When to Care: Temporal Displacements and the Expertise of Maintenance Workers in Public Transport

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Abstract
Fueled by digital developments modern wage labor is increasingly subject to new forms of temporal objectification. In the field of public transport, maintenance workers must deal with two recent developments. Predictive maintenance and the digital tracking of time temporally displace maintenance and repair work. When dealing with disruptions, such systems favor anticipatory measures and retrospective evaluation over work practices in the immediate aftermath. This challenges the professional expertise of workers and limits their ability of caring for the infrastructure on their own terms. While this limits the scope of practical knowledge in dealing directly with disruptions, it also opens up new avenues for autonomy and creates opportunities for reevaluating practical knowledge in other areas. The ability to improvise is increasingly important given that the systems are often unreliable and operate on the basis of vague assumptions. Instead of a de-skilling, a temporal shift occurs. Practical knowledge becomes important beyond immediate repair practices, namely before and after disruptions are dealt with.

Keywords
maintenance; repair; care; knowledge; public transport; railways

Introduction
Modern wage labor has always been subject to temporal objectification. In the history of industrial capitalism, chronological time and the idea of efficiency are closely linked (Gregg 2018; Adam 1992; Ballard 2007; Thompson 1967). On the one hand, modern organizations work on the basis of “fictional expectations” (Beckert 2016) and attempt to plan work practice and its outcomes—for example, by employing planning tables and sticking to schedules (Conrad 2019). On the other hand, the efficiency of actual work practices was and is measured by tracking the time spent on tasks—the time clock as a managerial tool comes to mind (Gregg and Kneese 2019). The former temporal objectification is an attempt to control things beforehand, the latter aims to govern work ex post. In an age of increasingly accelerated time (Rosa 2013) both forms of temporal objectification have been further amplified in their consequences. Predictive tools, often fueled by artificial intelligence, extend the scope, and reach of planning to new tasks...
that hitherto have been deemed unplannable. And the tracking of time reaches new levels of detail and becomes ubiquitous as work practices become increasingly quantified (Ajunwa 2023).

In the following article, I will show how the expertise of maintenance workers in public transport is challenged by these developments. Different forms of knowledge come in conflict with each other for instance: (1) a quantitative notion of objectified knowledge, and (2) more implicit and improvisational forms of practical knowledge. I argue that attempts to objectify practical knowledge by engineering or management often are in vain. Maintenance workers have to adapt their work practices to a “workflow from without” (Bowers et al., 1995) resulting in a greater need for informal knowledge when they decide to take action and care about problems. Consequently, while a “logic of care” (Mol 2008) is constantly challenged by temporal displacements, new opportunities to take care of the infrastructure arise, nonetheless.

The data on which my argument builds consist of ethnographic fieldwork and interviews with railway technicians of Swiss Federal Railways (SBB) undertaken in 2017 (Röhl 2022). This research was part of a project on public transport companies and how they responded to disruptions ultimately normalizing them as everyday part of their organizational conduct. Methodologically different sites were visited as part of a multi-sited ethnography (Marcus 1998) following disruptions on their journey through and beyond organizations in different media: meetings and briefings in the headquarters, work on the tracks and in signal boxes, oversight in control rooms, documents and data linked to disruptions, various accounts in the press, etc.

The article first highlights the materiality and temporality of maintenance and repair and its relation to the notion of care (1). It then discusses two cases of temporal displacement that challenge the expertise of maintenance workers in public transport, in particular their decision when to care about a problem: predictive maintenance and its engineered anticipation of breakdowns on the one hand (2), and the tracking of time as measurement of individual performance when dealing with disruptions on the other hand (3). Building on these two cases different forms of conflicting knowledge are identified and discussed in terms of a possible devaluation of workers’ expertise and thus autonomy (4). Linking the notion of care to different forms of knowledge and their temporalities this article contributes to a debate about the quantification of work practices and the opportunities to uphold professional expertise and autonomy despite them. Instead of finding a substitution of care practices by technologies employed by management, this article provides a nuanced view of the relationship between different forms of knowledge and their temporalities.

The Materiality and Temporality of Maintenance and Repair
STS research on maintenance and repair highlights the role of local, often innovative work practices and the practical knowledge required in upholding modern infrastructures (Jackson 2014; Denis and Pontille 2015; Denis et al. 2015; Strebel et al. 2019). Maintaining and repairing are not mere reinstalments of a technical status quo but also instances of “fixing” and defining social order (Henke 1999; Orr 1996). These questions of social order are linked to politically and normatively charged questions about agency, expertise and autonomy of technical workers. A certain level of expertise and autonomy are defining features of many professional jobs. Any newly introduced technologies that challenge these features are therefore seen as a potential threat to the status of the affected workers (Susskind and Susskind 2017)
The introduction of new technologies in the workplace, however, does not determine change in work practices but can be an occasion for change (Orlikowski 2007) with material arrangements and practice closely entangled with each other (Schatzki 2006). In this sense, workplaces and work practices are technologically mediated (Beyes et al. 2022). An important feature of modern work is its temporal organization. Work can be temporally measured as notions of productivity and efficiency gain ground (Gregg 2018; Adam 1992; Ballard 2007; Thompson 1967). Technological means of measuring and controlling time become important instruments of managerial control (Orlikowski and Yates 2002).

This managerial control and logic of planning can be at odds in a field where practical knowledge is paramount and things can seldom be planned but must be improvised (Graham and Thrift 2007). Similarly, the notion of care has gained traction in studies on maintenance and repair (see, for example, Russell and Vinsel 2019). Originating in studies about medicine, the “logic of care” (Mol 2008) is about adapting to local and individual particularities and ongoing efforts to attend to patients and their needs. While care and technology have often been seen as inhabiting opposed realms, both are indeed connected (Mol et al. 2010). Care practices rely on technology, and someone needs to take care of technological artefacts and infrastructures and attend to them. Transferring the notion of care to the field of maintenance and repair highlights that these practices are not neutral realms of technical matters but involve affects and other notions of sociality surrounding the cared for objects in questions: “We care because we care” (Jackson 2014, 232).

Such (technological) care practices rely on tacit practical knowledge that can only be partially formalized and thus become the object of managerial planning and control. This brings different temporalities into conflict with each other: on the one hand, repair and especially maintenance practices spontaneously adapt to local circumstances and rest on the ability to act in the right moment (i.e., kairos; see Cipriani 2013); on the other hand, planning and control with their distanced attitude towards such practices often rely on objectified time (i.e., chronos). Yet, care practices are also often embedded in planned environments and control itself can be seen as another form of care (Kenner 2018). Care has thus an ambivalent relationship to both situated and objectified temporalities.

Taking these tensions as a starting point, the article asks how the work of maintenance crews is challenged by two technological changes that aim to limit the scope of practical knowledge in dealing with disruptions. I will show that the work of technicians is not in danger of de-skilling but rather temporally displaced. This temporal displacement entails a shift in the role of local knowledge. Engineering and managerial means to control disruptions and how they are handled aim to objectify practical knowledge. Yet, as I can show, they also lead to an increasing relevance of practical knowledge in unforeseen ways.

Temporal Displacement I: Predictive Maintenance and the Anticipation of Disruption

The history of railways is also a history of the systems preventing trains from colliding. Like modern cars, the first trains operated on sight (Perkin 1970). Since it takes a long time to decelerate a train, this was not feasible and unsafe as soon as the speed and number of trains increased. Instead, signaling block systems became the standard. The railway is divided into several blocks. Each block can only be occupied by one train at a time with automated signals preventing another train from entering. Switches thus also need to be configured accordingly.
Like other technological infrastructures this system needs specialized personnel for its maintenance and repair. SBB has several teams in place at different locations all over its network. The maintenance crew stationed in Zurich is responsible for a larger area surrounding Zurich. They change between shifts where they are doing routine maintenance and installing new components and shifts where they are on-call when signals or switches stop working. In the case of such breakdowns, they receive tickets via an online platform. These tickets have different priority levels ranging from one (highest priority) to four (lowest priority).

One of the most common problems these railway technicians encounter in their on-call shifts are stuck switches. After a while the lubricant on the switch blades attracts so much dirt that the blades cannot turn any longer and get stuck. When this happens, a ticket is created and depending on the location of the switch a priority level is set automatically. In any case, the technicians consider this a routine problem requiring a proven routine solution. Usually, the technicians just have to remove some dirt and apply some fresh oil before a message generated by the system reports that the problem has been fixed.

How are these tickets and the associated incidents created or reported? Whereas most disruptions and incidents were formerly reported by persons, this is now mostly an automated affair. A myriad of sensors is at work reporting when something is amiss. If a switch, for example, cannot be turned, there will be an automated error message that becomes a ticket to work on for the service technicians.

Recent technological developments go even a step further: “predictive maintenance” (Selçuk 2017; Ciocoiu, Siemieniuch and Hubbard 2017) enables technicians to initiate maintenance and repair before an actual problem occurs. Consequently, maintenance only needs to occur when it is necessary. In public transport predictive maintenance is also becoming more important: for example, to diagnose faulty signals or, as in our case, to estimate the lifetime of switches. Diagnostic systems measure the control current in a switch comparing it to a reference value (Körkemeier and Robbe 2011). If the value is exceeded, the system reports an error. This happens—according to the model—when the switch blade is moved against resistance, for example, when the amount of lubrication is insufficient or when an object is obstructing movement. Consequently, problematic switches can be singled out before they finally stop operating. Developers of such diagnostic systems want to take this idea one step further. By integrating additional data (for example, on the weather) and making use of machine learning, prognosis is supposed to become even better and timelier (Böhm 2015). The goal is the timely and exact prognosis of a switch’s “Remaining Useful Life” (RUL). RUL is measured in days and gives an estimated time period before a switch stops working, making it possible to prevent problems before they occur (see figure 1).
Zurich central station, headquarters of the service technicians: It is a quiet morning. The technicians and I are sitting around in the break room, drinking coffee, and joking. Around 7:50 a.m. we receive our first ticket. We are excited to finally be on the road. A diagnostic system reports a problem with a switch at Thalwil (a suburb of Zurich) station (priority level 4). As soon as we reach the highway in our van, we are informed of a more urgent problem at Zurich central station (priority level 1). This means we have to immediately drive back to where we came from. The absurdity of the situation makes us laugh. After the technicians have solved this problem, we can return to Thalwil. The system does not report an error any longer. Still, the technicians want to make sure that everything is alright. They perform their usual maintenance routine: cleaning the switch blades and applying some oil.

Sometime later we tell Harry—a veteran technician—of the incident. He informs us that this particular switch has been maintained just a few days ago. He fears that exactly this causes problems with the diagnostic systems—instead of alleviating the situation. Harry complains that the diagnostic system in general causes more problems than it solves. In former times they had more time to properly maintain switches ensuring their reliability. In his view, it would be better to employ more personnel than to acquire these expensive and unreliable systems.

Error messages that are disappearing without any actions on behalf of the technicians are suspicious to them. Just to be sure they fall back to proven routine measures—in this case cleaning the blades and applying fresh oil. According to them it cannot hurt to take care of the switches in any case. This attempt of a “dissolution” (Orr 1996, 122 f.) of the disruption follows a common logic of maintainers that it is better to do something than do nothing—even in cases when the cause of a problem is not known. By sharing stories and information in the common room they realize that their attempts of fixing things could be the cause of the problem in the first place. Their arguments are purely correlational, that is, without knowing if and why lubricating the switches is the actual cause of the trouble with the diagnostic system. In their exchanges they work on a critical narrative about sensors which is dispersed and extended upon among technicians.

Figure 1: RUL prognosis: x axis: time until actual breakdown in days, y axis: predicted RUL in days. (Source: Reproduction and translation of figure 1 with permission from author, Röhm 2015, 50).
Why does Harry dislike the diagnostic system? Several things are at stake from the standpoint of the technicians. Foremost they see their professional autonomy endangered by sensor technologies. From an engineering standpoint, technical problems become solvable through the automation of maintenance enhancing decision-making by letting sensors decide when a switch needs care. Sensor technology and diagnostic systems provide a calculable and seemingly reliable diagnosis. Additionally, personnel can be relieved from a time-consuming task giving management the opportunity to employ less technicians.

Via sensors technical expertise is shifted from the technicians to the engineers and their attempts to make technical problems plannable. This “delegation” (Latour 1994) brings the engineers indirectly onto the tracks and thus gets them “in contact” with the technicians. If this shift in expertise, however, is coupled with a lack of trust, nobody feels accountable (Ciocoiu, Siemieniuch and Hubbard 2017, 1183). This is exactly what is happening here: Harry mistrusts the error messages generated by the diagnostic system. And he disseminates his mistrust to his colleagues who experience similar troubles with diagnostic systems. The technicians no longer feel responsible for occurring problems and dealing with them is a tiresome duty to them. When their proven measures do not seem to have an effect (or maybe even a negative one), they no longer feel accountable. With other components they are not only responsible for their repair but also for their maintenance. If a component breaks down, it could be because of their negligence in maintaining it. The diagnostic systems described here, are only partially in their jurisdiction. Diagnostic systems are mostly a black box for the technicians that only the developer can open.

Two models of technical problems are at stake. On the one hand we find a model which rests on a logic of ongoing care (Mol 2008) and knowledgeable improvisation (Weick 1993). Here, technicians rely on their practical knowledge and experience to decide when to intervene on the tracks and to determine the intervals of their maintenance practices. This is, on the other hand, confronted with a model building on the idea of calculative prediction and the technical prevention of problems. Like other “organizational encounters with risk” (Hutter and Power 2005) this model attempts to tame uncertainty by preemptive measures—in this case, by objectifying the temporality of maintenance (as RUL measured in days). While the one logic opts for soft forms of prevention, the other can be characterized as technical and calculative planning thus not only anticipating but shaping futures (Amoore 2013). Alas, the technical solution of engineers is not a general cure of technical problems. While diagnostic systems mitigate some of the more severe consequences of switches breaking down, problems occur nevertheless and much more frequently and earlier. The system now reports that a switch needs maintenance long before the technicians would have made their move.

Sensor technology thus merely shifts the boundaries of what is considered a technical problem: Is it the switch blade that is actually stuck? Or the one that is just a little harder to move? In the figure of the engineer (figure 1) only the shift that is stuck is considered a problem. This hides that the technicians working on the switch receive a ticket in either case and have to take care of the component singled out by the diagnostic system. The railway network as a whole is still working without any interruption, but they have to enter the tracks and take care of the switch in both cases. For the engineers it is all about preventing major disruptions in the “great machine” (Schivelbusch 2014, 11), i.e. the railways network as a whole, for the technicians it is a question of whether they have to act or not.
In general, maintenance and repair work in public transport must operate under difficult conditions. Most work has to be done while trains are operating, thus creating problems for the safety of the crews working there (Sanne 2008). This also makes their diagnostic work particularly challenging. Most of the time they cannot do a proper analysis of the situation at hand but must rely on trial-and-error methods applying routine measures of maintenance and repair. If the problem vanishes by applying a routine method, then a likely cause has been found. Diagnosis and repair go hand in hand. This leaves a certain degree of uncertainty—the cause could always be something else and the repair method just worked by chance. Dealing with this uncertainty two diagnostic strategies can be identified: a pragmatic and an analytic strategy. Most technicians follow a pragmatic strategy. They want to get things done as quickly as possible. Thus, as soon as the system tells them that a technical problem is solved, they are satisfied. Harry is one of the few technicians that prides himself as pursuing an analytic strategy. Even when a problem is seemingly fixed, he remains suspicious. Recalling further occurrences of similar problems with the same component at another place or another component at the same place, his curiosity is triggered. What if there is a systematic problem underlying these individual occurrences? That is why he can often be seen after the end of his shift double-checking on components and testing his hypotheses by looking and measuring at different places. It gives Harry great pleasure and pride to find these underlying problems thus preventing future problems (see also Sanne 2010; Orr 1996). It is exactly this attitude that makes him such a sought-after colleague whose expertise is valued. He truly cares about the railway network and its operation in a way that goes beyond merely identifying individual problems.

In line with recent literature, the example of predictive maintenance also highlights that AI systems are “neither artificial nor intelligent” (Crawford 2021, 9) and that “automation is a myth” (Munn 2022). A lot of human work is necessary for supposedly “automated” AI systems to operate—rare-earth elements need to be mined, clickworkers have to classify images and train algorithms, and so forth. Once AI and other algorithmic tools are in use, the work does not stop. For example, the environment in which video surveillance systems are used need to be prepared to allow for the identification of objects such as luggage in crowded areas of an airport (Neyland and Möllers 2017). AI and algorithmic decision-making are thus not (fully) automated systems but are bound up in human practices (Seyfert and Roberge 2016) and part of “performative struggles” that need to be resolved (Glaser et al. 2021, 13f.). Algorithmic systems thus are not replacing human workers but rather shifting their professional roles (Susskind and Susskind 2017). The central question is when to (take) care. Should technicians maintain things when the model provided by the diagnostic system tells them, or at fixed intervals dictated by their working rhythms and experience, or when they feel that they should look at particular components because something seems off? And this is linked to questions of agency: should sensors and software govern maintenance or the experience of human technicians? A logic of planning, engineering and technological fixes collides with the logic of care, with the wisdom of technicians and their practices of tinkering and trial and error. The engineer’s dream of preventing disruptions seems to be in vain: they are not so much preventing disruptions but temporally extending their reach: technicians have to go on the tracks even earlier and see what can be done. For them it is still a disruption that needs to be fixed. A less severe disruption, but nevertheless a disruption. Accordingly, the technicians see their autonomy at stake here and try to uphold it by valuing their practical knowledge. While they need to take care of the diagnosed problem eventually, they know that they can
postpone its repair; and they also know from experience which repair routines work with the newly installed systems and which ones are bound to fail.

In contrast to a prescription of fixed intervals of maintenance or the need to fix immediate problems, predictive maintenance changes the very notion of what a disruption is and when things need to be taken care of. Disruptions are temporally displaced by extending them ex ante and lowering the threshold of what counts as a problem. Maintenance and repair practices are not initiated by the technicians and their caring attention to switches and signals but by objectified measures that lie beyond the scope of technicians. Yet, technicians still need to apply practical knowledge in evaluating the outputs of predictive systems to gage their reliability.

**Temporal Displacement II: Measuring Minutes of Delay and Assigning Blame in the Aftermath**

Predictive maintenance is an attempt at anticipating and thus avoiding disruptions before they happen. Other means are in place to evaluate the severity of disruptions and their consequences after they occur. As I will show, this discourages thorough maintenance practices in favor of measurable short-term effects thus undermining workers’ practical knowledge and care for the switches and signals. Instead of taking care of switches and signals and their proper working in the future, workers are looking for means of shifting blame.

With the introduction of a software system, SBB is attempting to evaluate the work of the employees entrusted with the maintenance of the infrastructure. To this end, the ticket system is linked to another data infrastructure. The “Ereignis Zugsicherung” (ErZu) system automatically determines how many minutes of delay were caused by an individual disruption in total. This information is also recorded in the ticket. All delays of affected trains at the following stations are added up. From SBB’s point of view, this makes it possible to determine the severity of the disruption and its impact on the railway network. For the technicians, on the other hand, the aggregated minutes of delay remind them to remedy the disruption as quickly as possible. If a disruption causes 250 or more minutes of delay, they are obliged to write a report explaining why such a severe disruption could occur.

As with other data practices measuring minutes of delay is not a simple act of recording but requires preparation of data that is often “broken” (Pink et al. 2018) and might lead to a transfer of false results. Consequently, technicians check the automated assignment of aggregated minutes of delay to their department for accuracy before transferring it to their superiors. An important task at the desks of the railway technicians is therefore to keep a record of the allocated minutes of delay. The following fieldnotes illustrate this point.

Meanwhile, Matthias sits at his computer and works on an Excel spreadsheet in which disruptions and the minutes of delay they caused are recorded. The table also contains a description of the disruption, a category, and a code for the responsible department. Matthias’ main task is to edit the descriptions and add categories and departmental codes. His department (safety systems) has the code 51, while the track construction department has 53. Sometimes it is necessary to rebook, for example, if it is clear that it was not a fault of the safety systems department but of the track construction department (for example, due to construction work and not a lack of maintenance). Whenever there is time, Matthias goes through the list and edits it. He also reports that it once happened that the category “train driver not ready” was booked to “our department,” which then had to be rebooked because this was “not our responsibility.”
By manually checking and editing the list Matthias reacts to an assumption implemented in the software about the cause of malfunctions. The ErZu system automatically books minutes of delay to the department responsible for servicing and maintaining the defective component. While this provides an incentive to process repairs as quickly as possible, it also rests on the assumption that a lack of maintenance (by the responsible technicians) has led to the failure. Of course, there are cases in which the technicians can claim other causes. A distinction can be made here between causes internal and external to the organization. Internal causes relate to the behavior of other departments. For example, it happens from time to time that the track construction department damages signals or switches during its nighttime construction work. Causes outside the organization include storms, the misconduct of other transport companies or suppliers who have delivered faulty components.

From a managerial perspective, minutes of delay are also used to measure the performance of individual departments and thus localize responsibility at the same time. They are consequently also a means of “assigning blame” (Potthast 2007; translation by Röhl). The causes of a disruption are not identified in structural or organizational contexts, but in the misconduct of individual organizational members. Accordingly, the assignment of minutes of delays to individual departments is highly normative and processes of “blame shifting” (Hood 2010) occur: employees in individual departments attempt to blame another department for an incident.

In general, minutes of delay refocus the work of technicians who adapt their maintenance and repair practices accordingly. Incidents that do not generate minutes of delay (for example, because they affect only irregularly used tracks) are given lower priority. Disruptions that do generate minutes of delay, on the other hand, receive preferential treatment. The aggregated minutes of delay assume both an individual attribution and a precise temporal localization and delimitation of the disruption. With this individualistic and limited notion of disruptions, the minutes of delay set short-term incentives to remedy disturbances quickly. In contrast, long-term and systematic care (Mol 2008) is not recognized. If one leaves it at the superficial, possibly short-term elimination of a problem, one can therefore refer to organizational rules in order to reject responsibility for recurring problems.

Measuring minutes of delay builds on older forms of evaluating productivity temporally. The timetable is still an important point of reference in public transport. As “logistical media” (Peters 2013) timetables coordinate several actors and their activities. Like other coordinating media they are at the same time prescribing norms (Suchman 2011) making deviations visible as delay. The difference is that minutes of delay are an attempt of pinpointing failures by measuring overall consequences of disruptions. Aggregated minutes of delay thus temporally displace disruptions by extending their reach ex post. Transport companies and their workers deal with disruptions long after switches have been oiled and problems have been fixed. Measuring minutes of delay is a managerial attempt of controlling disruptions in their aftermath favoring quick and superficial short-term solutions in the immediate presence of a problem in favor of long-term diagnosis and care.

Yet, practical knowledge remains important. Maintenance workers need to be able to amend and process data. And they also should know what counts as legitimate reason for a severe disruption or when they can shift blame. For this they require knowledge about the recent event on the tracks and their surroundings and how the organization as a whole works. At the same time, their ability to care for signals
and switches and make use of their practical knowledge on the tracks is hampered by these managerial means.

From “When to Care” to “Who Cares”: Practical Knowledge and its Use

Asking when to care is also asking which kind of knowledge is best suited to deal with technical problems—and this in turn is linked to questions of representation. How can technical problems be diagnosed—via technical sensors or human senses? When do we know that a problem is fixed? How do we evaluate consequences of disruptions? How do we assign responsibility? At least, three forms of knowledge are at stake: objectified knowledge, routine knowledge, and improvisational wisdom.

1. Objectified Knowledge: Sensor-based diagnostic systems and time-tracking systems stand for an objectified form of knowledge. This is the realm of explicit knowledge (episteme) and consists of factual if–then clauses that describe the status of the technical infrastructure: if the measured value exceeds this reference value, then something is amiss, and maintenance needs to be done. If a disruption is reported, delays are recorded until the problem is fixed. Engineering and managerial technologies seemingly leave no room for interpretation and instead promise to substitute both a subjective gut feeling and traditional fixed-interval maintenance with a “mechanical objectivity” (Daston and Galison 2007).

2. Routine Knowledge: Technicians rely on a vast body of routine knowledge in taking care of switches and signals. This includes routine procedures and means of fixing things (like applying oil on switch blades) and established intervals of checking and maintaining technical components of transport infrastructures. Diagnostic knowledge of technicians includes routine ways of fixing things, but also knowing when to care for things, that is when to maintain switches and signals. They “make matters speak” (Sanne 2010, 54) by using their senses but also by “talking about machines” (Orr 1996) with their colleagues—trading stories and information about past problems.

3. Improvisational Wisdom: With objectified forms of knowledge becoming more ubiquitous and creating problems of their own, technicians need to find ways of integrating their routine body of knowledge with technical systems of diagnosis and tracking. Maintenance and repair are linked to improvisation and innovation (Graham and Thrift 2007; Russell and Vinsel 2019). When error messages occur and suddenly disappear, or when minutes of delay are falsely attributed, technicians must connect this information to their past experiences, their organizational knowledge, and colleagues’ stories in a meaningful way. Only then can they make informed decisions about when to care. Thus, deciding on a feasible action requires a “trained judgement” (Daston and Galison 2007) that neither can be reduced to objectified forms of knowledge nor to routine bodies of traditional knowledge.

What kind of value is attached to these different forms of knowledge? Since safety concerns are serious issues in public transport, it is unlikely that the work of railway technicians will be fully automated and thus deskilled by a widespread use of diagnostic systems (see Lester 2020). Humans are seen as supervisors of machines and need to be “on the loop” (Mellamphy 2021) in order to take over when diagnostic systems themselves are prone to technical errors. At the same time, however, hopes for an upskilling are also misled. Unlike past accounts of the “postindustrial age” (Hirschhorn 1984) the need for human oversight is partially substituted by sophisticated algorithms.
In general, the work of railway workers is and was always governed by external measures. The timetable accompanied the railway since its early days and is a prime example of a modern, objectified sensibility of time (Schivelbusch 2014). Railway workers have since then become less autonomous and more controlled (Kemnitzer 1977). Like other workers their work is increasingly governed by external managerial measures such as timetables and performance indicators. New diagnostic and tracking systems are well suited to this logic of a “workflow from without” (Bowers 1995): They are external initiators of work. Tracking minutes of delay assigns incentives that might not align with the practical relevancies of workers— in turn, they must adapt not only how they maintain and repair but also how they document and report their work. And even when technicians choose not to trust diagnostic systems, eventually they must deal with tickets created by predictive maintenance. In one way or the other they are held accountable for the technical problems reported by them. In case of second-order error they must account for their belief in the wrongdoing of the diagnostic system. Their autonomy as workers is thus at least indirectly affected by predictive maintenance. Yet, second-order errors of diagnostic systems leave some room to uphold the importance of maintenance workers’ knowledge. Their improvisational wisdom, their ability to tinker on the fly is needed when unexpected things happen.

Both predictive maintenance and tracking minutes of delay are attempts to objectify maintenance work by engineering and managerial measures devaluing local knowledge of technicians to some extent. Yet, instead of limiting practical forms of knowledge (routine knowledge and improvisational wisdom) these attempts strengthen routine knowledge and improvisational wisdom. While a “zone of uncertainty” (Crozier and Friedberg 1980, 34) becomes limited in one instance, new opportunities to uphold one’s expertise and thus autonomy arise. Technicians learn when to really care: Which disruptions need their immediate attention even though the priority levels suggest otherwise? When does it pay off to investigate a disruption thoroughly? When can they shift blame? Workarounds and informal organizational knowledge are paramount. Technicians exchange information about incidents in “their” part of the network and the work done on the tracks by them or other departments. And on that basis they can act and work with the external constraints limiting their autonomy. This is in line with research on automation in other fields such as aviation (Hancke 2020). Instead of unburdening humans, automation requires highly skilled professional that not only have the necessary operative skills but know how to monitor and question automated systems.

Organizational knowledge is not something that can be fully encompassed by formal accounts, but a situated practice and thus subject to negotiations (Gherardi and Nicolini 2000). Here, these negotiations are enacted in absence of the relevant groups. Technicians negotiate with engineers and managers solely via the technologies at hand in their daily practice. By temporally displacing disruptions, engineers and managers are attempting to preempt and postpone decisions of workers on the ground and turning them into engineering and managerial problems. This suppresses direct negotiations and conflicts by blackboxing them in technology and relegating them to an infrastructural background (Star 1999) leaving the workers with nothing more than a certain cynicism: “There’s always trouble with these kinds of systems!”

While the railway technicians regain autonomy in other places where they rely on practical knowledge, one could still ask for a better way of developing diagnostic and tracking systems. How can practical knowledge become a part of these systems and not be viewed as something to overcome by engineers and managers alike? After all, they fail in their attempts to objectify knowledge and control
disruptions. Instead of replacing practical knowledge and care, sensors and tracking systems relegate it to other times and areas where it might be less useful than in the places where it is needed most—in the immediate presence of faulty signals and switches on the tracks, where workers should take care.

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