A new canary in the coal mine?
On birds, AI and Early Warning Systems

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In 1914, the *Coal Mining Institute of America* in Pittsburgh, Pennsylvania, discussed the susceptibility of living organisms to the toxins typically encountered under the surface of the Earth. The report "Experiments with Small Animals and Carbon Monoxide" suggests that "[o]f the common small animals, canaries are best adapted for exploration work" (Burrell/Seibert 1914: 244). In the case of a significant increase in carbon monoxide underground, canaries would express signs of distress, in the form of behavioral changes or collapse, much earlier than other species. Compared to mice or guinea pigs they show another advantageous capacity, namely to "recover quickly if exposed to fresh air" (ibid.: 243). The susceptibility of the birds would allow for coal workers to evacuate the mine before the toxic gas reaches a hazardous concentration. As for the origins of this practice, prior to its implementation in the United States, the authors point to the usage of canaries in England and "presumably in places on the continent also" (ibid.: 241) as well as to the late 19th century (self)experiments of John Scott Haldane. However, the canary in the coal mine is also discussed against the background of a much longer tradition of interpreting animalistic and especially avian behavior as signs for future developments (cf. Reif 2011; Keck/Lakoff 2013; Neo/Tan 2017; Keck 2020). If the whole system – including the mine inspectors and workers, the evacuation plans as well as the birds themselves – would be taken together as an ensemble, it could be addressed as a prototypical Early Warning System (EWS). These have been developed against various lethal threats from earthquakes to drought and in various scientific and infrastructural fields. Conservationist Ian Spellerberg refers to the canaries as a "biological early warning system" (2006: 157).

As canaries of the digital age, Early Warning Systems were prone to be augmented by the innovative powers of Artificial Intelligence. In this investigation, the genealogy of the data-heavy EWS is used as a starting point to observe – with reference to the editors' research project – how Artificial Intelligence is changing science (Echterhölter et al. 2021). The use of often large amounts of monitored data and the implementation of statistics can be seen as cornerstones of these technologies for crisis detection and prediction, therefore the application of Machine Learning Technology, deployed as prediction machines, comes as little surprise and is underway in several international and national agencies.[1] Key for the implementation of these systems is how scientists and institutions conceptualize the impending crisis by relating the future to the threatened self in a specific way. To suggest the crucial elements at play in EWS and to assess the role of AI in this field of disaster research, we use a broad notion of EWS, introduce and compare various kinds of analogue, digital and AI-based systems in various fields and highlight their respective epistemological potential.

Initially, the argument is made that Early Warning Systems contribute to the perception of a constant state of crisis, with signs detectable to those capable of interpreting them. The use of sensors or sentinels, such as birds or AI, is seen as a means of mitigating the impact of potential hazards. Following this logic, the development of digital Early Warning Systems since the 1970s can be described as technologies of *preparedness* (Lakoff 2008; Lakoff 2017). To guarantee preparedness, EWS models with necessity hinge on one crucial aspect: signals have to be detected in large amounts of data about natural states or social behavior, and for this, thresholds have to be set. This presupposes a conceptualization of what constitutes a signal point to processes of 'normalization', in the sense of what is seen as a catastrophic development and what is not worth issuing a warning for. The promise of the whole procedure is to detect patterns of threat in the environment and to intervene long before the environment becomes lethal.

As a second step, three examples of early warning models, which build on the trope of bird behavior as signals for an impending systematic crisis, will be introduced. These should serve as illustrations of how institutions make use of

1 Cf. Lamsal/Kumar (2020); for disaster mitigation see the UNDRR collection on "Artificial Intelligence for Disaster Risk Reduction" (https://www.preventionweb.net/collections/artificial-intelligence-disaster-risk-reduction); for a current EWS project with explicit use of AI methodology in Germany see "Daten- und KI-gestütztes Frühwarnsystem zur Stabilisierung der deutschen Wirtschaft" by Fraunhofer Heinrich Hertz Institut (http://www.daki-fws.de).

detection potential found in birds but also in statistical machines, in order to acquire more timely future knowledge and enable better preparation for crises. In a sense, the studies presented show how AI takes the place of the bird in timely warning concerns.

The examples of canaries as animalistic intelligences of birds or machinic intelligences like AI can furthermore serve as an incentive for a reflection on the discourse revolving around the intelligence and the 'knowledge' of AI. It is argued that instead of concentrating on the question whether a machine is able to 'pass as human', the limitations of human abilities in sensation and cognition, as revealed by animals or AI, can provide guidance for analyzing the discursive construction of 'the human'.

1. An epistemology of Early Warning Systems

Early Warning Systems appeared most prominently in the 1960s and 1970s. An attempted genealogy of these technologies can take on two (mutually informing) directions. One of them leads to the military context of WWII, where information EWS were implemented in order to predict attacks via the use of intelligence data (Austin 2004: 4). This 'birthplace' might also serve as an explanation for the functional similarities of EWS and radar technologies – these byproducts in the search for a laser beam gun (Pircher 2010: 52–54). In the literature on EWS, other traces of direct interference from the military context to other scientific fields are easily found, as for example the "Weak Signals" approach by Igor Ansoff (1975) – a US mathematician and former member of the RAND Corporation which served as a blueprint for EWS in business administration (Hammer 1998: 216–225).

A second genealogical thread for EWS is taken up by Irasema Alcántara-Ayala and Anthony Oliver-Smith in their article "Early Warning Systems: Lost in Translation or Late by Definition?" (2019). They trace the origins of EWS back to the devastating famines in Ethiopia and Sudan in the 1980s. As a consequence of the death of more than one million people caused by starvation, the 'Famine Early Warning System' (FEWS) was established by USAID. It operated via the constant monitoring of data of different kinds, enabling a mapping of impending famines which should lead to a timely response (ibid.: 321–323). The authors consider the FEWS a prototype for EWS in other areas like disaster risk reduction for earthquakes, floods, storms and more.[2] In epidemiology, another field where EWS have gained prominence, significant efforts were made during the early 2000s with the establishment of WHO's Global Outbreak Alert and Response Network (GOARN) or the Program for Monitoring Emerging Diseases (ProMED) (Hall 2020).

Even though it is important to stress that EWS in different fields do not necessarily consist of the same constituents, certain dynamics, such as the importance of monitoring changes in data or behavior, are shared by most EWS. The United Nations Office for Disaster Risk Reduction (UNISDR) defines EWS as an "integrated system of hazard monitoring, forecasting and prediction, disaster risk assessment, communication and preparedness activities systems" (2016: 2). The *Berghof Handbook for Conflict Transformation*s utilizes the term "Early Warning System" to refer to "any initiative that focuses on systematic data collection, analysis and/or formulation of recommendations, including risk assessment and information sharing" (Austin 2004: 129). By relying on this logic, EWS share many characteristics and constituents with other forms of predictive and anticipating technologies like forecasting, sentinels, barometers, risk assessments or scenarios.[3] Given these shared epistemological features and the timing of EWS technologies' emergence, it is possible to consider them as integral components of a shift in the operational mode of governance, as articulated by anthropologist Andrew Lakoff (2008). Based on Foucault's analysis of different modes of *Gouvernementalité*, Lakoff holds that in the mid-20th century there has been a shift in state rationale when confronted with threats of different kinds. While 17th-century monarchies, in their fight against adversaries, relied on a logic of interdiction that was followed by the 19th-century reliance on prevention (especially with the emergence of the hygienic movement and its use of statistics), the mid-20th century saw a shift to *preparedness* for the emergence of threats. For this latter paradigm, Lakoff identifies the use of scenarios as decisive technologies against threats by "unpredictable, potentially catastrophic events" (Lakoff 2008: 403). However,

2 According to the authors, the development of EWS in these fields went hand in hand with a departure from long long-term perspective in favor of technicistic solutions for "shorter-term occurrences of events" (Alcántara-Ayala/Oliver-Smith 2019: 322). The Indian Famine Codes of 1880 are sometimes considered historical forerunners of the FEWS (Enten 2008: 13–15).

3 The genealogies of EWS could of course in principle be prolonged into analogue times, when disaster warning had other names, for instance with the history of human observers acting as seismographs. Cf. Coen 2012; Pietruska 2017; Edwards 2013.

and this is important to note, these different governing rationales should not be viewed as mutually exclusive (ibid.: 421). The emergence of the EWS concept with its reliance on the use of data analysis and statistics does fall into the period of the shift to preparedness, which is also acknowledged by Lakoff himself, saying that important building blocks of the preparedness apparatus were found in "more exercises, more vulnerability assessments [and] improved early warning systems" (Nucho 2022; cf. Lakoff 2017). EWS can thus be located within the preparedness paradigm although they should not be regarded as tantamount to scenario technologies. Whereas the latter "function […] to authorize knowledge claims in the absence of actual events" (Lakoff 2008: 419), the rationale of EWS is to deprive a potential threat from its 'event character' as an irruptive catastrophe and instead conceptualize it as a trend-like deterministic development. The threat can be detected 'early', i.e., 'early enough', or 'earlier than last time' (Hall 2020) with the use of the right instruments.

As one commenter on the FEWS noted in *Science*: "The signs are there if they can be recognized. As stress occurs, behavior changes." (Walsh 1986: 1146)[4] Catastrophe in this rationale is always latently present and can be detected by using the right instruments. The implementing institution must know 'what to look for', i.e., which parameters to monitor, and where to set the threshold for triggering an alarm. Sometimes the ability of parameter and threshold setting depends on experience: what kind of behavior, or what change in behavior, is interpreted as a signal of an impending crisis? This ability to detect the right information is exemplified by J.S. Haldane's experimental work as discussed in Burrel and Seibert (1914):

> The authors of this paper do not hesitate to say that, because of his greater experience in experimenting with small animals, Dr. Haldane might detect outward symptoms in a mouse that would escape the authors' attention. (ibid.: 242f.)

Despite the morally questionable approach of exposing living creatures (including the scientists themselves) to potentially lethal concentrations of poisonous gasses, the usage of their sensory abilities went hand in hand with an

4 For the FEWS, behavioral changes which are considered to be signals (or signifiers) of an impending crisis are e.g., an increase in the sale of jewelry or a rise in the consumption of roots, grasses and berries (Walsh 1986).

intimate relationship with the animal and knowledge about what constitutes a symptom. What is needed for an EWS to be effective is likewise double or multi monitoring. At a first stage, the bird or the machine monitors changes in the environment, which leads to a change in their behavior. At a second stage, the EWS consists of anomaly detection, i.e. monitoring the bird's or the machine's behavioral changes and interpreting them accordingly. Thereby, EWS contribute to the determination to which changes can reasonably be said to constitute a crisis and to which developments can still be considered as 'non-critical' or 'normal'. This dynamic is especially prevalent for EWS in the field of the social sciences.

As part of the preparedness paradigm, these technologies "bring the future prospect of catastrophes into the present as an object of knowledge and intervention" (Lakoff 2008: 23). They thereby contribute not only to the question of 'what is a crisis' but epistemologically shift the onset time of crises towards an earlier point in time.

The following presentation of three (partly) AI-based EWS further illustrates some important constituents of EWS and highlights the functional role of AI technology. Before that, however, it is necessary to recapitulate some of EWS' characteristics as being a) often implemented in the aftermath of crises, b) part of a preparedness logic, c) reliant on data/environment monitoring, signal detection and threshold setting, d) contributors to the question of what counts as a crisis, respectively as normal e) conceived as triggering a precise and effective warning.

2. Quasi-avian Early Warning Systems

In computer science, the trope of the canary as an early warning mechanism was introduced in the 1990s by Cowan et al. (1998; 1999). Here, the canary is a mere name for a function of programming, yet recognizably the function is the one of signaling danger. The security system *Stackguard* protects against buffer overflow attacks in a way which "seeks not to prevent stack smashing attacks from occurring at all, but rather to prevent the victim program from executing the attacker's injected code" (Cowan et al. 1999: 3). The programme thereby follows a logic of preparedness by mitigation. Concerning the functioning of this technology, what is essential to grasp for the purpose of this article is that by storing more data in a buffer (a region of memory used to hold data temporarily) than it can handle, hackers can cause that buffer to 'overflow' with extra data. This potentially enables them to overwrite the return address of a program. Normally, after executing a function like a calculation task, e.g., the processor should go back to the return address. In the case of a stack buffer overflow, "[w]hen the function returns, instead of jumping back to where it was called from, it jumps to the attack code" (Cowan et al. 1998: 64). This can lead to the attackers gaining administrative authority over a computer system.

As a solution to this threat, the authors present the security mechanism of the 'stack canary' which they jestingly introduce as: "[a] direct descendent of the Welsh miner's canary" (ibid.: 3). The canary is a 'value' (a number or a word) which is placed next to the respective return address. In the case of an attempted overwriting of the return address, the canary word is overwritten and thereby changed "before jumping to the address pointed to by the return address word" (Cowan et al. 1999: 3). This change constitutes a warning signal which should cause the program to display an error or to terminate before the attack can cause significant harm to the computer system. The signal thereby relies on a shift in 'code behavior'. What is absent in this digital application is the aspect of data collection and threshold setting, since the overwriting of the code is not gradual but follows an either-or logic.

As an inducement for their efforts to enhance security when using stack canaries, the authors point to the Morris Worm of 1988. This is considered to be one of the first major malware attacks, infiltrating approximately 10 percent of all internet systems, thereby revealing their vulnerability (Furnell/Spafford 2019: 31). The emergence of the stack canary after the launch of the Morris worm illustrates the 'productive force' of catastrophes: EWS and other infrastructures of preparedness tend to be modelled and built primarily in the aftermath of system failures. Vulnerabilities are revealed and consequently followed by attempts to mitigate the damage in case of a future occurrence.

A further application of the 'canary-logic' in the area of computer science is a technique called 'canary release'[5]: When introducing a new version of a software, instead of presenting the new version as a whole to a general audience, only some users are chosen to test the innovation. With this technique, the software company can track and collect data on how the new version affects the production environment (Sato 2014). For this example, one could say that the users become the birds whose behavior is to be monitored. It therein bears a similarity to the second example of an Early Warning System study titled

5 Also 'phases rollout' or 'incremental rollout'.

"Earthquake Shakes Twitter Users: Real-time Event Detection by Social Sensors" (Sakaki/Okazaki/Yutaka 2010).[6]

This study represents a comparatively early model of using social media behavior as data for detecting and predicting catastrophes. Similar approaches have gained considerable public recognition, especially in the field of predicting epidemic events like in the case of Google's Flu Trends (Cukier/Mayer-Schönberger 2013: 1–32).[7] In the Japanese earthquake study "each Twitter user is regarded as a sensor and each tweet as sensory information" (Sakaki/Okazaki/Yutaka 2010: 852). Like for the literal canary in the coal mine, here, a change in tweeting behavior is interpreted as a signal for an impending catastrophe. While for the former, this catastrophe is a hazardous rise in CO concentration, Sakaki, Okazaki and Yutaka propose a model to mitigate the effects of earthquakes via the issuing of early warnings. They do so by analyzing event-relevant tweets and trying to localize them with the use of an algorithm; thereby trying to determine the epicenter of an earthquake. Of course, this system can only detect earthquakes that are felt by a considerable number of people with access to the internet. The event-relevant tweet words are rather obvious ones like 'shaking' or simply 'Earthquake!' (ibid.: 852). The earthquake warning can be rolled out only after a large number of Twitter users have already experienced the ground shaking, wherefore it cannot be regarded as a technology of latency. The authors argue that the model still has the quality of an *early* (or earlier) warning system due to its inbuilt earthquake reporting system. They argue for sending out personal messages (e-mails in this case) as warnings to people in the region, instead of using TV broadcasting. By applying this method, the warning time could allegedly be reduced significantly (ibid.: 857f.). Overall, the study suggests that Twitter can be a valuable tool for earthquake detection and response and highlights the potential of social media as a source of real-time information in emergency situations.

As a third recently published study, the "Spark Streaming-Based Early Warning Model for Gas Concentration Prediction" by Huang et al. (2023) shall be introduced. It illustrates the practice of threshold setting through the

6 For the timely detection of earthquakes there exists a long tradition discussing the potential use of animal behavior monitoring. Cf. Tributsch 1978; Pschera 2016: 63–65; Liu/Dhakal 2020; critical of this idea: Hough 2016.

7 For a critical account on the usefulness of Google's tool, respectively its methods, cf. Lazer et al. 2014.

optimization of parameters by using data for training and testing purposes. It can furthermore be seen as an instance of supersession of animal-supported EWS-labor by algorithm-supported EWS-labor. The model is intended for usage in Chinese coal mines. Having the biggest mining industry worldwide, the need to reduce systemic malfunction caused by gas exposure in China is evident. Building upon neural network-based gas concentration prediction models, the "Spark Streaming framework (SSF)" should "provide […] a new way of thinking for intelligent gas prediction and early warning" (Huang et al. 2023: 2). It operates by using data sets of gas concentration collected from the mine's 'face' (ibid.: 6f.).[8] Throughout the training process, an optimization of the prediction parameters – number of neurons in hidden layers; number of hidden layers, batch size, time steps – is established (ibid.: 6–9). The resulting prediction model together with the gas sensors at the face is used to determine the gas thresholds whose transgression should trigger a warning. Gas concentration below the set threshold is labelled 'normal'; transgressions are classified as level 1 and level 2 warnings (ibid.: 9–11). Hence, the EWS determines the conditions of the normal and the abnormal state. The quality of the gas concentration prediction model is measured by comparing it with real-world data of gas diffusion, resulting in an accuracy level above 90 percent (ibid.: 14). The authors assess this value to be sufficiently high as to guarantee "accurate predictions and graded warnings of gas concentrations […] for the safe production of coal mines" (ibid.: 15).

This study suggests a supersession of the bird's gas-detecting body by electronic sensors and the neural network's architecture. The use of canaries (besides mice and ponies) in coal mining, however, was already brought to a halt in the 1980s. "Modern technology is being favored over the long-serving yellow feathered friend of the miner in detecting harmful gasses", the BBC reported in 1986. "Miners are said to be saddened by the latest set of redundancies in their industry but do not intend to dispute the decision" (ibid.). The birds' designated successors were electronic monitoring and detection devices referred to as 'electronic noses', analyzing gas concentration data and displaying it on a digital screen. All three of them, the canaries, the gas nose and the proposed technology by Huang et al., should contribute to bringing a (for humans) latent danger to the surface. They can be interpreted as created systems with readable symptoms as warnings. One of the main differences between the use of the

8 This refers to the surface where mining operations are currently progressing.

animals compared to the later auxiliaries is that the latter operate with quantified data on gas concentration. In doing so, they contribute to the delivery of Gabriel Tarde's prediction, taken up and complemented by Bruno Latour: "[Thanks to statistics] public broadsheets will be to the social world what the sensory organs are to the organic world." (Latour 2010: 115; comment in original) In this logic, statistical tools could for example be seen as a help for detecting social upheaval before the breakout of political crises. This suggested use of statistics as auxiliaries for making quantifiable data 'the sensory organs' of the social world should be seen as an epigraph for the following argument, which builds up on the epistemological 'closeness/similarity' of animals, birds in this case, with statistical data analysis (not only) in the field of EWS.

3. EWS, AI, and Kinds of Intelligence[9]

The asserted epistemological 'closeness' of animals and statistical machines may appear paradoxical, since, of course, in many ways these are not alike; it becomes clearer when considering their proclaimed ability to predict danger. Both animals and statistics can offer knowledge about the (otherwise unknown) future for the human, if the latter is able to use them; thereby extending his sensory functions as well as his future-knowledge. "The signs are there, if they can be recognized. As stress occurs, behavior changes." (Walsh 1986: 1146) Considering the examples of birds as early detectors of hazards, as in the case of gas concentration, often goes hand in hand with the metaphysical notion of (these) animals having a 'sixth sense', which allows for them to be used as EWS. The same can be said about snakes or elephants which change their behavior, e.g., fleeing the area or producing sounds prior to an earthquake before it can be recognized by seismologic sensors or humans (Tributsch 1978). Their abilities point to a limitation of the human which calls for their utilization by the latter in order to be better prepared for environmental risks.

Concerning the case of statistics as important tools in the *Taming of Chance* (Hacking 2010), the metaphysical aspect of the knowledge obtained by it is less apparent. After all, the quantification of human behavior served the purpose of introducing a law-like structure – "the law of large numbers" (ibid.: 95–104) – into social affairs. However, the subject of prediction or anticipation, even if it

9 Compare the project "Kinds of Intelligence" by the Leverhulme Center for the Future of Intelligence (http://lcfi.ac.uk/projects/kinds-of-intelligence/).

is based on the usage of statistical correlation and probability, in many cases carries a metaphysical, uncanny or magical baggage with it. For example, it could be noteworthy to mention the conception of statistical knowledge attributed to Florence Nightingale, herself a founding figure of statistics: "[T]o understand God's thoughts, […] we must study statistics, for these are the measure of His purpose." (Pearson 1924: 415) Or, to invoke a more recent example from the stream of Big Data correlation: Schönberger and Cukier (2013) discuss the uncanny anecdote of a retail company analyzing a woman's shopping behavior which indicates a high probability of her being pregnant. This allows the company to 'know' about the pregnancy before the woman's parents do (Schönberger/Cukier 2013: 57f.).

However, common ground between different cases of animals detecting hazardous gases, based on physiognomy and sensory functions, in relation to a company's detection of the pregnancy, based on the use of algorithms and large amounts of data, might be that both are used to bring to the surface potentially significant environmental changes. They deal with something which lies beyond the scope of human cognition. This constitutes a knowledge that is unlike human intelligence, unless the human learns to make use of it. Its utilization leads to an extension of the 'human senses' for detecting latent but yet impending danger, which can only be accessed by collaboration with e.g. animals like the canary or information machines like statistics; or (more recently) by relying on the application of AI with its "statistical anatomy" (Alpaydin 2016: 27). In this logic, the threat is already there, only the right senses to detect it have not yet been found.

The notion of an expansion of the human senses, and thereby future-knowledge about danger, can serve if not as a lens then at least as an inducement for an argument about the knowledge and the 'intelligence' of AI. The two probably most prominent tropes called upon when discussing the question of whether or not computers and machines can *reasonably* be called 'intelligent', are the proposal for the Dartmouth Conference of 1956 with its proclaimed conviction "that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy et al. 2006 [1955]: 12) as well as the famous 'Imitation Game' proposed by Alan Turing six years earlier. This thought experiment, which later came to be known as 'Turing Test', relies on a computer's ability to imitate human-like behavior in a way that makes it impossible for the human dialogue partner to distinguish between human and machine. If this imitation is successful, the machine can be deemed as intelligent (Turing 1950). The critique on this proposed conception of intelligence is well known and need not to be rolled out again. The trope of a 'sixth sense' etc. for catastrophe prediction in animals and statistic-based EWS invites us to shift the focus away from the question, if applications like Chat GPT can pass a Turing Test, which would justify them being labelled as 'intelligent'. Instead of concentrating on the mimicking of human thinking by artificial neural networks, we can 'reverse' the question and highlight the way the concept of intelligence is evolving in the course of its contestation vis à vis other forms of knowledge; namely those forms of knowledge which are always already discursively excluded from speaking truth and thereby excluded from knowing. This approach is in line with Benjamin Bratton's critique of the 'intelligence' in the Turing test, when he writes

> The threshold by which any particular composition of matter can be said to be 'intelligent' has less to do with reflecting human-ness back at us than with testing our abilities to conceive of the variety of what 'intelligence' might be. (Bratton 2015: 75)

The analysis of (catastrophic) future prediction points to two knowledge-related discourses for grasping the concept of intelligence – artificial or not.[10] The first one obviously revolves around the question what kind of knowledge statistics have to offer, respectively what kind of world-knowledge is 'revealed' by the use of quantification and statistical analysis. Historical research on *The Rise of Statistical Thinking* (Porter 2020) shows us that it is not only since the coining of the term 'AI' that these technologies were "associated with an impressive extension of the domain of knowledge and not with its limitations" (ibid.: 163). It can thereby shed light on the discourse about the (statistics and data-based) artificial intelligence.

Apart from this, the preoccupation with EWS, based on animalistic as well as non-animalistic signal detection, opens up a second realm of possibly fruitful analyses concerning the question of what kind of knowledge AI 'has', or better 'offers'. Instead of concentrating on the question whether AI can pass as having acquired human-like intelligence, we can turn our attention to the ways the knowledge of those has been discussed (and created), which most certainly don't pass as 'intelligent', since they constitute the necessary 'Other' of 'human intelligence'. This concerns, to various extents, the thinking of children, non-

10 Whatever non-artificial intelligence might be.

European indigenous groups, people who are differently abled mentally as well as non-human animals. The psychological attempts to grasp and possibly utilize these other forms of sensing and knowledge can shed light on the construction of intelligence. Not least because of the ways artificial intelligence is repeatedly brought into connection with children, non-human animals etc., by comparing their problem-solving abilities with each other. Turing himself proposed: "Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child's?" (1950: 456) But also, in media reports dealing with scientific developments in AI, we regularly come across headlines in the manner of "AI had IQ of four-year-old child" (BBC 2015). For the case of animals, a good example would be the recently published study by Wasserman, Kain and O'Donoghue (2023), which deals with the learning mechanisms of pigeons that are said to bear significant similarities with the type of learning of machine learning algorithms, particularly reinforcement learning. The authors point to BF Skinner's planned usage of pigeons as 'brains' for his experimental guidance system for directing ballistic missiles to possible WWII military targets. Skinner himself justified this choice as follows: "We have used pigeons, not because the pigeon is an intelligent bird, but because it is a practical one and can be made into a machine, from all practical points of view." (Capshew 1993: 851). Although the usage of birds in this example cannot be interpreted as a defensive EWS but rather served as a measure of attacking the enemy, it illustrates the deployment of non-human cognition and sensing by humans and at the same time makes a comparison to machines. The human makes use of these abilities of the other and thereby expands, to invoke Tarde again, their 'sensory organs'. This rationale also applies to the implementation of Early Warning Systems of various sorts. Concentrating on the reliance of catastrophe prediction abilities, be it via the monitoring of small animal behavior in coal mines or deviations in 'tweeting behavior' via the use of AI, cannot only contribute to an investigation into the gears of the preparedness-apparatus (Lakoff), it can furthermore, as it was argued above, help shed light on the question of 'knowing the human'.

To conclude this investigation into Early Warning Systems and their potential transformation via the use of machine learning, it will be useful to again invoke the report on "Experiments with Small Animals and Carbon Monoxide". Considering the differences between men (not humans) and small animals in feeling distress when exposed to dangerous concentrations of carbon monoxide, Burrell and Seibert assert that "a man is in an excellent position to determine effects upon himself [whereas] small animals may feel distress but not show it." (1914: 243). The reasoning here implies that there are traces to be found in the animal's 'feelings' beneath the behavioral surface. The human, via interacting with the animals and monitoring their behavior, can utilize these feelings by 'making the animal speak', i.e., detecting symptoms even before the animal becomes 'aware' of them. For EWS models like in Sakaki/Okazaki/Yutaka (2010), where the users become birds, whose tweeting behavior is monitored, it is the algorithm's job to identify behavioral patterns as indicators for catastrophes; ideally, even before the users explicitly show their distress. By gathering ever more data about environment-monitoring sensors, be they avian, human, or other, and analyzing them ever more effectively, they will potentially become utilizable for hazard detection even easier and, most importantly, earlier. What will remain unaltered by this extension of the 'sensory organs' via implementing machine learning technology in EWS, however early the signs for danger might be detected (or created), is the determination of what is even perceived as a danger to be prepared for and further: a danger for whom? We can remain skeptical whether it will be the birds having the final say in this matter.

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