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In the Land of the Blind, the One-Eyed Man Is King: Knowledge Brokerage in the Age of Learning Algorithms

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Abstract. This paper presents research on how knowledge brokers attempt to translate opaque algorithmic predictions. The research is based on a 31-month ethnographic study of the implementation of a learning algorithm by the Dutch police to predict the occurrence of crime incidents and offers one of the first empirical accounts of algorithmic brokers. We studied a group of intelligence officers, who were tasked with brokering between a machine learning community and a user community by translating the outcomes of the learning algorithm to police management. We found that, as knowledge brokers, they performed different translation practices over time and enacted increasingly influential brokerage roles, namely, those of messenger, interpreter, and curator. Triggered by an impassable knowledge boundary yielded by the black-boxed machine learning, the brokers eventually 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.

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Keywords: learning algorithms • artificial intelligence • algorithmic brokers • knowledge brokerage • knowledge sharing • knowledge translation

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, Zhang et al. 2020, Lebovitz et al. 2021, Van den Broek et al. 2021). By combining large data sets with advanced computational and statistical methods to make connections between data points—a process that is called "machine learning" (Burrell 2016, Brynjolfsson and McAfee 2017, Davenport 2018)—learning algorithms generate algorithmic predictions (Faraj et al. 2018). Learning algorithms deserve specific scholarly attention, as we cannot rely on the existing understanding of "intelligent technologies" in organizations (Von Krogh 2018, Bailey and Barley 2020, Huysman 2020, Pachidi et al. 2021). Earlier "rule-based" technologies, such as expert systems, reflected the expert knowledge that was coded into them (Forsythe 1993), and developers could explain their outputs. In contrast, through machine learning, the input data and the knowledge of developers are autonomously transformed into algorithmic predictions. The downside of machine learning is that it is difficult for humans to discern how and which connections between data points are made, which makes it challenging to understand how algorithmic predictions are generated. This problem is often referred to as the "opaque nature" (Burrell 2016, Christin 2020) or "black box problem" (Pasquale 2015, Anthony 2021) of learning algorithms.

The opaque nature of learning algorithms makes trusting and using algorithmic predictions in practice problematic (Bader and Kaiser 2019, Lebovitz et al. 2019, Glikson and Woolley 2020). As a potential solution, recent studies posit that "algorithmic brokers" (Kellogg et al. 2020) could emerge to facilitate the use of these systems by translating predictions to users (Henke et al. 2018, Gal et al. 2020, Sachs 2020). The work of algorithmic brokers should therefore resemble what is referred to in organizational theory as "knowledge brokers" (e.g., Carlile 2004, Pawlowski and Robey 2004, Meyer 2010)—actors who enact translation practices to solve knowledge boundaries between communities (Brown and Duguid 1998). These knowledge boundaries are defined by the practices that are easily shared by actors within communities and equally difficult to share by actors from different communities. For algorithmic brokers, this means solving a knowledge boundary between a machine learning community and a user community.

A machine learning community can be defined by the shared practices of developing algorithmic predictions; a user community represents actors who share domain knowledge and intend to use algorithmic predictions. Previous studies argue that for brokers to translate between communities requires a thorough understanding of the practices of both communities (Brown and Duguid 1998, Sturdy and Wright 2011, Røvik 2016). However, in the case of learning algorithms, algorithmic predictions are generated by combining inputs (i.e., data and developers' knowledge) with machine learning (Von Krogh 2018). Because of the black-boxed nature of learning algorithms, these aspects of the machine learning community remain hidden, even for developers (e.g., Faraj et al. 2018), which leads to a puzzle that goes beyond the current understanding of knowledge brokerage: How do brokers translate algorithmic predictions when they cannot understand how these are generated?

To answer this question, we offer a 31-month ethnographic study of a Dutch police department that implemented predictive policing—that is, 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" performed different translation practices through which they enacted increasingly influential knowledge brokerage work (i.e., in the form of messenger, interpreter, and curator). Our study offers an integrative perspective on organizational theory and emerging technologies and reveals the emergence of a new phenomenon: the algorithmic 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 and Duguid 1998, Pawlowski and Robey 2004, Meyer 2010, Burgess and Currie 2013). 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 communities (e.g., Dougherty 1992, Carlile 2004, Boari and Riboldazzi 2014), because, in their efforts to resolve such boundaries, brokers can generate new boundaries between themselves and the communities they are intended to connect. In addition, our findings contribute to translation theory (e.g., Czarniawska and Sevón 2005, Mueller and Whittle 2011, Nielsen et al. 2014, Røvik 2016). Whereas current translation theories 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.

Research on Knowledge Brokers

Sharing knowledge between actors coming from diverse professional or organizational settings is considered a key organizational competence and the topic has occupied many organizational scholars (e.g., Nonaka 1994, Von Hippel 1994, Østerlund and Carlile 2005, Pachidi et al. 2021, Safadi et al. 2021). Initially, knowledge was mainly considered as an object that had to be made explicit before it could be transmitted (e.g., Nelson and Winter 1982, Teece 1998). However, organizational scholars started to counter this perspective by arguing that knowledge is embedded in practices (e.g., Cook and Brown 1999, Brown and Duguid 2001, Tsoukas 2003), which means that knowledge is shared through sharing practices. The practice-based perspective on knowledge has gained traction ever since and has triggered many interesting research avenues, such as how practice-based knowledge can be distributed, managed, and supported by technology (Orlikowski 2002, Levina and Vaast 2005, Faraj et al. 2016).

Taking a practice-based perspective on knowledge helps us to see that knowledge sharing is a complex process, since the tacit elements of knowledge that are "rooted in action, procedures, routines, commitment, ideals, values, and emotions" (Nonaka and von Krogh 2009, p. 636) can lead to interpretative differences between actors residing in different communities (Lave 1988, Brown and Duguid 1998, Orlikowski 2002, Carlile 2004). For example, Barley (1986) has shown how interpretative differences can emerge and grow when the implementation of a CT scanner requires knowledge sharing between technology developers and technology users. In such situations, a so-called "semantic boundary" (Carlile 2004) hinders knowledge sharing as the communities' practice-based knowledge[1] continues to reproduce this boundary. Crossing a semantic boundary therefore requires creating shared understandings (Dougherty 1992).

Some scholars argue that diverse actors can develop a shared understanding when they participate in shared practices (Brown and Duguid 1991, Lave and Wenger 1991, Orr 1996). However, most studies argue that such shared practices are unusual and emphasize that crossing a semantic boundary requires a particular group of "knowledge brokers" to operate in-between communities by becoming familiar with them in order to gather and disseminate information and knowledge (e.g., Hargadon and Sutton 1997, Brown and Duguid 1998, Carlile 2004, Evers and Menkhoff 2004, Burgess and Currie 2013, Chiambaretto et al. 2019). Accordingly, organizational scholars have paid attention to the role of knowledge brokers in areas such as engineering (Johri 2008), science (Barley 1996, Kissling-Naf 2009), information technology (Pawlowski and Robey 2004), and recently regarding emerging technologies, such as learning algorithms (Kellogg et al. 2020). Knowledge brokers perform a kind of "boundary work" (e.g., Soundarajan et al. 2018, Langley et al. 2019), yet differ from what are known as "boundary spanners" (e.g., Ancona and Caldwell 1992, Levina and Vaast 2005) in that knowledge brokers do not belong to or come from the communities they intend to connect (Gould and Fernandez 1989, Fleming and Waguespack 2007, Meyer 2010, Haas 2015).

The concept of knowledge brokers is derived from the field of broker studies (e.g., Gould and Fernandez 1989, Burt 1992, Obstfeld 2005, Stovel and Shaw 2012, Heaphy 2013) and traditionally resides in the structural network approach (e.g., DiMaggio 1993, Fernandez and Gould 1994, Reagans and McEvily 2003, Leonardi and Bailey 2017). Taking this perspective, brokers are considered to occupy a "structural hole" (Burt 1992) between disconnected actors and to benefit from unique access to various communities and knowledge sources (DiMaggio 1993, Fernandez and Gould 1994). Studies on *brokerage work* move away from the structural network perspective, in which a broker's role is determined by one's position in a network, to take a more practice-based perspective on how brokerage roles are enacted in practice (e.g., Wenger 1999, Fernandez-Mateo 2007, Lingo and O'Mahony 2010, Obstfeld et al. 2014, Edacott and Leonardi 2020). These studies emphasize how brokerage work emerges when new tasks are created that existing communities are unwilling or unable to take on (Barley 1996, Heimer and Stevens 1997, O'Mahony and Bechky 2008, Huising and Silbey 2011). For example, Kellogg (2014) examined how, in the face of organizational reform at a hospital, brokers took on tasks that medical professionals and lawyers did not consider to be part of their occupational domain.

In the case of knowledge brokerage, these new tasks are typically related to translating knowledge in order to ensure that actors across different communities can understand each other. Knowledge brokers therefore enact translation practices through which they present the knowledge of one community in such a way that it gains a shared understanding and can be put in practice (Tushman and Katz 1980, Barley 1996, Grady and Pratt 2000, Paul and Whittam 2010, Boari and Riboldazzi 2014). To enact such translation practices, knowledge brokers depend on their interactions with the communities with the aim to (1) *decontextualize* knowledge in order to *translate knowledge from* one community into more abstract representations (e.g., words or texts) and to (2) *contextualize* the abstract representations in order to *translate to* another community (Callon 1984, Latour 1986, Czarniawska and Joerges 1996, Doorewaard and van Bijsterveld 2001, Nielsen et al. 2014, Røvik 2016). Translation thus requires a deep understanding of both communities, which makes performing translation a knowledge-intensive practice in itself.

For knowledge brokers, who are not members of any of the communities they intend to connect (Gould and Fernandez 1989, Fleming and Waguespack 2007, Meyer 2010, Haas 2015), understanding these communities can thus be a challenging and extensive task (Brown and Duguid 1998). This becomes even more problematic with the recent emergence of "algorithmic brokers." Below, we unpack why the unique, black-boxed nature of learning algorithms offers new challenges to knowledge brokerage work.

Brokering Learning Algorithms

Learning algorithms are calculative devices used for "machine learning," a subfield of the broader field of "artificial intelligence" (AI). Whereas AI technologies, on the surface, appear to mainly consist of abstract statistical equations, there is always a community of computer scientists behind it, who construct the abstract mathematical representations through situated, embodied, and social practices (Lave 1988). AI technologies consist of three parts: task inputs, task processes, and task outputs (Von Krogh 2018). Task inputs comprise the input data and the knowledge of the developers, for example, of constructing, cleaning, and preparing data sets and of coding the initial decision logic of the learning algorithm. Task processes refer to machine learning, that is, making and adjusting connections between a large number of data points, which changes the decision logic as initially coded. The task outputs are the algorithmic predictions, which can be put in practice by users and are often used as new data points for the learning algorithm.

Whereas the task inputs are relatively transparent (e.g., data sets can be looked into, and developers can be asked about their practices), the task processes (i.e., machine learning) present a challenging new phenomenon, as machine learning becomes increasingly difficult for humans to understand (Brynjolfsson and McAfee 2017, Faraj et al. 2018, Gal et al. 2020). This is referred to as the "opaque nature" (Burrell 2016, Christin 2020) or the "black-box problem" (Pasquale 2015, Introna 2016, Ajunwa 2020, Anthony 2021) of learning algorithms and mainly occurs because the procedures used for machine learning differ fundamentally from "demands of human-scale reasoning and styles of semantic interpretation" (Burrell 2016, p. 2). To illustrate this point, Burrell (2016, p. 9) discussed 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." Thus, whereas humans use their ability to interpret and put a message into context to assess if an email is spam, a learning algorithm uses words commonly associated with spam (e.g., click, dollar, price), is trained to rank these words by weight, flags an email based on the aggregate of the weights of all words, and becomes better at doing this over time through machine learning.

Understanding how algorithmic predictions are generated therefore requires not only discerning the task inputs (e.g., the data used to develop and train the model or the internal decision logic as coded by developers) but also unpacking the machine learning, that is, how the learning algorithm's internal decision logic changes when the algorithm learns from data. However, the inherent difference between machine learning and human reasoning makes the opaque nature of learning algorithms a fundamental issue and keeps even developers in the dark about how the internal decision logic of these systems evolves over time (Michalski et al. 2013, Faraj et al. 2018). As a consequence, black-boxed machine learning is a specific area of concern in the field of computer science, which triggered these scholars to study "explainability issues" and how to alleviate them (e.g., Doran et al. 2017, Kirsch 2017, Lipton 2018, Preece et al. 2018, Miller 2019, Mittelstadt et al. 2019, Robbins 2019, Barredo et al. 2020). They argue that the nature of learning algorithms is a double-edged sword: their key strength (i.e., learning from large data sets to arrive at predictions) is simultaneously their main problem. The explainability issues are also gaining traction with organizational scholars, who increasingly emphasize that when users are confronted with algorithmic predictions that cannot be explained or understood, they experience difficulties trusting, using, and maintaining control over the role of learning algorithms in their decision-making processes (Zarsky 2016, Bader and Kaiser 2019, Lebovitz et al. 2019, Christin and Brayne 2020, Gal et al. 2020, Glikson and Woolley 2020, Durán and Jongsma 2021).

To overcome the explainability issues of learning algorithms in organizations, organizational scholars emphasize the need to make algorithmic predictions comprehensible and actionable to users (Bolin and Andersson Schwarz 2015). This requires new tasks related to translating algorithmic predictions in practice (Henke et al. 2018, Gal et al. 2020, Kellogg et al. 2020, Sachs 2020, Shestakofsky and Kelkar 2020). As the practices of developing algorithmic predictions of the machine learning community and the domain practices of the user community are not easily shared, a semantic boundary creates an opportunity for knowledge brokers to step in and take up translation tasks (Carlile 2004). By translating algorithmic predictions to users, algorithmic brokers (Kellogg et al. 2020) are seen as providing a potential solution to the explainability problem established in computer science (Henke et al. 2018).

Yet, an interesting puzzle arises regarding the ability to translate algorithmic predictions. As we have discussed, theories on translation taught us that to enact translation practices requires knowledge brokers to interact with and understand the communities involved (e.g., Brown and Duguid 1998, Røvik 2016). Such interaction is significantly hindered in the case of learning algorithms. More precisely, whereas brokers can interact with developers to discover the knowledge of the machine learning community, the black-boxed machine learning prevents them from fully understanding how algorithmic predictions are generated. In translating predictions to users, algorithmic brokers are thus confronted with a new situation in which understanding the input data and the knowledge of developers is not enough to comprehend how algorithmic predictions are generated. Accordingly, our aim is to analyze which practices algorithmic brokers enact when they encounter black-boxed learning algorithms—in other words, when they operate "in the land of the blind."

Methods

Research Setting

Our study focuses on the implementation of the so-called "Crime Anticipation System" (CAS), which was internally developed by a team of so-called "data scientists" at the Dutch police. The development of CAS 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. In contrast to, for example, the fragmented organizational structure of the U.S. police force (see e.g., Van Maanen 1973, Brayne 2020), 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, although after its implementation at local police departments, 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[2]) took the lead in the development of CAS and was therefore the main "brains" behind the learning algorithm. All other data scientists were responsible for maintaining the system and performing updates.

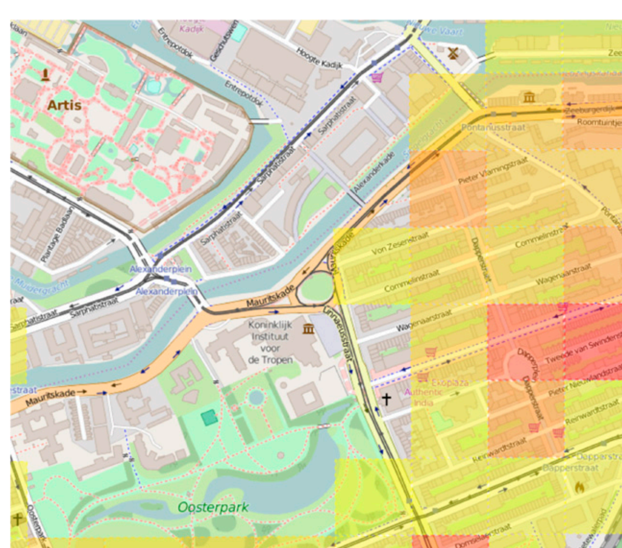
In 2013, the data scientists finished the first version of CAS, which predicted a week in advance where and when a crime was most likely to occur. During the test phase, the work of "intelligence officers," who could help local police managers to use the crime predictions, emerged. In the Findings section, we will go into detail about the emergence of these intelligence officers as algorithmic brokers. Here, it is important to emphasize that the implementation of CAS therefore included data scientists as developers, intelligence officers as algorithmic 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 and hierarchical organizational structure of the Dutch police. The "user community" consisted of the police managers who were intended to use the crime predictions in their operational decision-making practices, such as allocating police resources. They transferred data-related tasks to intelligence officers, and, because the nature of police work is 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 "machine learning community" consisted of the data scientists, the data, and the CAS learning algorithm. To create CAS, the data scientists were inspired by the U.S. version "PredPol." Whereas the police could have bought into 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 not to 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 trained using large amounts of data, CAS was developed with data of 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 they have a high impact on citizens, which means that they are 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 scientists constructed a data set with historic high-impact crime data. They divided the country into squares of 125 m^2 and used three years of historical data for every square. Across the three years, they used biweekly reference moments, which resulted in 76 lines of data per square. Each line of data consisted of eight 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 and female inhabitants, and average age of inhabitants) and 28 crime-specific variables (e.g., for burglary, variables such as time since the last burglary and 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 moment. 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. 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 1). Data extraction, model building, and map generation were automated and happened on a

Figure 1. (Color online) Visualization of Predictions as Perceived in the User Interface



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.

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 algorithmic predictions fundamentally different from police occupational knowledge and were convinced that these predictions could and should be generated away from the police. As a result, the data scientists only occasionally interacted with intelligence officers (via email or organized meetings held on average twice a year) and rarely spoke with police managers.

Data Collection

We performed ethnographic research with the aim of theory elaboration to make theoretical advancements (Fisher and Aguinis 2017). We conducted our fieldwork with 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 three days a week, observing and taking part in the intelligence officers' work. All observations were conducted when CAS was already in use, and details about CAS 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 and that the intelligence officers performed this work instead.

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, and 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 algorithmic predictions. This further established the first author's 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, and tiredness, and the pride and joy of being able to come up with a fitting recommendation.

In addition, the first author also conducted 33 formal semistructured 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 multiactor perspective. These actors 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.

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 were 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 1.

Data Analysis

Throughout the data collection, we engaged in regular conversations to reflect on observations, ask ourselves what these meant, and link them 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 work and 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 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 and 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," and "police managers") and used these groups to construct a visual map that portrayed how certain activities triggered specific events (Langley 1999).[3] We then engaged in further rounds of axial coding, that is, unraveling more thematic relationships and contrasts through coding across concepts (Strauss and Corbin 1990), and noticed that the intelligence officers' efforts to understand both the machine learning community and the police community played a central role in how their work changed over time. We compared and contrasted the intelligence officers' interactions with the learning algorithm, the developers, and the associated algorithmic predictions, as well as with the police community, through which five key translation practices emerged: (1) extracting, (2) examining, (3) transferring, (4) domesticating, and (5) substituting (see Figure 2).

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

Table 1. Description of Data Sources and Their Uses

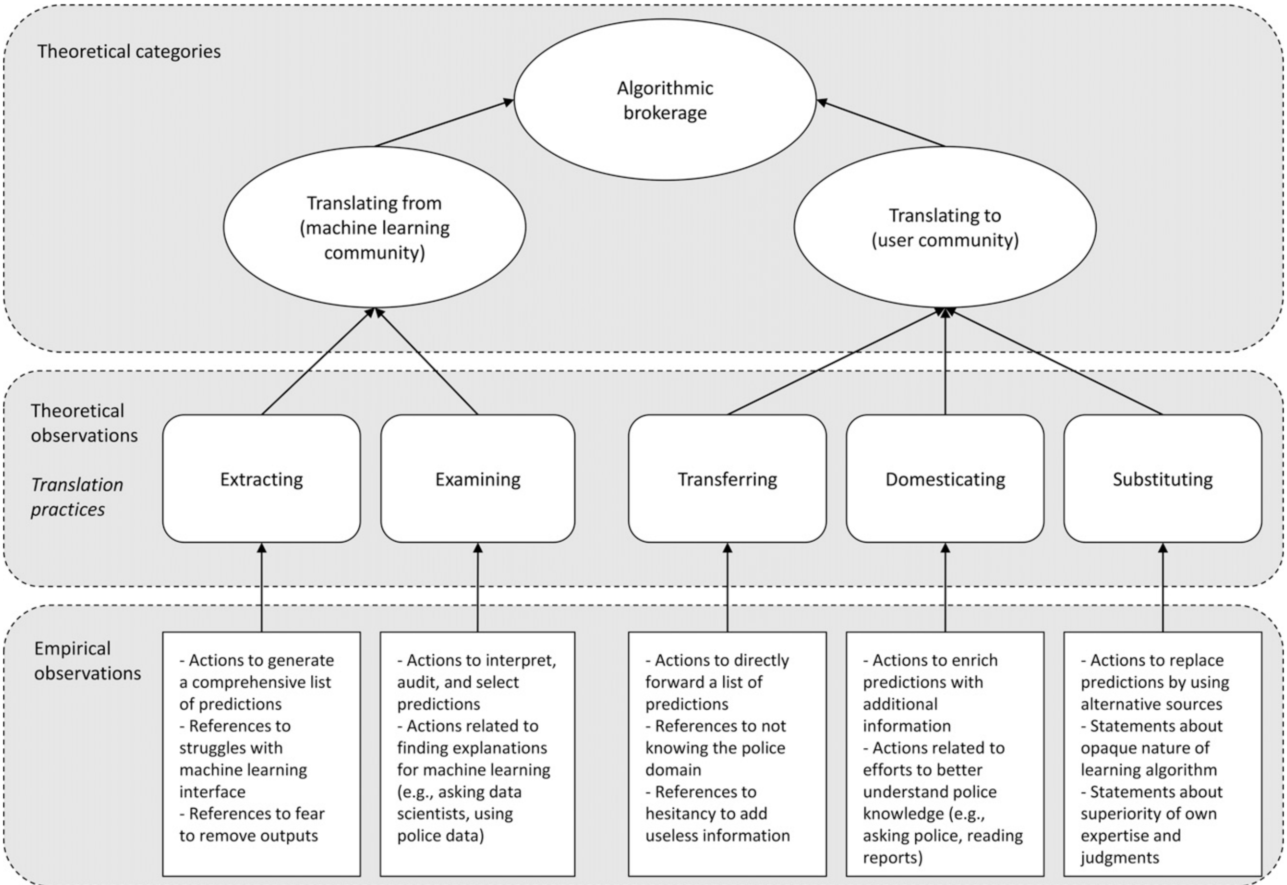
Data types	Amount/duration	Use in analysis
Primary data		
Observations of intelligence officers' work	*Between October 2016 and April 2019, 565 hours*	*Provided rich insight into the daily practices and lived experience of intelligence work and their interactions with data scientists and police managers.*
Meetings with data scientists	2 (average duration: 2 hours)	Provided insight into the intelligence officers' attempt at giving feedback to the data scientists and the data scientists' responses.
Management meetings	47 (average duration: 2 hours)	Provided insight into the changing dominance of intelligence work and how the managers responded.
Briefings	123 (average duration: 15 minutes)	Provided insight into the translation of intelligence work to daily police practice.
Intelligence gatherings (regional and national)	14 (average duration: 2 hours)	Provided broader insight into how intelligence officers' work evolved regionally and nationally.
Formal interviews	*Total: 33 (average duration: 1 hour)*	*Enriched and deepened our understanding of the worlds of the communities 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		
Meeting documents	32	Provided insight into managerial decisions and helped to establish the chronology.
Strategy documents	3	
Intelligence documents		
Role descriptions	11	Provided insight into the developments in the role of the intelligence officers and helped to establish the chronology.
Intelligence outputs	28	
Educational documents	6	
Additional documents		
External sources	24	Provided insight into the backgrounds to CAS and enriched our understanding of the police occupational world.
Crime and activity reports	237	

the cumulative efforts to translate algorithmic predictions in practice.

Findings

After a two-year development period, in 2015, the data scientists performed a test to see whether the CAS could be nationally implemented. They deployed the learning algorithm 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 importance 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 them (e.g., finding crime numbers, suspect data, or information about criminal networks). Intelligence officers were "hidden" in a back office, the work was generally regarded as low-status, the education level

Figure 2. Conceptual Scheme



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 algorithmic predictions to make them meaningful for police work. They 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:

> You need to have somebody [i.e., an intelligence officer] 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. (Data scientist Dennis)

The intelligence officers were thus expected to find underlying causes for predictions, but the data scientists assumed that they did not need to understand how the learning algorithm generated predictions 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 were thus asked to fulfill brokerage work without full insight into how algorithmic predictions were 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 enacted three consecutive roles—namely, those of messenger, translator, and curator. We discuss how these efforts were hindered by the inability to understand machine learning and how this eventually led the intelligence officers to believe that the predictions should be substituted by their own alternatives.

Algorithmic Broker Acting as Messenger

The main aim of intelligence officers' work was to make abstract algorithmic predictions meaningful for local police managers. The predictions were available to the intelligence officers by means of an interactive map, where they could select the location, the crime type, and the time frame. Because police managers never looked at the map, they asked the intelligence officers to generate a weekly overview of the predictions, which could be used as input for scheduling police resources. Generating such an overview was a laborious task for the intelligence officers. For example, they had to click on every time frame in a drop-down menu,[4] 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 time frame 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—for example, "burglary, Monday, between 12:00 and 16:00, [street name]." Per crime type, the final list made in Word included on average one predicted time frame and one or two predicted areas a day.

Through this process of extracting predictions, a comprehensive list of predictions was generated. However, because the map did not offer any insights into the causes, 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 toward 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 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 exhaustive lists of predictions, the police managers did not receive the lists with much enthusiasm; the document was too long, and the 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 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 police community, intelligence officers initially tried to determine whether the algorithmic predictions would make sense to police managers if they extracted them from the system and transferred them as a list (see Table 2). By performing translation practices in the form of "extracting" and "transferring," the intelligence officers enacted a brokerage role that can best be described as a "messenger." It soon became clear, however, that the differences between algorithmic predictions and the 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 interpreting the predictions. In other words, the intelligence officers had to better decontextualize the algorithmic predictions from the machine learning community in order to contextualize them to the police.

Algorithmic Broker Acting as Interpreter

To translate algorithmic predictions to the police, the intelligence officers realized they lacked a deep understanding of the machine learning community and the police community and invested in learning more about both.

Learning About the Machine Learning Community. The intelligence officers recognized that they had to better understand the computational and statistical techniques used in CAS. As intelligence officer

Table 2. Overview of Intelligence Officers' Brokerage Work

Characteristics of brokerage work	Messengers		Interpreters		Curators	
	Details	Data segments	Details	Data segments	Details	Data segments
Understanding of machine learning community	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) "Sometimes I have such a blackout, then I really don't know what to do." (Intelligence officer Louisa) "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) "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) "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) "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 user community	Struggling to understand the police community	"We are still struggling to find the best way to use CAS for informing police decision making." (Intelligence officer Eva) 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) 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) 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) "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."

Table 2. (Continued)

Characteristics of brokerage work	Messengers		Interpreters		Curators	
	Details	Data segments	Details	Data segments	Details	Data segments
						(Intelligence officer Wendy) "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 the predictions, I look at the police data." (Intelligence officer Joey) "We need to look at the data about previous crimes to trust the predictions." (Intelligence officer Michael) "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) "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) 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 about the burglaries, which helped her see a connection and pattern between them. (Observation notes) "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 working 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) "Police just want more information. They want to	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) "[Name of police database] is the place where the data is collected on which the predictions are based." (Matt	No further interaction	"Well, we let it go now. The [intelligence officers at] police stations know best about crime details." (Data scientist Dennis)

Table 2. (Continued)

Characteristics of brokerage work	Messengers		Interpreters		Curators	
	Details	Data segments	Details	Data segments	Details	Data segments
		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)		to intelligence officers in an email)		
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) "We [police managers] need concrete action points." (Head of police department George) "[Explanations will help] to increase the acceptance of predictions [by police managers]." (Internal document)	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) "Now, police managers ask us to report it. It used to be, like, 'this is CAS, there's an increased chance in burglary,' and that was it. And then you'd wish that police officers would do a bit of driving around over there. Now we're requested 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) "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)

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?” Consequently, the first step was to interact with the data scientists to find out more about their practices and to see if the causes of predictions could be made transparent. 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” (data scientist Jules) and that generating the best predictions required complex techniques for pattern recognition in vast amounts of data, which made the learning algorithm opaque. As a consequence, the 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.”[5] 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 common-sense 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 understand the data science practices, the data scientists did explain the 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, as this was determined by the learning algorithm and unknown even to the data scientists. 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 practices of the data scientists.

Dedicated to fulfilling their tasks as brokers, they decided to leave the data scientist aside and started to examine the predictions by inspecting the input 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.” For example, to understand why burglaries were often predicted in the morning, insight into how the time frame of crime predictions was calculated was needed, which triggered the intelligence officers to dig into the police database and look for time stamps in burglary reports. It appeared that, if a burglary occurred in a period when people were away from home, the report included a time frame (e.g., 08:00 to 18:00) instead of one time stamp (e.g., 08:30). 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) instead of including the full time frame.

Taking their assignment to create connections between the machine learning community and the police community 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 time frames, 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 machine learning and their human 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 algorithmic predictions were 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 the crime predictions came from, most of the time 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. To better understand how this was so influential, we first turn to how the intelligence officers also put efforts into better understanding the police community.

Learning About the User Community. Initially, the intelligence officers also struggled with translating the crime predictions to the police. To solve this issue, they started to interact more directly with the police to gain a better understanding of the police community. 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), 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, pictures of criminals sent to the police via community WhatsApp groups). They also learned from interacting with police managers that short and action-oriented descriptions best fit the police community. "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.'"

Figure 3. (Color online) Police Officer and Intelligence Officer Together Making Sense of a Prediction

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 time frames (from an average of 28) and two locations (from an average of 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 include 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 burglary reduction (minus 47% compared with 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 toward 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 brokerage work. They appointed the intelligence officers as key figures for informing their operational and strategic decisions by inviting them into their management meetings. To "make crime predictions more central" (police manager Harry), they scheduled about 20 minutes at the beginning of these meetings for intelligence officers to present their advice.

In sum, to translate algorithmic predictions to the police, the intelligence officers realized that they themselves first had to better understand how these predictions were 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, which solidified a knowledge boundary between the machine learning community 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 community 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 2). By performing translation practices in the form of "examining" and "domesticating," the intelligence officers enacted a knowledge brokerage role that 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 understanding the black-boxed machine learning.

Algorithmic Broker Acting as Curator

Now that the intelligence officers became used to their ascribed expertise as algorithmic brokers, they searched for ways to deal with the opaque algorithmic predictions and discussed this with their head of department. He suggested that the difference between machine learning and their human interpretation was in fact so large that it could not be overcome 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 community 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 from police data were that they realized that they used many more data sources in their knowledge brokerage work than those included in CAS. Intelligence officer Joey expressed a shared sentiment: "To be honest, I trust CAS less than I trust the information I can gather from the police databases." They also became increasingly vocal among 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."

Whereas data scientists believed that the intelligence officers continued to make the crime predictions meaningful to the police and helped police managers to make their operational processes "smarter and better" (data scientist Jules), in the meantime, the intelligence officers substituted CAS with more explainable solutions that supported their human judgments. For example, the intelligence officers requested that their local IT desk 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 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 include a new method for calculating crime time frames, by using and visualizing a weighted average of the time windows of past crimes. When the intelligence officers compared the times calculated by their tool 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 for an example of CAS predictions compared with outcomes of their new tool, but the transparent and explainable nature of their new tool helped them in to make substitutes that they thought would best fit the police. 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, whereas 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 encouragements to come up with "concise" predictions, for example, 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." Eventually, these occurrences during meetings made them believe that the police managers took their advice seriously without the need for any references, and they 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:

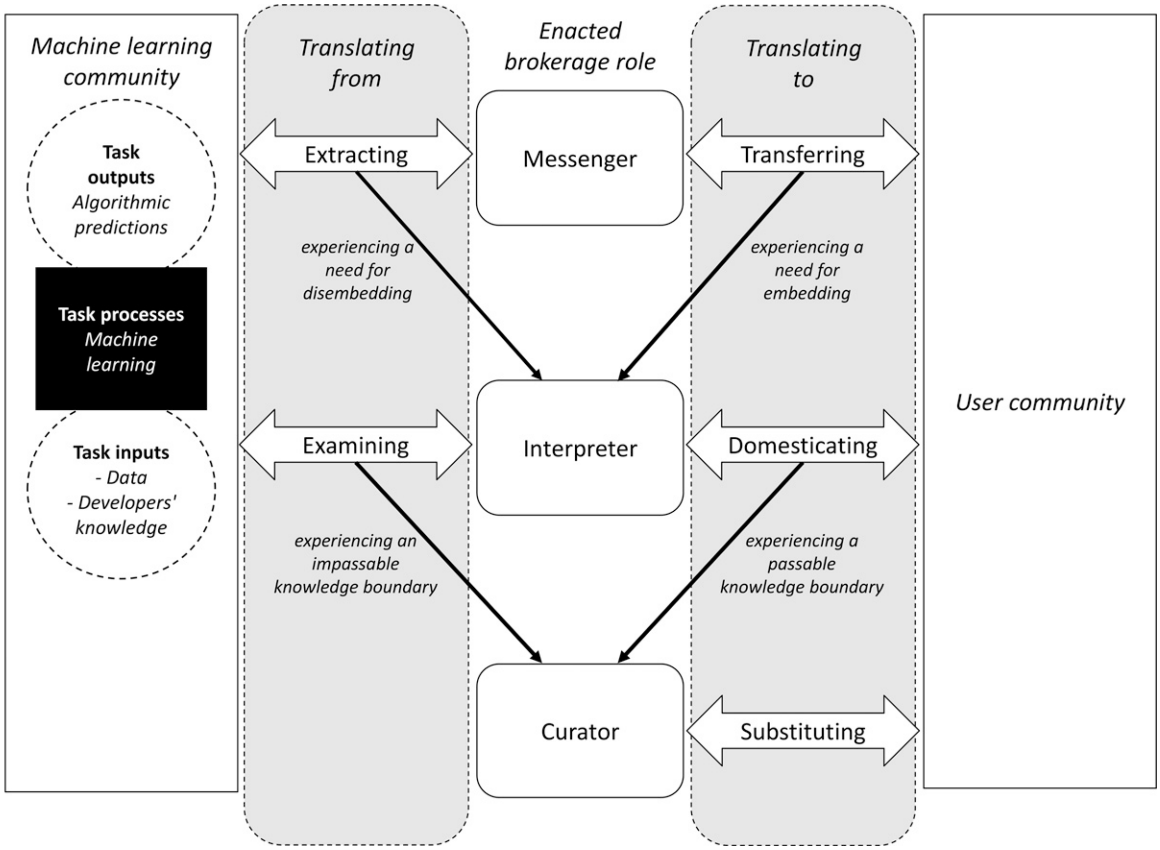
> We are now considered more as a partner of police managers. Before, we would usually wait for police managers to give us a task. Now, it's just: we are a department and we have something to say too. And we have good suggestions. That's the difference. We changed into an intelligence department having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

In sum, the intelligence officers eventually realized that the boundary between machine learning 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 2). As such, by performing translation practices in the form of "substituting," the intelligence officers enacted a brokerage role that can be best described as a "curator," in which they grew to become more influential and were eventually considered more as a partner to the police managers.

Discussion

Building on the findings of our case, we offer a general explanation of how algorithmic brokers translate predictions to users (see Figure 4). In particular, we observed how brokers perform translation practices that allow them to enact increasingly influential algorithmic brokerage roles. The brokerage work changes over time, because when they attempt to translate algorithmic predictions, knowledge differences emerge between the brokers and the communities they intend to connect. At the start of the brokerage work, brokers lack sufficient understanding of the machine learning community and the user community and cannot do more than act as messengers. They do so by interacting with the learning algorithm's task outputs, extracting and transferring predictions. This, however, leads to failed attempts of decontextualizing the algorithmic predictions from the machine learning community and of contextualizing them to the user community. To solve this, realization sets in that translation requires deeper insights into both communities. This means a move away from merely acting as a messenger to an interpreter role, aiming to examine the algorithmic predictions and domesticating them in the user community. Although it is possible for the brokers to reach a deeper understanding of the learning algorithms' task inputs, that is, the developers' knowledge and the input data, the opaque nature of machine learning prevents them from fully understanding how algorithmic predictions are generated. Because of this, the brokers experience an impassable knowledge boundary between them and the machine learning community, which triggers them to act as curators and substitute the algorithmic predictions with their own human judgments.

Figure 4. Theoretical Model of Brokering Algorithmic Predictions



This study shows that bringing together the fields of emerging technologies and organizational theory allows for the emergence of a new phenomenon, that of algorithmic brokerage work with its dynamic and influential nature. More specifically, the current divide between the two academic fields has resulted in a scholarly understanding of knowledge brokerage in which the need to comprehend the communities to be able to translate has been taken more or less for granted (Barley 1996, Vogel and Kaghan 2001, Meyer 2010). Our study shows that the recent rise of learning algorithms with its black-boxed machine learning brings to the fore the need for uniting the two fields. Particularly, our case of knowledge brokerage in the age of learning algorithms highlights the complex and important practice of translating from the machine learning community for knowledge brokerage. Studying the translation practices of algorithmic predictions reveals that knowledge brokerage work can become increasingly influential, even to the extent that brokers can eventually substitute the algorithmic predictions, and gives us a better understanding of how and why this growth in influence happens. Below, we offer the key contributions of our study.

Creating New Knowledge Boundaries Through Algorithmic Brokerage Work

One of the core findings of the research presented in this paper is that algorithmic brokers enact different translation practices over time and can thereby create new knowledge boundaries between them and the communities they intend to connect. This dynamic perspective on brokerage work offers new insights into the literature on knowledge brokerage and to translation theory.

Previous studies argued that knowledge brokerage tasks emerge when a semantic boundary hinders two communities from sharing knowledge (Dougherty 1992, Carlile 2004, Boari and Riboldazzi 2014) and reasoned that knowledge brokers could resolve boundaries and align perspectives by enacting translation practices (Tushman and Katz 1980, Barley 1996, Wenger 1999, Grady and Pratt 2000, Paul and Whittam 2010). 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 algorithmic predictions. Building on Røvik (2016) and based on our empirical findings, we consider "extracting" and "examining" as practices to translate from the machine learning community, and "transferring," "domesticating," and "substituting" as practices to translate to the user community, 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 communities involved (Brown and Duguid 1998, Carlile 2004, Sturdy and Wright 2011, Gal et al. 2020). 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 machine learning is impossible. Through the brokers' translation practices, which are influenced by a lack of understanding of how algorithmic predictions are generated, a knowledge boundary solidified between the machine learning community and the brokers. As we mentioned earlier, most research on knowledge brokerage focuses on the semantic boundary that brokers should be able to resolve (Dougherty 1992, Carlile 2004, Boari and Riboldazzi 2014). Our case shows that, in the efforts to resolve a semantic boundary through translation practices, knowledge boundaries can solidify between knowledge brokers and the communities 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 predictions from one community to another, this study also emphasizes the dynamic and changing nature of translation, which offers a contribution to translation theory (e.g., Latour 1986, 2005; Law 2002; Czarniawska and Sevón 2005; Røvik 2016). Moreover, whereas translation theory scholars have paid extensive attention to how ideas are translated to specific fields and organizations (e.g., Saka 2004, Mueller and Whittle 2011, Nielsen et al. 2014, Ciuk and James 2015), only a few studies have focused on how knowledge is translated from its original source (Furusten 1999, Suddaby and Greenwood 2001, Heusinkveld and Benders 2005). These studies, so far, have not addressed what translation entails if knowledge boundaries are impassable, such as in the case of learning algorithms.

Finally, by uncovering the emergence of an impassable knowledge boundary between the algorithmic brokers and the machine learning community, our study points to the importance of including technology in our understanding of knowledge sharing. Our study points out that the practices commonly understood to contribute to knowledge sharing (such as personal interaction and shared activities) can become counterproductive in the case of black-boxed machine learning and can even lead to communities moving further apart.

Becoming Influential Curators Through Algorithmic Brokerage Work

Another core finding of this study is how, by performing different translation practices, the knowledge brokers enact roles that change to become more influential over time. Especially the emergence of algorithmic brokers as curators, acting as "kings in the land of the blind" adds to our understanding of the work of knowledge brokers as influential and consequential.

Research on knowledge brokerage has largely regarded the work to be that of neutral intermediaries dealing with the knowledge of others (Barley and Bechky 1994, Barley 1996). However, 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 curators' caretaking practices triggered the public to consider them as experts of art objects (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 artists and collectors 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 toward the wider public and were usually blindly trusted by collectors. The story of art curators is particularly helpful, because it reveals how, through caretaking practices, the curators changed 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 brokerage work as neutral, the algorithmic brokerage work in our study becomes so influential that brokers can substitute outputs with their own judgments.

It is interesting to note that, by using the analogy of the historical trajectory of the work of art curators, this study departs from the current interest in "data curators" who are mainly considered to act as content creators, data cleaners, or data editors (e.g., Karasti et al. 2006, Muller et al. 2009, Carah 2014, Kellogg et al. 2020). Some studies describe how data curation happens "behind the scenes" of technology development and is 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 brokers who enact the role of curators shifts this perspective toward the output of learning algorithms, just like the output of art. This study therefore emphasizes the need to acknowledge that algorithmic 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 algorithmic predictions are (re)presented to users.

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., Doran et al. 2017, Kirsch 2017, Lipton 2018, Preece et al. 2018, Miller 2019, Mittelstadt et al. 2019, Robbins 2019, Barredo et al. 2020). 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 toward user community without recognizing the need for explaining how algorithmic predictions are 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 (Zhang et al. 2020, Van den Broek et al. 2021). Involvement in terms of understanding each other's thought worlds requires more long-term investments and new skills for developers, brokers, and domain experts or users (Waardenburg et al. 2021). For example, developers need social skills to understand the user needs, domain experts need technical skills to understand the reasoning behind and limits of these technologies, and algorithmic brokers need skills that allow them to cope with the black-boxed machine learning without feeling the need to completely substitute predictions when they cannot understand how they are generated. Developing such skills will provide a first step to overcome the knowledge boundary between the machine learning community and the user community.

This study also shows that algorithmic brokerage work does not neutrally and objectively represent algorithmic predictions but likely includes the human interpretations of the brokers. Whereas 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, p. 300) emphasized, "The more the transfer process is regulated by authorities, the less transformable the transferred construct is for the translator." Also, our case highlights data access as an important resource that enables brokers to translate algorithmic predictions to the user community. Yet, whereas 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.

In addition, 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 explanations of algorithmic predictions and blindly left the responsibilities of translating with the intelligence officers. Although brevity and action orientation are virtues in the police community, this might be different in other communities, such as radiology, where the decision-making practices of the users might require as much evidence as possible (e.g., Kim et al. 2021). We encourage future studies to look at other communities to further understand the differences in explanations required and to provide 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 communities. Due to this hierarchical setting, the knowledge brokerage work turned out to be largely one-directional. It would be interesting for advancing our knowledge on algorithmic brokering to also include more innovative or flat research settings, in which different relationships exist between developers and users (such as cocreation or agile technology development), which opens possibilities to study more unidirectional exchanges. Finally, our study focused on a relatively basic and simple version of a learning algorithm, which nevertheless had fundamental consequences for work and organizing. With the emergence of more advanced and even more opaque learning algorithms and computational techniques such as tools based on deep learning, these consequences can be further enlarged. We 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.

Conclusion

Learning algorithms, because of the black-boxed machine learning, offer an extreme case for understanding how knowledge brokers enact translation practices. In this study, we provided a case of knowledge brokers who aimed to translate algorithmic predictions from a machine learning community to a user community. Translation has always been the core of knowledge brokerage work, yet so far has been mainly taken for granted in organizational literature. It is now, in the age of learning algorithms, of significant importance to question how knowledge brokers are able to translate from a machine learning community, since machine learning has become increasingly difficult to understand. As this study shows, when the outputs of one community are opaque to all actors involved, brokers can become "kings in the land of the blind" and decide to substitute algorithmic predictions 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.

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Endnotes

[1] To simplify, we use the word "knowledge" in relation to the practice-based perspective in the remainder of the text.

[2] All original names have been removed; the names mentioned are pseudonyms.

[3] Further details can be retrieved in full from the corresponding author.

[4] The four-hour time frames, seven days a week, meant clicking $(24/4) \times 7 = 42$ times to get a weekly overview.

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

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