generated. By trying to become more familiar with machine learning, the brokers perform different translation practices over time and enact increasingly influential brokerage roles, i.e., messenger, interpreter, and curator. When, finally, the algorithmic brokers come to the conclusion that they can never understand how machine learning knowledge is generated, they act like "kings in the land of the blind" and substitute the algorithmic predictions with their own judgments.

In Chapter 4, I build on the three unique features of AI systems that I unpacked in Chapters 2 and 3 – i.e., their dependence on large amounts of data, the opaque nature of machine learning, and the to generate new insights – and use unique insights from five different cases across various industries to ask how the "implementation line" can be crossed in the case of AI, in which technology development and organizational deployment are often worlds apart. I identify three different AI implementation practices – i.e., organizing for data, organizing for explainability, and organizing for new insights – and show how, through these implementation practices, developers and organizational actors are required to engage in continuous and reflective "collaborative learning."

This dissertation contributes to the discussion on the production and use of knowledge that has been core to the field of organization theory for decades. By taking a practice perspective, I unpack how new, machine-based knowledge is developed, implemented, and used in practice and with what consequences for work and organizing. Moreover, by including and theorizing the specific features of AI systems and their relation to organizing, this dissertation responds to the call to bridge the divide between technology development and organizational change. Also, this dissertation links to the field of information systems by going beyond the "AI hype" to unpack the challenges that emerge when organizing for machine learning knowledge in practice.

Finally, this dissertation also has practical implications. I urge managers to let go of the "AI hype" and instead consider AI implementation as effortful, skillful, and requiring long-term involvement. AI systems can therefore not be considered as a quick and easy solution to large amounts of data, nor as crystal balls that will magically lead organizations to new insights. Instead, long-term and direct involvement will provide managers with behind-the-scenes knowledge about the skills and efforts required for producing and using AI systems in a successful way.

# Acknowledgements

"*When the order to move on comes, the Warrior looks at all the friends he has made during the time that he followed the path. He taught some to hear the bells of a drowned temple, he told others stories around the fire. His heart is sad, but he knows that his sword is sacred and that he must obey the orders of the one to whom he offered up his struggle. Then the Warrior thanks his traveling companions, takes a deep breath and continues on, laden with memories of an unforgettable journey*." Paulo Coelho - Warrior of the light

---

This PhD journey was, at times quite literally, a wild ride. It allowed me to enter a new world, meet new people, and develop as a researcher but also as a person. Of course, I could not have gone through this journey on my own and many people have helped me along the way. I have so many people to thank and, though I realize that this tribute will never fully reflect how grateful I am to each and every one of them, I will make an attempt at putting it into words.

Let me start with the one who has made this all possible for me: Marleen Huysman. Marleen, we started off in the formal relationship of you being the promotor and me the PhD student but I quickly realized that for you there is no such thing as a "teacher vs. student" relationship. I cannot thank you enough for the unwavering trust you have given me. From letting me go and find my way with the police, to letting me stay there for three years because I felt it was important, to presenting at conferences at a very early stage, to developing my teaching skills in complete freedom, to making me the main author of our book, you have always given me the space, freedom, and trust to develop as an academic. At the same time, you have taught me how to stay open to change and to always, always, always reflect on your thoughts and ideas. I will cherish all the endless giggles (often about some undefined, unrelated topic) and I look forward to many more brainstorm sessions that go way out of line and end up with what we believe (for an hour) to be brilliant ideas.

Next, I would like to thank Anastasia Sergeeva. Anastasia, I am so happy that I can call myself your first PhD student and that I can now also call you my friend. Your excitement for research not only motivated me from the start but has also helped the study to become what it is today. As my "daily supervisor," I could always count on you to listen to me when I was struggling and to help me get it together when I was complaining. You have taught me how to deal with sometimes overwhelming feedback and how to formulate my own opinion in parallel. We have written in bars and restaurants and even at your home to get some of the revisions done (always with the promise of having snacks close by). With your endless support, you helped me mature in such a way that, when you had your own "baby" to finish, I was able to continue without you. I am very grateful to have seen you become a mom and I look forward to seeing our work and friendship grow further alongside your beautiful son.

I am truly grateful to all the people of the Dutch police who have helped me along the way. Jan-Kees, Dominique, and Joke, thank you for helping me gain access. Dick, thank you for all the help in unpacking the AI system. Peter, Laura, Denise, Arthur, Ikraam, Annelies, and Willemijn, thank you for letting me be part of your department for so long. To the emergency response department that I was allowed to join for a full year: listing all your names here would be too much, so I am saying a collective thank you to all of you for letting me become part of your group. You have changed my life in many ways. I think you all agree if I mention just one name in particular. Nick, how much I would have loved for you to see the final "book." Your words are written across the pages, to never be forgotten.

I would also like to thank the members of my reading committee: Professor Kate Kellogg, Professor Mark de Rond, Professor Hans Berends, Elena Parmiggiani, and Ronald van Steden. I am very proud and honored to have a committee with names that are fundamental in organizational theory as well as information systems scholarship. Thank you for your time and your valuable feedback on my manuscript.

There is also a long list of other academic colleagues that I would like to thank for helping me develop as a researcher. Mohammad Rezazade Mehrizi, without you and the knowledge management course I would have never believed I could become a researcher. Joao Vieira da Cunha, thank you for your unlimited enthusiasm about my research and for introducing me to IÉSEG School of Management. Joe Nandhakumar and Zhewei Zhang, thank you for the great teamwork in the AI for legislation project. Marlous Agterberg, thank you for co-authoring the "Managing AI wisely" book and teaching me the skills of effective outreach. Mark de Rond, thank you for having me over at Cambridge Judge Business School and for taking the time to share experiences and talk about the impact of doing fieldwork when I most needed it. Michael Barrett, Shaz Ansari, Jennifer Howard-Grenville, and Thomas Roulet, thank you for taking the time to talk about research when I was visiting Cambridge Judge. All the PhD's at Cambridge Judge, thank you for making me feel at home. Adrian Marrison, thank you for continuing to share experiences, ideas, and excitement about our ethnographic work. And a big thank you to all the academic colleagues who have shared insights, provided feedback, or just listened with interest during summer schools, seminars, and conferences I was fortunate enough to attend.

A very special thanks to the very special group that I have been part of for the last six years. To all the colleagues who were part of KIN Center for Digital Innovation: Hans, Frans, Bart, Frank, Maura, Philipp, Fleur, Joey, Hakan, Sascha, Marijn, Amanda, Mahmood, Sander, Mark, Julian, Claudia, Serge, Susan, Natalja, Nick, Julia, Wendy, Dennis, Jovana, Kathrin, Tomislav, Mario, Lorna, Leighann, Katya, Michael, and Christine. Thank you for making KIN feel like home. Florence, thank you for always being there when I (and everyone else) need you, for sending happy emails, and for always thinking of others. I do not know how I would have planned "academic life" without you.

There are, of course, also people I would like to thank separately. Piet and Regina, thank you for always listening attentively to my stories and for teaching me about the "uselessness" of capitalizing words. Elmira, thank you for being my partner in crime in studying AI. Talking and hanging out together has been a great inspiration and I am happy

to have shared a large part of the PhD with you. I look forward to seeing what you will achieve in the upcoming years, for you have already shown that the sky is the limit. Let's continue to support and inspire each other. Bomi, while our chats about "PhD life" have been of great help to me, it was those about nails, outfits, and jewels that made (home) office life much more fun and a lot brighter. Thank you for your endless enthusiasm and happy attitude. I look forward to having many more of these conversations in the future.

Ella, from the moment we shared a hotel room for EGOS in Tallinn and, let's be honest, an airplane seat (almost), I knew we had "something special." I can always count on you to come up with some book you have read in some kind of field no one has ever heard of, a joy we continue to share. With topics abound, our conversations always inspire me and now we can even have them in Dutch. I am forever grateful that you shared with me with your secret when you knew you were expecting a little baby and that you trusted me to help you with the Dutch meaning of her name (I still have not gotten over that responsibility though). Thank you for making me part of your life.

Melissa, still strangers on the introduction day of our master's program, we sat side by side not knowing where the future would take us. Only 30 minutes later you complimented me on my shoes. I knew then that we would become best friends. Inseparable from the start, you have been with me through it all. We ran after late-night busses in Konstanz (of all places), partied in Cambridge, and moved couches in Lille. No matter how stressful a situation, your down-to-earth approach to life has always brought me back to what really matters. I do not know what I would have done without you but I know for sure that it would have been a lot less fun. Thank you for always being my wing-woman and for making sure that whatever life throws at us we can and will approach it with a smile.

Lyn, the day you came into my life was the happiest day of my life. Not only because you were a little sister (and not a brother which I feared more than anything) but because from that day on we were with the two of us. I could braid your hair like I did with my dolls,

boss you around as any elder sister does, and teach you all the stuff I already knew being nearly four years older. Little did I know back then that when we got older there would be so much that I could learn from you. If there is one person that has shown strength and resilience, it is you. Where others would have given up, you persisted with a smile and unwavering trust in what the future would hold. Thank you for always being by my side and for teaching me to stay true to yourself, no matter what.

Jochem, here we are, officially at the end of our "VU adventure." So many years since we first met and so many stories to tell. You warned me once that, at times, you could be a bit nitty-gritty; if only I knew. I have never met anyone as determined to get the best out of himself and his work as you and you have encouraged me from the start to do the same. From late-night arguments over theoretical concepts to brainstorming on our bikes, I can count on you to, by definition, enthusiastically disagree with my point of view. In many things the exact opposite, we are a great team and I could not think of anyone else I would want to disagree with as much as with you. Thank you for becoming such a great cook during the final year of my PhD and for never having me do the dishes. Thank you for always challenging me, for it has taken us to where we are today. And thank you for always encouraging and supporting me. Off we go on our next adventure.

Finally, dear mom and dad, thank you for always having my back. You were there for me when I wanted to fly, accepted my eventual decision to stay grounded, and have been my biggest supporters through it all. Dad, you have shown me the importance of finding a job you love, of being willing to work for it as hard as you can, and that staying loyal and truthful is more important than anything. Thank you for taking me everywhere and for reading and discussing all of the pieces I wrote during my PhD. Mom, you have shown me what it means to fight for what you love, that being present is the greatest gift to someone's life, and because of you I have learned how to really "see." Up to this day, you listen to my endless stories (which started with reciting half-hour poems learned at primary school) and you help me think of solutions for the struggles I face. Thank you for always being there and for encouraging me to explore the world.

# ABRI dissertation series

1. Drees, J.M. (2013). The polycentricity of expansion strategies: Beyond performance as a main driver.
2. Arzlanian, S. (2014). Social networks and firm performance: Examining the relation between dimensions of social capital, social network perception and firm performance.
3. Fleisher, C. (2014). The contemporary career navigator: Individual and organizational outcomes of self-directed career management.
4. Wruck, S. (2014). Warehouse operations revisited – Novel challenges and methods.
5. Volk-Makarewicz, W. (2014). Advances in derivative estimation: Ranked data, quantiles, and options.
6. Van Anholt, R. (2014). Optimizing logistics processes in cash supply chains.
7. Polat, T. (2015). Active aging in work: Motivating employees to continue working after retirement.
8. Ossenkop, C. (2015). What you see is what you get!? Looking into ethnic diversity and professional careers in Dutch organizations.
9. Engel, Y. (2015). Venturing into the unknown, but not for the first time: An examination of firm-founders' careers & entrepreneurial decision-making under uncertainty.
10. Kolbe, L. (2015). The mindset of the R&D professional: Decision making in innovative context.
11. Pachidi, S. (2015). Crunching the numbers: Studying the enactment of analytics in an organization.
12. El Baroudi, S. (2015). Shading a fresh light on proactivity research: Examining when and how proactive behaviors benefit individuals and their employing organizations.

13. Eijdenberg, E. L. (2016). Small business growth in east African least developed countries: Unravelling the role of the small business owners.
14. Lysova, E.I. (2016). What does your career mean to you? Understanding individual career and work behaviors through the prism of the meaning of career.
15. De Mol, E. (2016). Heart and brain: The influence of affective and rational determinants in new venture teams: An empirical examination.
16. Daubner-Siva, D. (2016). Dealing with dualities: A paradox perspective on the relationship between talent management and diversity management.
17. Berkhout, J. (2016). Topics in Markov chain theory and simulation optimization.
18. Van-Werven, R. (2017). Acquiring resources for a new venture: A study of the micro-level linguistic practices of startup entrepreneurs.
19. Prats Lopez, M. (2017). Managing citizen science in the Humanities: The challenge of ensuring quality.
20. Kaandorp, M.S. (2017). Creating from within: A study on interpersonal networking approaches and intuition in task-related interaction.
21. Van Grinsven, M. (2017). A patient is not a car; Lean in healthcare: Studying agency in the translation of management concepts.
22. Muleta Eyana, S. (2017). Entrepreneurial behavior and firm performance of Ethiopian tour operators.
23. Van Ee, M. (2017). Routing under uncertainty: Approximation and complexity.
24. Van Dijk, M. (2017). When I give, I give myself: Essays on individual contributions to societal goals.
25. Oostervink, N. (2017). Self-organizing knowledge: Examining the conditions under which professionals share and integrate knowledge.
26. Mousavi, S. (2017). Managing innovation for sustainability- A dynamic capabilities approach.
27. Cai, W. (2017). Awakening employee creativity in organizations.
28. Kranzbuhler, A.M. (2018). Orchestrating the customer journey: Four essays on how to create meaningful customer experiences.

29. Chabala, M. (2018). Small firm growth in a least developed country: How small firm owners affect the growth of their firms in Zambia.
30. Choongo, P. (2018). Sustainable entrepreneurship in Zambia: The engagement in and effect of sustainable practices in small and medium-sized enterprises.
31. Hilbolling, S. (2018). Organizing ecosystems for digital innovation.
32. Van der Wal, A. J. (2018). Harnessing ancestral roots to grow a sustainable world.
33. Hofstra, N. (2018). Individual decision-making in operations: A behavioral perspective.
34. Mu, Y. (2019). Management of service innovation quality.
35. Stephenson, K.A. (2019). Paperless professors: A study of changing academic work and workspaces.
36. Hummel, J.T. (2019). Collaboration and innovation between heterogeneous actors.
37. De Jong, G. (2019). National carriers, market power and consumer loyalty: A study of the deregulatory international airline industry.
38. Szabo, A. (2019). The adoption of governance practices in hospitals: The role of multi-level frames of board members in making decisions about practice adaptation.
39. Sagath, D. (2019). Entrepreneurship in the Dutch space sector: The role of institutional logics, legitimacy and business incubation.
40. Günther, W. A. (2019). Data as strategic resources: Studies on how organizations explore the strategic opportunities of data.
41. Laurey, N.R. (2019). Design meets business: An ethnographic study of the changing work and occupations of creatives.
42. Gorbatov, S. (2019). Personal branding: Self-presentation in contemporary careers.
43. Baller, A.C. (2019). Improving distribution efficiency in cash supply chains.
44. Hoogeboom, M. (2019). Optimizing routes with service time window constraints.
45. Bosman, T. (2019). Relax, round, reformulate: Near-optimal algorithms for planning problems in network design and scheduling.

46. Van Duin, S.R. (2020). Firms' economic motivations and responsiveness to supervision.
47. Abdallah, G.K. (2020). Differences between entrepreneurs in Tanzania's informal and formal sectors: Opportunities, growth and competencies.
48. Glasbeek, L. (2020). Social enterprises with exceedingly tight resources: Implications for work and leadership.
49. Shabani, A. (2020). Supply chain networks: Quantitative models for measuring performance.
50. Plomp, J. (2020). Job crafting across employment arrangements. Proactivity on the interface of work and careers.
51. Engbers, M. (2020). How the unsaid shapes decision-making in boards: A reflexive exploration of paradigms in the boardroom.
52. Oskam, I.F. (2020). Shaping sustainable business models: Stakeholder collaboration for sustainable value creation.
53. Bunea, E. (2020). Leading and leisure: How serious leisure influences leaders' development and effectiveness.
54. Yang, C. (2020). Firm Survival and innovation in emerging markets: The case of China.
55. Tcholakian, L. (2020). On becoming historically conscious leaders: Exploring the underlying effects of transgenerational transmission of collective traumas.
56. Doornenbal, B.M. (2020). The impact of status hierarchy on individual behavior and team processes.
57. Mühlhaus, J. (2020). 'Mapping' the broader social and geographic space and its interplay with individual careers and work identities.
58. Schlegelmilch, J. (2020). Where we work: Physical workplaces in a digital world.
59. De Groot, M.B.T. (2021). Cracking the code on wealth preservation: It is not about Money.
60. Seip, M. (2021). Firms and Intellectual Property Rights: who, which, when and where.

61. Schäfer, U. (2021). Moral disengagement as a social phenomenon: Effects of moral disengagement on moral judgments of others and shared cognition in groups.
62. Erdös, T. (2021). Change process beyond goals: The client in the context of the working alliance in coaching occupations of creatives.
63. Kersten, M. (2021). Navigating the tensions of digital transformation in high reliability organizations.
64. Vullinghs, J. T. (2021). Changing perspectives: Studying the temporal dynamics of organizational leadership and employee wellbeing.
65. Brokerhof, I.M. (2021). Fictional narratives at work: How stories shape career identity, future work selves and moral development.
66. Botke, J.A. (2021). Understanding the transfer-to-work of soft skills training: Examining transfer stages, the role of work factors and self-efficacy.
67. Ikonen, I.H. (2021). Influencing consumer choice for healthy foods at the point of purchase: The role of marketing communication and food pricing strategies.
68. Frascaria, D. (2021). Dynamic traffic equilibria with route and departure time choice.
69. Van Mourik, O. (2021). Learning from errors: Barriers and drivers in audit firms.