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AI and Algorithmic Management in European Services Sectors

Prevalence, functions, and a guide for negotiators

Steven Rolf

New Technologies at the Workplace

FRIEDRICH EBERT STIFTUNG

NEW TECHNOLOGIES AT THE WORKPLACE

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This report was prepared in cooperation between UNI Europa and the FES Competence Centre on the Future of Work.

Contents

Glossary

AAMS (AI and algorithmic management system)
Software systems used by managers to hire, train, manage, evaluate, and/or reward or discipline workers. AAMS contain some element of automation of management, from simple automation of particular processes, up to and including AI which appropriates and integrates many managerial functions.

AI (Artificial Intelligence)
A broad range of software functions. By far the most common are machine learning technologies (see ML).

ATS (Applicant Tracking Systems)
Software for assisting managers with hiring, from CV screening to cover letter analysis.

Bossware
Software used to manage workers. See AAMS.

ChatGPT
A large language model (see LLM) which generates text using AI.

CRM (Customer Relationship Management) software
A subset of ERP software for firms which are driven by their relationships with clients. Measures sales, leads, and a range of other metrics.

Datafication
Breaking down jobs into small component units so that they can be digitally measured and evaluated.

ERP (Enterprise Resource Planning) software
Usually the main software platform that medium and large companies run on, incorporating processes, including management, HR, accounting and more.

Gamification
Incentivising workers to perform through computer game-like uses of metrics and scores.

KPI (Key Performance Indicator)
Metrics commonly used in workplaces to measure employee performance.

LLM (Large Language Model)
An algorithm which uses big data and natural language processing to mimic human interaction and respond to queries.

LMS (Learning Management System)
Recommend training resources based on performance, qualification and skills.

ML (Machine Learning)
The use of algorithms to identify patterns in data and generate rules from them, which can be applied to other contexts.

Taskification
Breaking down jobs into small component units, so that they can be digitally measured, evaluated, and controlled. *(See datafication).*

WMS (Warehouse Management System)
Software used by warehouse managers to streamline and integrate flows of goods, work processes and storage.

Executive summary

This report discusses the growing use of AI and algorithmic management systems (AAMS) in European service industries.

- AAMS are proliferating at speed throughout the European service sector. They are spreading beyond the platform economy, and becoming prevalent in 'ordinary' workplaces such as offices, restaurants, and contact centres. In large part, this is because they are being embedded in pre-existing enterprise software.

- While AAMS vendors loudly acclaim their advantages and benefits, their products pose stark threats to workers. They harbour a risk of illegitimate surveillance of workers, intensification of the pace of work, creation of knowledge imbalances between workers and managers, and (often poor) decisions being made without sufficient oversight.

- The report provides an overview of AAMS functions. These are extremely wide-ranging and cover key managerial functions, including coordinating, directing, evaluating and disciplining workers. AAMS are deployed at every stage of the employee lifecycle, including recruitment and hiring, training and development, task allocation and scheduling, and performance management and productivity-tracking.

- The report examines four specific examples of AAMS: two for sales work (Salesforce and ActivTrak), and two for warehouse management (Infor and Blue Yonder). They demonstrate how AAMS help managers exert granular control over individuals and teams through the algorithmic generation of performance metrics and recommendations for managerial action (including firing). They also demonstrate the extraordinary information imbalance produced by AAMS.

- Next, the report draws on a range of reports to offer suggestions to trade unions for collective bargaining over AAMS in the European services context. It emphasises the urgent need for effective negotiation and regulation to mitigate potential risks, both for employees as well as for firms which are at risk of being misled by 'snake oil' AAMS vendors.

1

INTRODUCTION

The study forms part of a broader research agenda by Friedrich Ebert Stiftung (FES) and UNI Europa into the growing significance of AAMS for European workers, and prospects for collective bargaining to assert worker control over these new and proliferating tools. A companion report presents a survey cataloguing collective bargaining practices on AI in the European services sectors.

AI and algorithmic management systems ('AAMS') have proliferated in European service work during recent years. Such software packages promise to boost productivity, offer greater insight into and control over work processes, enhance and speed up decision-making, and cut unnecessary costs by smoothing workflows. These tools collect significant volumes of data on workers and workflows from many different sources, and analyse them using statistical techniques (including machine-learning). They generate either recommendations to managers to help their decision-making, or instructions given directly to workers to implement. AAMS are used for a wide range of functions across the fields of recruitment, training, scheduling, and performance management.

Firms are racing to adopt such digital technologies (Stuart et al 2023). AAMS are proliferating across service sectors from logistics, catering and healthcare to white collar workers (in-person and remote) in finance, law and ICT (Eurostat 2022). They are impacting workers across skill grades. No longer restricted to *Fortune 500* companies, significant innovation and competition has also reduced the cost of such tools, enabling smaller and medium-sized firms to begin to deploy them (OECD 2021).

However, there is growing concern that AAMS may also harm both employees, and firms more generally. This is not because they threaten to destroy substantial numbers of jobs, despite such claims being intermittently made.[1] Indeed, AAMS can be thought of as an alternative to automation, which usually requires large and risky capital investments from firms in new equipment to eliminate human labour (Schaupp 2023). Rather, AAMS threaten to illegitimately surveil workers and their personal data, create a divide in access to knowledge between managers and workers, to speed-up work to (or past) breaking point, and to take operational decisions including productivity measurement, worker remuneration and even hiring and firing without sufficient human oversight. Further, AI and algorithmic management tools are often 'black-box' technologies which use machine-learning techniques to evaluate data and make recommendations and decisions. As such, they are opaque by design – and often not well understood by managers who use them.

While commonly associated with the platform or gig economies, demand for AI- and algorithmic-management systems is booming amongst managers in 'conventional' firms. Many workers may not be aware that managers are utilising automated management systems (Brunnerová, 2022). Indeed, many lower-level managers may not be aware of how performance metrics they use to manage, hire and fire are generated by algorithmic and artificial intelligence-based software functions. Finally, firms are understandably reluctant to reveal the extent of their deployment of AI and algorithmic management tools – with some of them being keen to exaggerate their adoption, and others to understate theirs. Consequently, it remains difficult to identify exactly how widespread such systems are, and even harder to postulate how significant they are for the firms which use them.

This short report has three aims. The first is to provide a broad overview of the main functions of AI and algorithmic software tools, and review estimates of their prevalence (part 2). I explore why managers want to deploy such systems, how they do so in practise, and what they expect to gain from doing so (including implementation difficulties, unintended consequences, and failures). Second, I zoom in on two prominent pieces of 'bossware' which use AI and algorithmic management tools: one in the context of remote working, and the other for in-person warehouse work (parts 3 and 4). Third, I provide suggestions for approaches to collective bargaining over AI and algorithmic management tools in the European context. The conclusion touches on shifts in the current regulatory environment and how workers might best be supported by policymakers as AAMS are rolled out.

1 See, for example, Frey & Osbourne (2017) and Eloundou et al (2023). For a critique, see: Benanav (2020).

2

AI AND ALGORITHMIC MANAGEMENT SYSTEMS IN EUROPEAN SERVICE WORK: PREVALENCE, OVERVIEW AND FUNCTIONS

AI and algorithmic management systems (AAMS) are proliferating in European service work. The core functions of management are to 'coordinate, direct, evaluate and discipline' workers (Crowley et al 2020). In each of these fields, AAMS, or bossware, can assist with or significantly appropriate a growing range of managerial tasks. Most research on AAMS is conducted in the platform or gig economy, where highly precarious and typically self-employed workers are directed by algorithms for task-based work (like delivery driving or ridehailing). However, demand for such systems is booming amongst directors in 'conventional' firms (Jarrahi et al 2021). Here, workers may enjoy employment contracts and interact regularly with a manager. But while most such workers are still directly and personally managed by a human boss, there is a growing likelihood that this manager in turn will be utilising algorithmic and artificial intelligence-based tools to take decisions which impact upon workers.

Because definitions of **AI and algorithmic management** vary widely, it is helpful to clarify their usage in this report. Algorithms are simply mathematical rules which produce pre-defined outputs ('if x = 1, then y = 2'). Basic algorithmic systems can be used by managers, for example, to monitor employee sick days and schedule a review meeting if they surpass a certain threshold – or to award bonuses automatically for good sales performance. Using them saves managers time from tasks they could in principle complete themselves. Rules which they apply are devised by humans and so, in principle, are transparent for workers.

Algorithms have been used for at least two decades to partially automate workflows, assign tasks to workers, evaluate performance, and enforce deadlines. Enterprise systems including such basic algorithmic managerial functions are provided by major software vendors like IBM and Oracle (Stohr & Zhao 2001). Increasingly, however, managerial algorithms are being supplemented by big data analysis and powerful machine-learning (ML) technologies. ML is by far the most common form of artificial intelligence (AI) in widespread use. Increases in computing scale and power enable ML algorithms to sift through huge quantities of data drawn from multiple sources – far more than a human could ever examine. Through brute force trial-and-error computing, ML technologies aim to identify correlations between datapoints that humans may not think to test (for example, between performance scores in onboarding training and likelihood of staying at a job for more than 6 months) (Choudhury et al 2021). Due to the huge computing resources needed to pattern-match data at scale, ML capacities are concentrated in a small number of powerful firms like Microsoft, Amazon Web Services, and Google. Smaller AI and algorithmic software vendors typically build their models using the resource of these AI giants (Widder et al 2023).

2.1 WHAT AI AND ALGORITHMIC MANAGEMENT IS, AND WHERE IT OPERATES

This section breaks down the uses of algorithms and AI into four broad categories: recruitment and hiring, training and development, task allocation and scheduling, and performance management and productivity tracking. Within these broader areas, subcategories where bossware is being utilised are identified – along with examples of software packages which provide these services. Trade unions may examine each area of their work environment to identify utilisation of AAMS.

As Table 1 shows, there are now a wealth of software packages and providers on offer to managers who wish to adopt AI and algorithmic management systems. **Applicant tracking systems** are increasingly being used to sift through worker CVs and identify the strongest candidates for interview based on experience and qualifications (Chen & Benson 2023). Meanwhile, **skill assessment platforms** rank candidates according to pre-hiring tests, including online evaluations and video interviews. Personalized **Learning Management Systems** (LMSs) recommend training resources based on performance, qualification and skills, while **feedback tools** gather worker feedback and identify patterns. For **task management**, AAMS can prioritise employee tasks, optimise workflows, and schedule team or review meetings. **Productivity tracking tools** such as time tracking and productivity calculating tools record time spent on tasks, identify inefficiencies in workflows and measure employee discipline. **Predictive people analytics** identify potentially underperforming employees and estimate attrition rates. **Performance management tools** collect productivity data, share team goals, mon-

Table 1:
An overview of AAMS functions

Field of management	Tool	Description	Examples of Software
Recruitment and Hiring	Applicant Tracking Systems (ATS)	Automated CV screening; Filters applications to identify promising candidates.	BambooHR, Taleo (Oracle), HireVue
	Skill assessment platforms	Evaluates candidate skills and fit with organisation, including video interviews, pre-interview testing, etc.	TestGorilla, Codility, Pymetrics,
Training and Development	Personalized learning management systems (LMS)	Recommends tailored training resources, based on performance and skills.	Cornerstone, Docebo, Litmos
	Employee engagement & feedback analysis	Collates feedback from workers & customers and highlight patterns	Glint (Microsoft), Leena AI, Surveymonkey analytics
Task Allocation and Scheduling	Task prioritisation	Recommends tasks which should be prioritised	Smartsheet, Microsoft Asana, Trello
	Resource management & optimisation	Recommends task allocations by optimising workflows	Monday.com, Wrike
	Meeting schedulers	Finds best times for team meetings.	Doodle, Microsoft Bookings
Performance Management and Productivity Tracking	Productivity tracking tools	Collect data from various sources to measure worker productivity (team and individual level) and identify weaknesses	Prodoscore, Hubstaff, Time Doctor
	Performance management tools	Shares team/worker goals, continuously monitors performance, produces performance analytics	Betterworks, SuccessFactors Performance and Goals (SAP)
	Automated time tracking	Monitors time spent on tasks.	Hourstack, Clockify, Toggl
	Predictive analytics/attrition	Predicts employees at risk of underperforming or resigning	Visier, IBM Watson (withdrawn), RapidMiner
	Chatbots and virtual assistants	Handles routine public and employee queries	Drift, Intercom, ChatGPT Enterprise
	Sentiment analysis	Uses natural language processing to gauge the mood of a team	Mindbreeze; MonkeyLearn
	Surveillance and monitoring	Keystroke capture, screengrabs, emotion recognition technology	Teramind, Veriato, Time Doctor

itor performance, enforce time discipline on workers through automated warnings, and provide 'people analytics' (metrics on performance for managers). **Chatbots** address routine queries from customers and assist customer service teams, and **sentiment analysis** uses natural language processing to determine team mood (Wise 2023). **Surveillance tools** capture keystrokes, screen activity, and (sometimes) claim to measure employee focus and 'time on task'.

In these areas and more, software vendors compete with one another to sell their products to managers. It is usually possible to deploy such technologies as standalone systems. But Wolfie Christl (2023b), director and lead researcher at Cracked Labs,[2] has documented how individual AAMS tools are increasingly sold as plugins for broader enterprise resource planning (ERP) systems and customer relationship management (CRM) systems. As noted above, these systems have been in use for over two decades in larger firms and have long deployed forms of simple algorithmic management. Fitting out enterprise-wide software with ML capabilities gives AAMS access to far greater quantities of data than they would otherwise be able to integrate. For instance, process mining software, such as Celonis and UiPath, can analyse vast quantities of 'event logs' for business processes to identify weak points – including data on workflows, teams, and individual workers (Christl 2023a).

2 See: https://crackedlabs.org/en

Large Language Models: a growing field of AAMS

Although still a small minority amongst AAMS, deployment of large language models (LLMs) designed to harvest enterprise-level data is a rapidly growing field. Firms are racing to sell solutions based on the architectures of LLMS like ChatGPT, Bard and Llama – through products like ChatGPT Enterprise. The director of the firm *Workmetrics,* writing for *Forbes,* suggests that:

> With tools such as ChatGPT and Bard having access to a year's worth of an employee's work, meetings and other output, HR can quickly create customized templates that prompt employees to provide specific details about their accomplishments, areas for improvement and future goals. The results can be used to identify areas where employees are excelling and where they need additional support. In turn, managers can have productive conversations during performance reviews and, ultimately, empower employees to develop in their roles.

To automatically evaluate workers' performance over time, and provide other personalised functions like recommending meetings and training, LLMs must mine large volumes of text and other worker data. This is highly risky from a personal data and privacy point of view. Like other forms of AI, LLMs are quite likely to generate incorrect ►►

►► or misleading conclusions due to their propensity to 'hallucinate' (see section 2.2 below). Use of LLMs also pose a major risk to workers' personal data, since fulfilling useful functions (such as suggested meeting scheduling) requires access to the text of employees' emails and calendars. The reliability, efficacy, and safety of such tools should be carefully monitored.

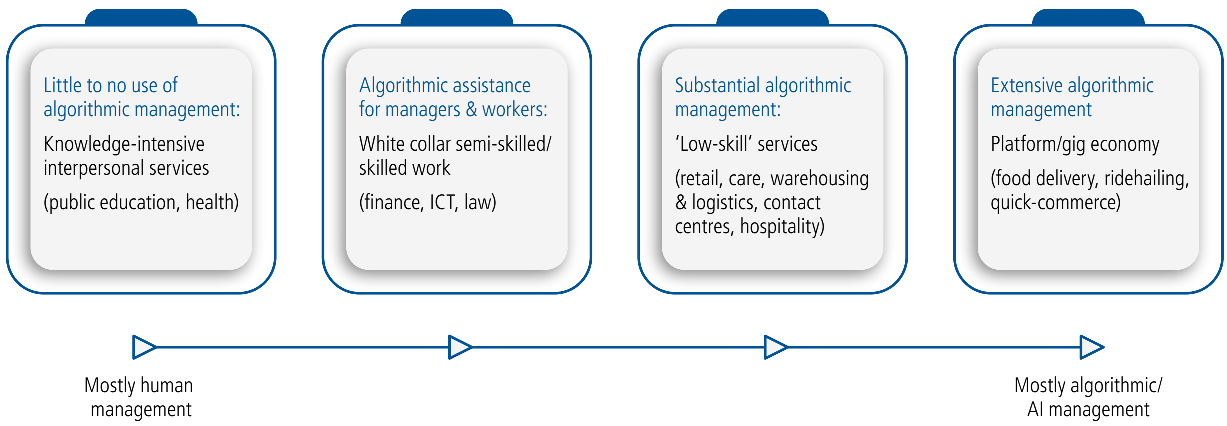
As noted above, the platform economy is in some ways a frontier industry for the use of such AAMS, where algorithmic and AI tools exert nearly full control over virtually all worker activities. For workers on food delivery and ridehailing platforms (for example), it is uncommon – or even impossible – to interact with a human boss.[3] However, most employees in conventional firms will not experience such extensive control over their work by AAMS. Instead, such tools are more likely to coordinate, direct, evaluate and discipline workers behind the scenes, in the form of recommendations to managers.

A White House report suggests that in some US service sectors (retail, transport and finance) around 20 per cent of workers are impacted by AAMS (White House 2022). Another recent large-scale European survey (COLLEEM II) suggests that while just 3 per cent of workers work under high levels of AAMS control in the gig and platform economies, a far higher 14.1 per cent of employees work under *some* degree of AAMS control (Fernandez Macias et al 2023). However, worker surveys are inevitably limited since many workers may be unaware of the use of AAMS by management (Holubová 2022). Furthermore, even management may not be aware of their deployment, as plugins into broader ERP and CRM software. Managers may also have significant discretion over whether AAMS recommendations are utilised (Wood 2020). Substantial organisational, departmental, and even individual levels of reliance on AAMs may exist – with some using such tools extensively, and others only occasionally (or choosing to disregard their recommendations).

As Figure 1 below shows, contemporary service sector jobs exist on a continuum of exposure to bossware. On the one hand, increasingly few jobs are not at all subjected to management by some form of algorithmic or AI-powered software.

The degree to which AAMS can be used depends considerably on the extent to which work can be subjected to 'datafication' and 'taskification': that is, broken down into small and micro-level tasks, which can then be digitally controlled, measured and evaluated (Mettler 2023). In some instances, workers are encouraged to compete against the algorithm or even co-workers in game-like systems ('gamification') (Hammedi et al 2021). AI and algorithms consequently affect workers in different service industries in substantially different ways. A skilled ICT worker may experience productivity benefits from automated recommendations for writing code, while a lawyer may quickly review thousands of pages of documents during a case for particular clauses using ML-programmed algorithms. However, a contact centre or in-store retail worker can be subjected to algorithmic task assignment, productivity measurement, surveillance, and discipline. Figure 2 below indicates how job roles are similarly and differentially effected by AAMS.

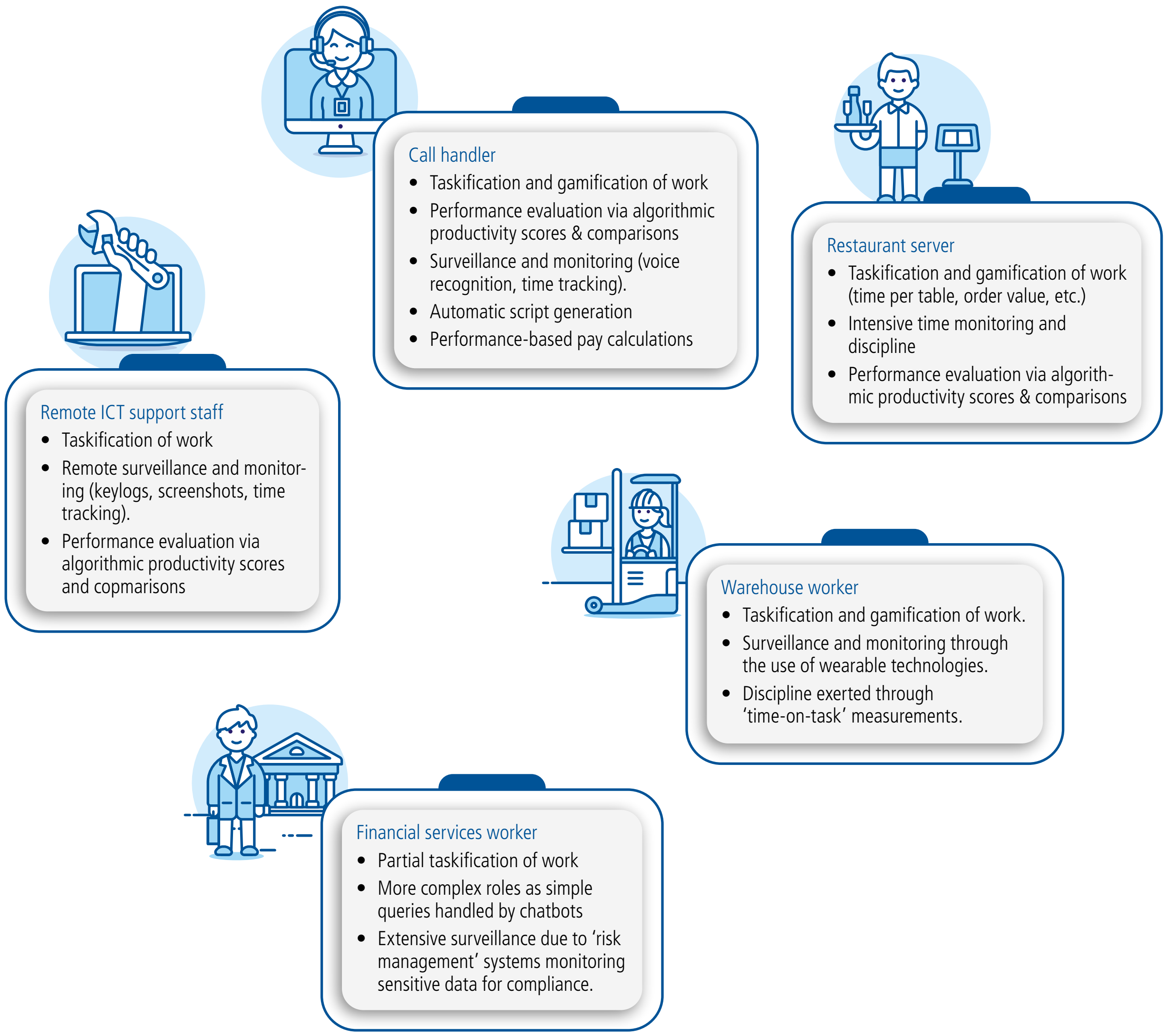
Figure 1:
The continuum of AI and algorithmic management in services



Adapted from Wood (2021) and Baiocco et al (2022)

3 See Aloisi & De Stefano (2022). It should be noted that total automation of management is an impossibility with current technologies, however, and therefore humans remain essential to organising the work process even where they remain inaccessible to their workers.

Figure 2:
Examples of exposure to AAMS across job roles



2.2 SNAKE OIL?

The array of new tools may seem dizzying. But extreme caution is needed when considering whether AAMS actually work as intended. Trade unions should look more closely at a range of potential hazards which come with their deployment.

Gary Marcus (2022) and other AI critics have pointed out that, while impressive, machine learning-based AI systems commonly exhibit serious errors and fabrications in their outputs (Alkaissi & McFarlane 2023). This is because they are not 'intelligent' systems at all, but rather simply powerful pattern recognition tools which make their predictions and recommendations based on past correlations.[4] AAMS can be misused in four ways. First, they can be given tasks which they are not actually able to perform (*impossible tasks*). Second, they can be badly designed and implemented (*engineering failures*). Third, they may hit unexpected barriers when deployed in the real world (*post-deployment failures*). Fourth, they may have their actual capabilities overstated or misrepresented (*hype*) (Raji et al 2022). Managers using AAMS are often unaware of several or all these risks.

For instance, in 2019, IBM claimed that their Watson Analytics tool for 'predictive attrition' could forecast with 95 per cent accuracy when a worker was going to quit their job. The claim circulated widely in the media (e.g., Rosenbaum 2019). IBM also invested over USD 4 billion in Watson Health, a health diagnostics product which claimed (amongst other things) to be able to make automated treatment recommendations for cancer patients. Watson Health experienced serious problems when applied in real world settings, and was sold off to a private equity firm in 2022, while IBM Analytics was discontinued in 2021 (O'Leary 2022).

4 For this reason, some have recommended dropping the use of the term 'artificial intelligence' and machine learning' altogether, in favour of specific descriptions of specific tools. See: Tucker (2022).

As such, Aloise and De Stefano (2022, 298–9) write that:

> [M]etrics often measure pointless parameters or underestimate preparatory activities such as ideation and planning. Concomitantly, workers are lured into self-monitoring their own performance through self-tracking dashboards, a practice that fosters conformity…. [but] data may be accidental, inaccurate and erroneous, [while] there is no evidence that metrics used to determine productivity correlate closely with outcomes.

Algorithmic and AI-based management software must by definition measure performance by reducing it to a series of metrics, which can then be targeted for interventions. This makes such systems vulnerable to 'Goodhart's law', which states that as a metric becomes a target, it ceases to be a useful measure of performance. This is because targets incentivise behaviour changes to meet their requirements, even if this comes at the cost of overall performance. As such, AAMS' functionality should never be taken for granted. Trade unions can play a key role in ensuring their efficacy and limiting harms to both workers and firms. Part 5 of this report provides suggestions for how active involvement of workers and trade unions can limit the downsides of AAMS and ensure they serve positive ends for both firms and employees.

3

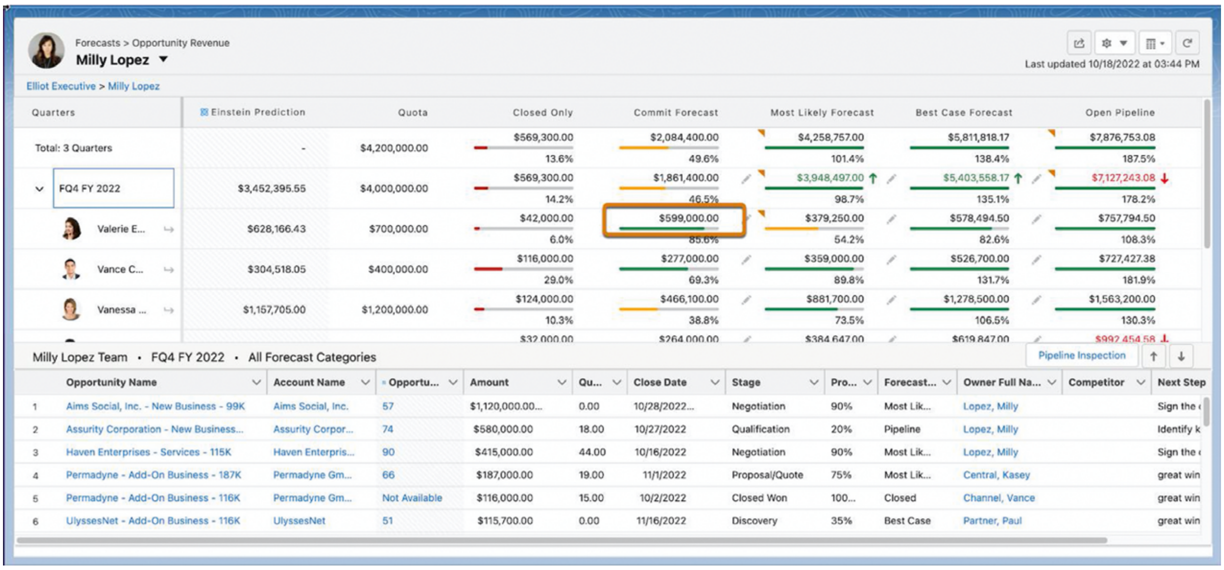
AI AND ALGORITHMIC MANAGEMENT FOR SALES WORK: SALESFORCE AND ACTIVTRAK

This section (3) and the following section (4) provide snapshots of the kinds of AAMS being used across two forms of service work: sales and warehousing. While enterprise software is a concentrated market, its application and integration with third-party packages is typically industry-specific. As such, these cases are not intended to be representative. Rather, they illustrate some common features of bossware in increasingly widespread use today across varied (in-person and remote) job portfolios.

Salesforce is a customer relationship management (CRM) platform, which provides tools for businesses to coordinate engagement with customers. It also provides a range of enterprise-wide functions from human resource management (HRM) to marketing and people analytics. Salesforce's suite of applications is designed to help firms improve sales by providing data-driven insights on markets, employees, and business processes. The software is highly customisable, and users can access a marketplace hosting of thousands of third-party apps (AppExchange) which provide additional functions. Salesforce is the world's leading CRM systems provider, with approximately 23 per cent of the global CRM market and 150,000 firms using its software. Europe is Salesforce's second biggest market and accounts for USD 4.5 billion in turnover, over a fifth of its revenues. Its major European clients include Santander, Ideal Standard and the Port of Rotterdam.[5]

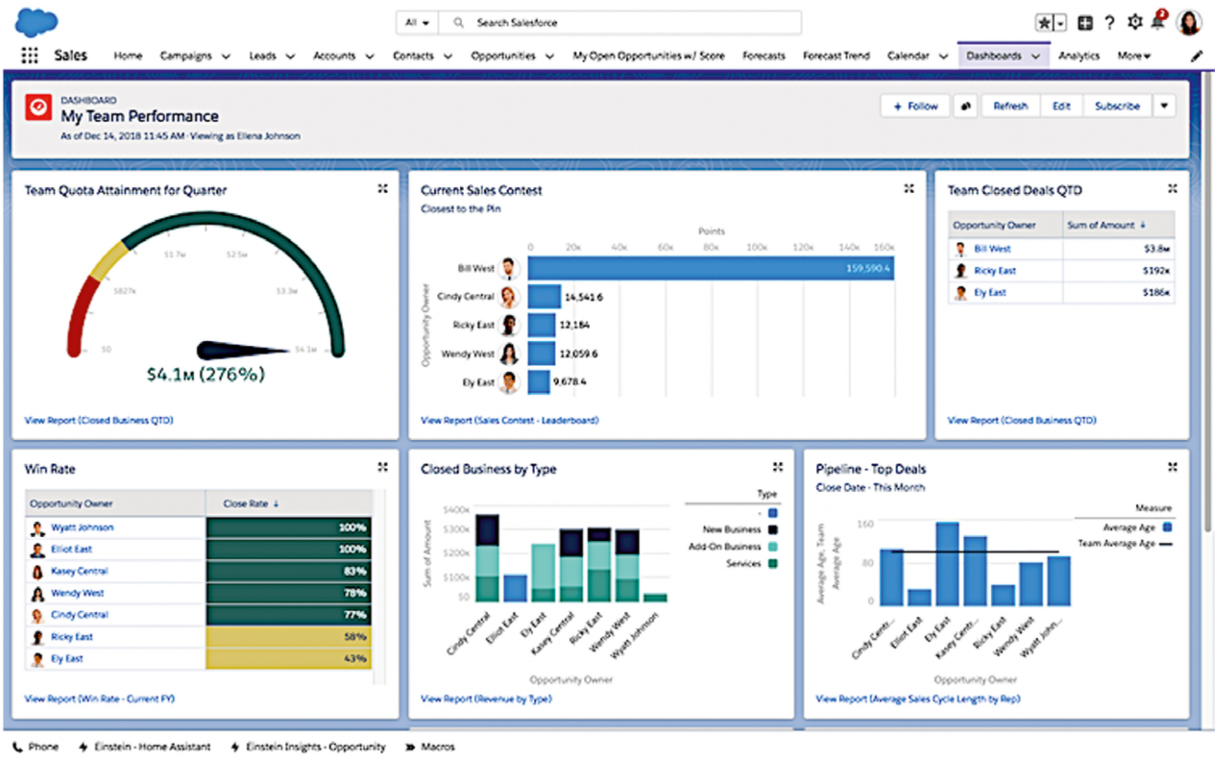
Salesforce can streamline and partially automate business processes and workflows, assigning tasks to particular employees and monitoring performance. It also provides managers with extensive data on performance of teams and individual employees. It integrates algorithms which systematise and quantify employee performance to generate metrics by which managers can measure and compares employee performance, along with machine learning and AI techniques to predict future productivity and identify weaknesses in employee performance. Figure 3 shows how individual employees are given 'Einstein Prediction' scores for monthly/annual sales, calculated with machine learning algorithms based on

Figure 3:
Salesforce employee forecast dashboard



5 See: https://www.salesforce.com/eu/customer-success-stories/#!page=1

Figure 4:
Sales leader dashboard



past performance and leads identified.[6] Managers can track actual ('closed only') sales values against these predictions and assigned quotas.

Managers can also access dashboards which use analytics to quantify and compare worker performance according to a range of metrics, including number and value of deals closed (see Figure 4). Data can also be harvested from a range of sources (both automatically and using human inputs) to compare employee performance with that of other firms, in order to track competition and monitor employees for 'best fit' – i.e., evaluate their suitability for continued employment.

Salesforce (2023) is today integrating functions from OpenAI's GPT technology, which can potentially access employee emails and calendars, alongside KPI and workflow data. Ostensibly to support employees by making recommendations on leads and scheduling, this also allows the software to monitor and calculate employee performance (Figure 5). KPI dashboards present detailed breakdowns on how and how often employees pursue particular leads ('sales activity by sales rep'). It also provides visual metrics on discount size so that unusually large discounts on sales prices can be investigated by managers, and employees frequently providing large discounts can have their performance monitored and evaluated.

Along with these internal AAMS capabilities, Salesforce can be integrated with a broad range of external applications which enable more detailed surveillance and monitoring of workers in order to facilitate algorithmic and AI-based management practises. One such application is ActivTrak. ActivTrak is an employee monitoring tool that provides detailed analytics on employees' use of time in order to measure productivity. The employee monitoring market is highly fragmented, but ActivTrak is one of the larger providers and claims to serve over 9,000 organisations and hundreds of thousands of users. Integrating ActivTrak with Salesforce is straightforward.[7] Doing so offers managers a suite of metrics by which to monitor employees including screenshots, app and activity monitors, which generate productivity reports on employee time use.

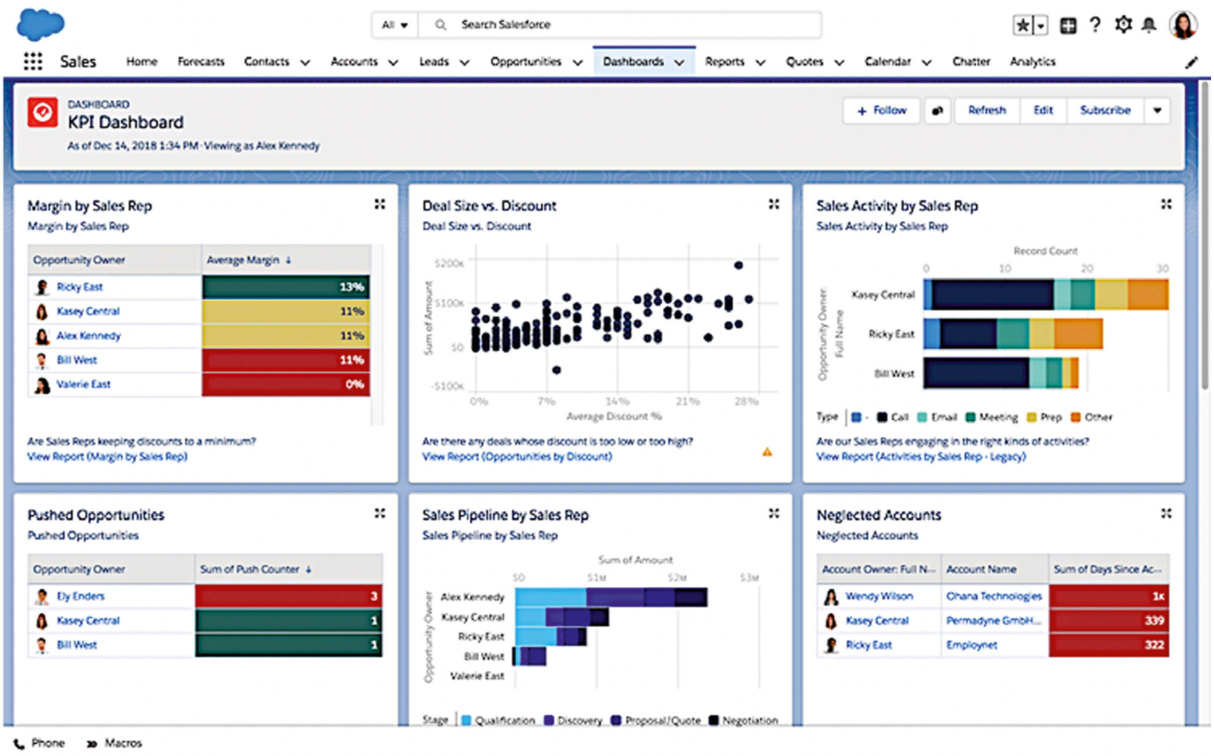
Employers can access detailed, real-time activity logs which demonstrate which application a given employee is currently engaged with. These are automatically categorised ('social media break', 'using printer', etc.) and 'alarms' can be sounded alerting managers to undesirable worker behaviour (Figures 6 & 7).

Using these detailed activity logs and productivity metrics, ActivTrak can integrate with broader CRM software like Salesforce to cross-reference productivity scores with numbers of assigned 'tasks' completed. Using these figures, workers can be ranked according to their 'average produc-

6 See: https://help.salesforce.com/s/articleView?id=sf.einstein_sales_forecasting.htm&type=5

7 See: https://www.activtrak.com/product/integrations/salesforce/

Figure 5:
Salesforce KPI Dashboard



tive hours per day', 'completed tasks per hour', and 'number of tasks completed' (Figure 8).

The example of Salesforce and ActivTrak shows how managers of white collar semi-skilled workers (in this instance, sales workers) have access to vast and multifaceted quantities of data about their employees' activities and use of time, alongside personal and potentially sensitive data. This raises major risks of unnecessary and unethical surveillance by management, alongside security risks of illegitimate access to workers' personal data.

Salesforce and sales work is not unique. Most white collar, semi-skilled workers are now subjected to similar forms of AAMS on a range of CRM and ERP software (such as Microsoft 365, Oracle, Infor, and SAP among others). Such systems – while all somewhat distinct – typically also gather substantial volumes of information about workers, including time use, performance metrics, and personal data. Most also offer various plugins similar to ActivTrak, or provide analogous functions themselves.

Figure 6:
ActivTrak Productivity Reports

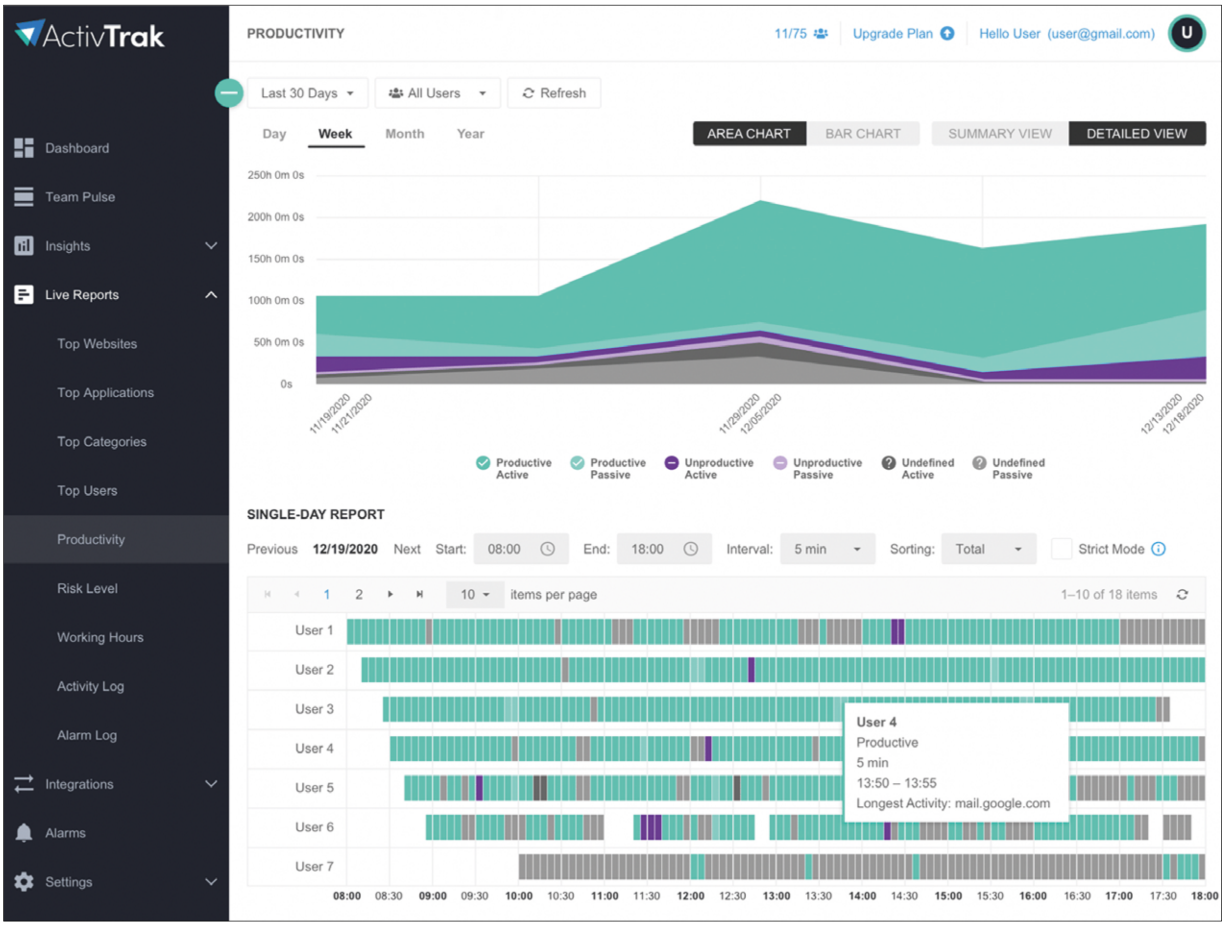


Figure 7:
ActivTrak Alarm Log

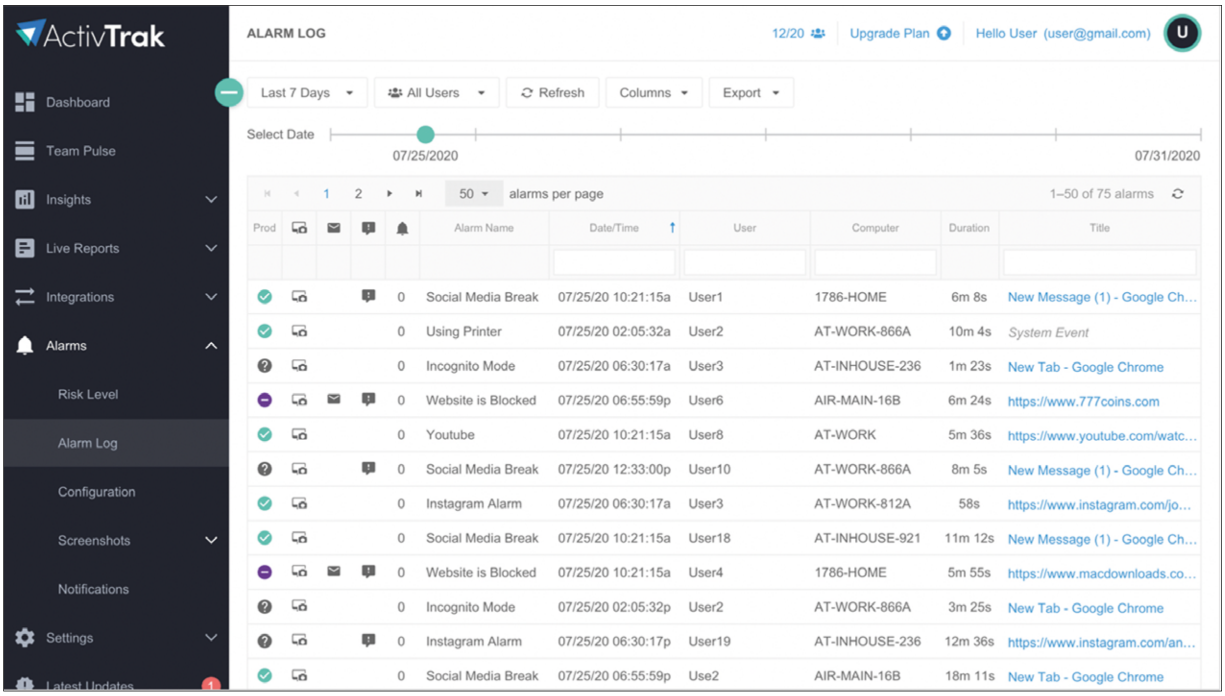
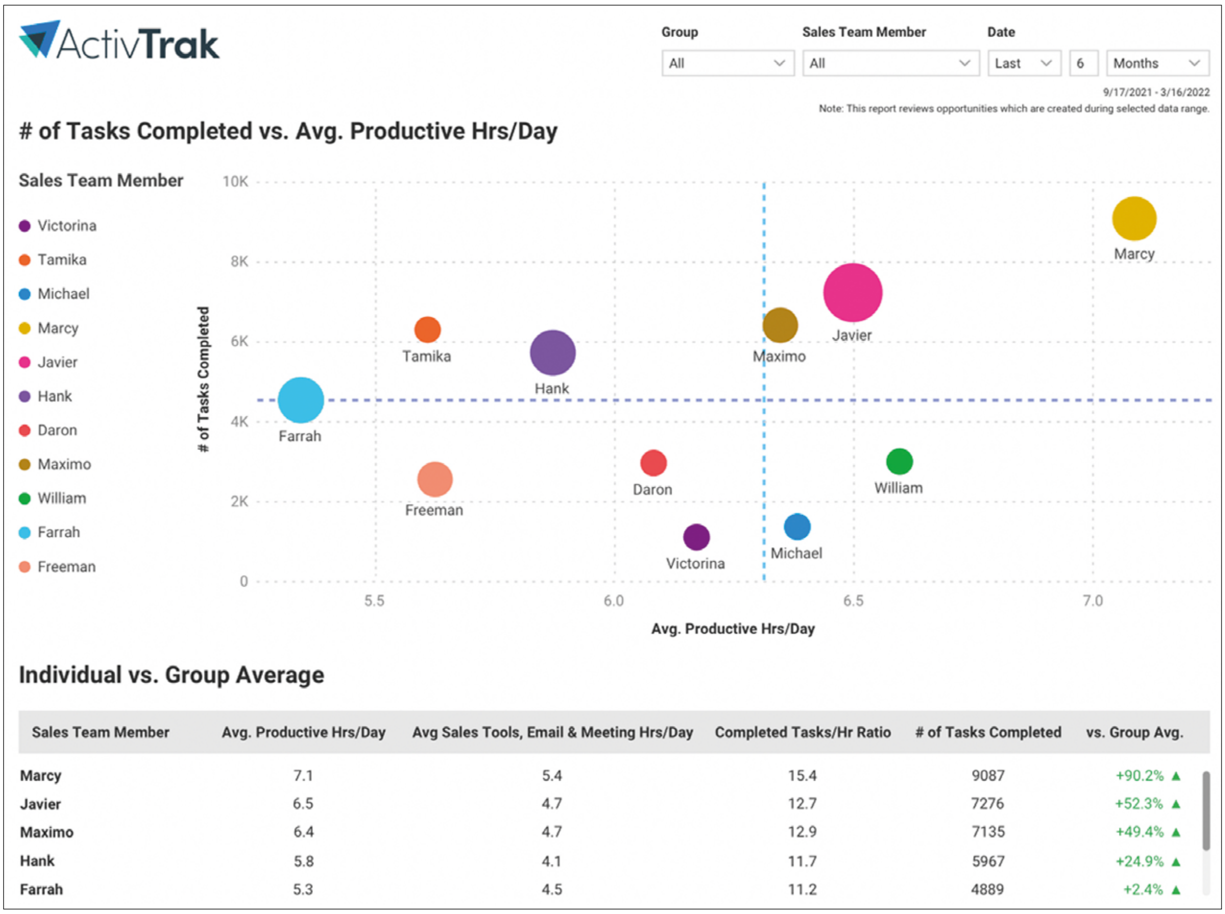


Figure 8:
ActivTrak for Salesforce Dashboard



4

AI AND ALGORITHMIC MANAGEMENT TOOLS FOR IN-PERSON WORK: INFOR AND BLUE YONDER WAREHOUSE MANAGEMENT SYSTEMS

In-person service workers are also increasingly impacted by AAMS. Although work processes typically look very different compared to white collar service work, the software used to manage workers often operates according to similar principles. Work is broken down into individual tasks. AAMS then closely track workers' performance through monitoring time use, motion, and other metrics gathered from handheld and wearable devices. They use this data to exert semi-automated control over workers' actions through digitalised directions, either directly to workers or via managers. Typically, AAMS for warehousing are embedded in broader 'warehouse managing systems' (WMS). WMS provides a wide range of functionalities to manage inventory, labour, and overall warehouse performance. WMS can themselves be integrated with firm or multi-firm supply chain management software.

This section examines the role of AAMS in the management of warehousing logistics work. It examines two prominent software packages used in warehousing, Blue Yonder WMS and Infor WMS. Blue Yonder and Infor are major players in the global WMS industry, with prominent clients including

Figure 9:
Infor WMS documentation, labour management and planning

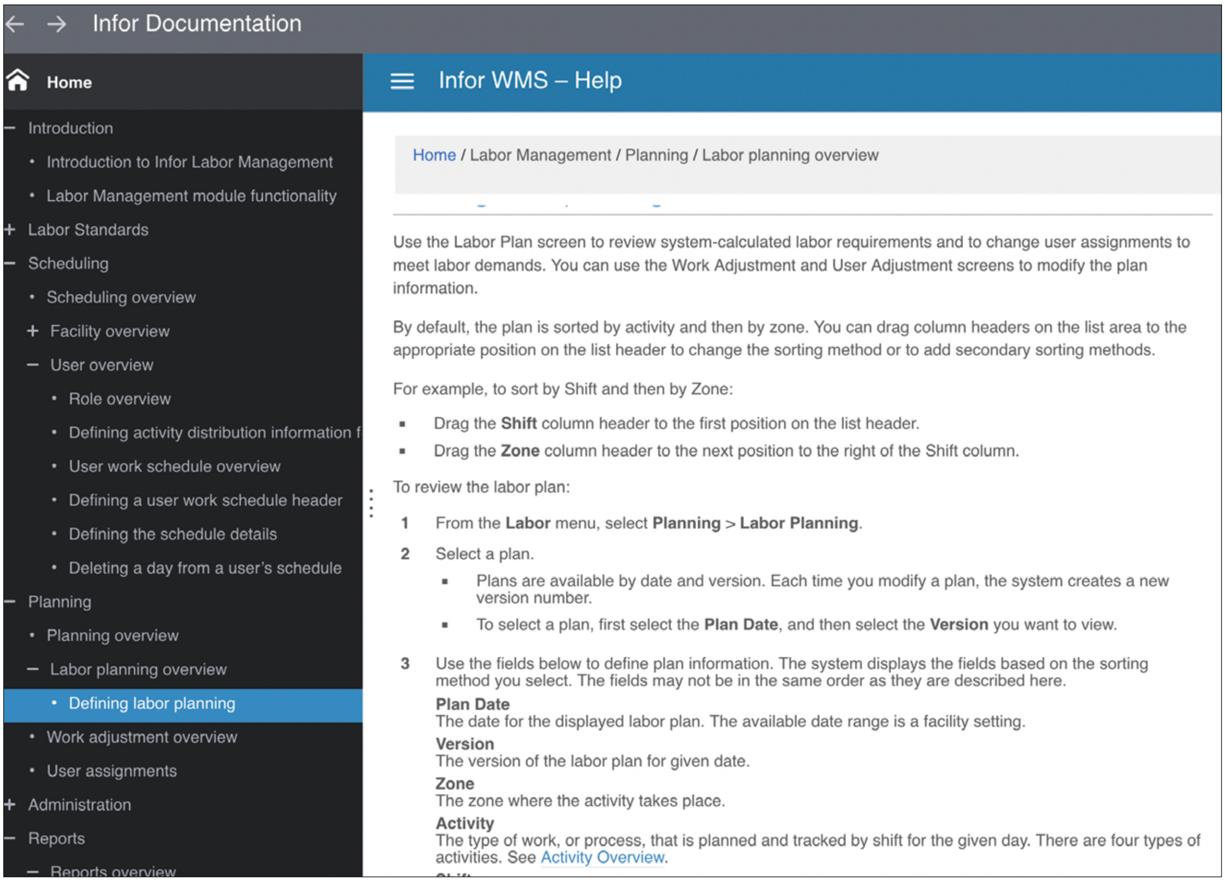
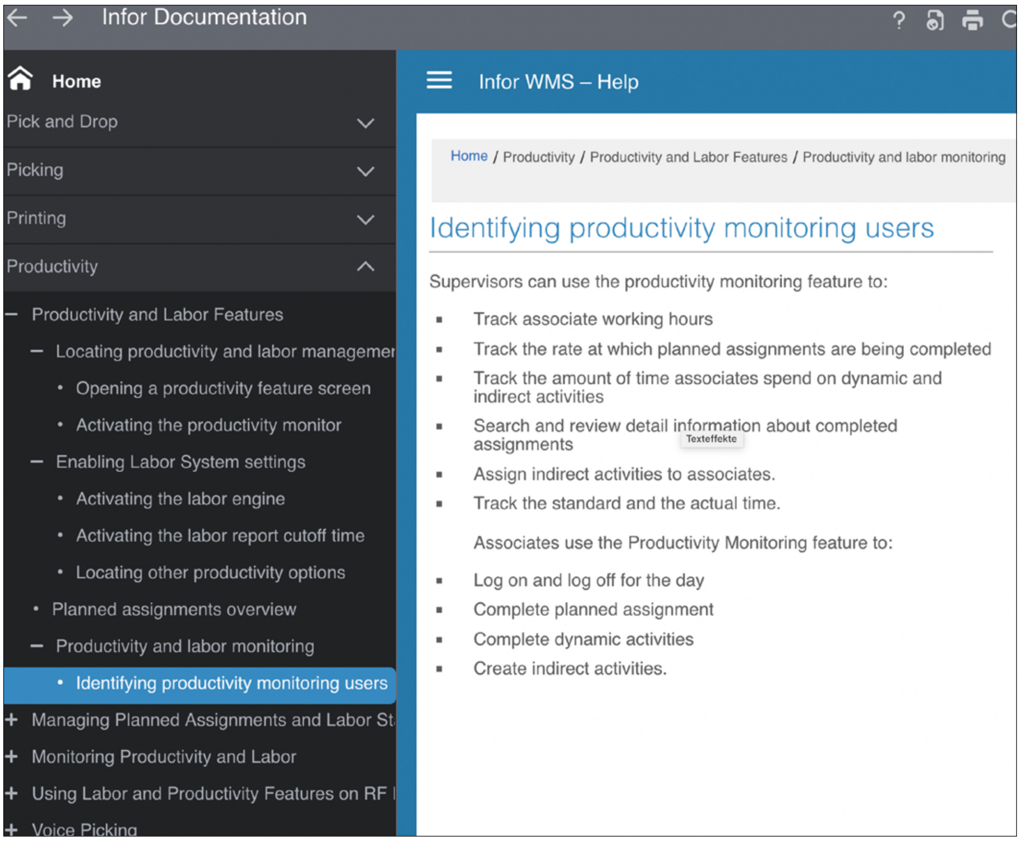


Figure 10:
Infor WMS documentation, productivity and labour monitoring



Carrefour, CVS, and DB Schenker.[8] According to Gartner research, Blue Yonder has 1,000 WMS clients and generated USD 190m in revenue in 2022, while Infor WMS had over 1,500 clients globally (Tunstall & Klappich 2023).

WMS have been used for decades to rationalise warehousing work, but are growing increasingly sophisticated as algorithmic and AI capabilities expand their functions (Krzywdzinski et al 2022). WMS track inventory and shipment flows, as well as forecast demand and assist with shift coordination. WMS assign duties by providing real-time information to direct employees, such as picking lists and directions to the next task. They integrate with devices such as radio frequency (RF) and barcode scanners, wearables like smart watches which track steps, speed and distance, and wifi-enabled headsets with 'voice command', directing workers about what and where to pick.

AAMS are embedded within WMS. They integrate data from multiple sources to direct workers and to track performance. For example, Infor WMS allows managers to 'calculate labour forecasting plans' based on expected throughput over a given future period. For managers, the 'system calculates planned work based on the information transmitted from WMS' down to the level of 'cases, tasks, pallets, and users for scheduled activity types'. Managers have flexibility to reorganise shift patterns based upon these recommendations (Figure 9).

Beyond scheduling work and directing tasks, managers can also access detailed and comparative performance reports on individual workers. These are generated through collating data from multiple sources. They can inform managers about how regularly workers complete tasks on time, how much time is spent on 'dynamic' activities (i.e., loading, picking and packing orders) versus 'indirect' activities, and compare performance for individual and groups of tasks against the standards of other workers (Figure 10).

Managers are typically able to view the results of such data analysis on worker performance in the form of graphic dashboards, not unlike those discussed in the previous section. Blue Yonder WMS provides managers with capabilities to measure a range of metrics on individual employees. These include hours spent on various tasks, and an algorithmically-generated 'utilization' score (indicating how intensely a worker's time is being deployed), and a 'performance' score (how quickly and efficiently they perform individual tasks compared to a defined standard and/or a firm-level average) (Figure 11).

8 See https://blueyonder.com/customers and https://www.infor.com/en-gb/solutions/scm/warehousing/warehouse-management-system. I examine two WMS because visual evidence of dashboards and user manuals are not available for a single system, while most WMS operate similarly.

Figure 11:
Blue Yonder labour management dashboard

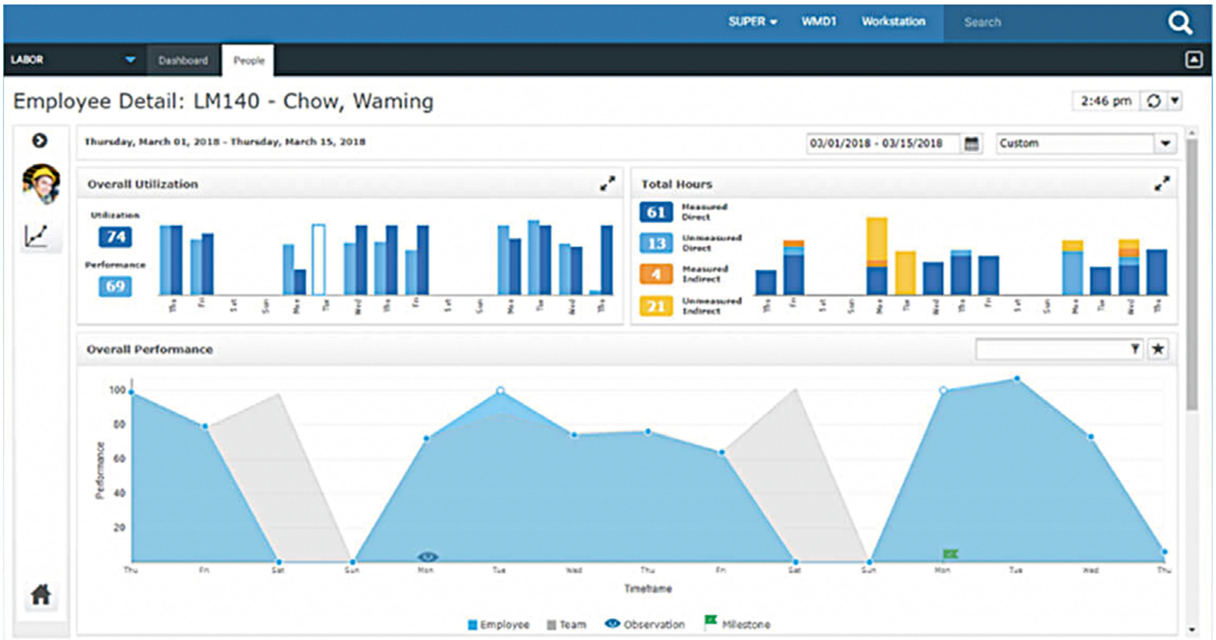
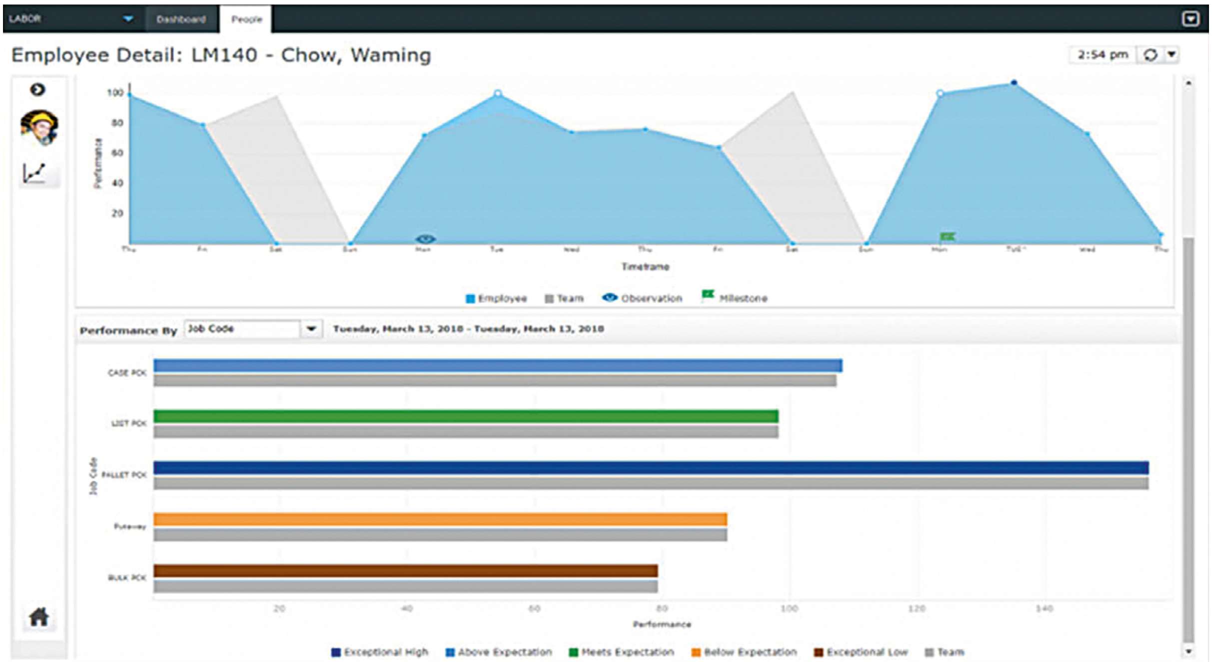


Figure 12:
Blue Yonder 'people' dashboard



Managers can also access detailed information on individual worker performance including a range of particular types of tasks. Tasks where performance can be measured include, for instance, pallet unloading and putting away goods. Performance is ranked in terms of a defined standard and compared to other employees, and colour-coded from 'exceptionally high' to 'exceptionally low' (Figure 12). This enables managers to identify weaknesses in employee and team performance in particular fields, and to discipline and/or retrain workers and teams.

WMS have enabled algorithmic and quantified management of warehouse workers for several years (Delfanti et al 2021). But growing AAMS capabilities means these functions are increasingly being integrated with a range of machine learning-powered tools which gather vast quantities of data from a wide range of sources to schedule work patterns, allocate tasks, and to metricise and worker performance.

5

COLLECTIVE BARGAINING AND NEGOTIATION FOR AI AND ALGORITHMIC TOOLS[9]

The range of intensive and often invasive AAMS tools used by management to coordinate, direct, evaluate and discipline workers can seem overwhelming. As noted in section 2, these tools can have highly negative consequences for workers. These include surveilling workers illegitimately, accessing their personal data without clear permission, creating asymmetries of knowledge between employees and managers, making workers work harder and faster, and taking decisions about how workers are paid and whether they are hired or fired without adequate human involvement. Furthermore, major issues surround whether AAMS actually function to effectively achieve the ends they set out to.

The deployment of AAMS need not bring negative consequences for workers. Much depends on how a system is deployed. If it is done well, with these risks in mind, then it can enhance skills, improve job autonomy and work quality, and reduce rote work and create more enjoyable and creative problems for workers to solve. Achieving these ends means several key principles must be adhered to by management when deciding if and how to implement AAMS in any given situation. A companion report demonstrates substantial enthusiasm amongst worker representatives to engage with employers over the use of AAMS, but limited progress so far in establishing forums for such engagement (Brunnerová et al 2024).

Trade unions can play a key role in ensuring that AAMS which are deployed are robust, safe, and enhance rather than degrade work. To do so, they should aim to intervene at every stage of AAMS introduction, by (1) understanding current organisational technologies and AAMS usage; (2) consulting in product purchasing to ensure unsuitable products are not considered by management; (3) overseeing AAMS implementation in order to ensure efficacy and responsible deployment; and (4) establishing a forum to monitor outcomes and adjust accordingly.[10] This process should be especially carefully followed for AAMS with a high risk of degrading work quality, risking worker safety, or compromising personal data.

All this requires strong workplace organisation, both at the grassroots level and in terms of well-informed representatives and negotiators. Trade unions should strive to equip negotiators with the tools they need to feel confident in understanding AAMS products.

STAGE 1: AUDIT, INVESTIGATE, AND EXAMINE CONTEXT

Worker representatives and trade unions should together with management conduct a full audit of where algorithmic and AI-powered management systems are being used already within an organisation. Management should provide a repository of such systems to trade union negotiators which is updated in a timely fashion. Key functions of these systems should be transparently available and communicated to negotiators – including through firms taking responsibility for establishing dialogue on technical matters directly between trade unions and the vendors themselves, or independent third-party expert advisors. 'High-risk' systems – which potentially degrade work, risk worker safety, or compromise personal data – should be mutually identified according to shared criteria, and subjected to close scrutiny.

Where a new product is being explored, management should provide a clear rationale for its introduction to worker representatives. Integration and data-sharing with existing systems should be made clear. Independent expert technical advice should be provided upon request. Certain forms of technology (e.g., those involving extensive surveillance, emotion recognition technology or invasive use of workers' webcams) which are inappropriate and/or unproven should be designated off-limits.

STAGE 2: AAMS PRODUCT PURCHASING

Shopfloor workers should be consulted as to which tasks can be effectively automated by AAMS, and what kind of systems may be desirable. Representatives should communicate closely with purchasing managers when they explore which AAMS systems/functions are available.

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9 The second study from this broader research project by FES and UNI Europa delves deeper into collective bargaining practices concerning AI within European service sectors. It presents a survey that catalogues these collective bargaining practices on AI in detail.

10 These recommendations are developed by the author and draw on insights from (among others): UNI Global Union (2023); Trade Union Congress (2022); Prospect (2022); Bell (2022).

If a decision to purchase a system is made, workers' representatives and trade unions should be given time and funding for external technical advice to examine product documentation and manuals in order to examine suitability and, wherever possible, communicate with sales reps prior to purchase. They should collectively consider whether it is suitable for performing the task intended by management. Wherever the given AAMS potentially falls into a high-risk category, a 'zero trust' attitude should be adopted towards the vendors and close scrutiny given (Laplante & Voas 2022). Systems which sell or otherwise make available worker data to third parties should be off-limits, and priority given to those which store data on-site.

STAGE 3:
THE IMPLEMENTATION PROCESS

Once a product has been purchased, trade unions and worker representatives should be consistently consulted throughout the implementation process. Shopfloor workers should be directly consulted on the ways AAMS alter work processes and workflows. Rather than 'human-in-the-loop', a human must be 'in command' of an AAMS – and that clear lines of responsibility to management drawn for any decision taken by it (which may affect either employees or the public). Unions must be able to verify that this is the case. Transparency and dialogue with negotiators should be maintained throughout this process, including discussion of any implementation difficulties or challenges (however technical they may appear).

STAGE 4:
ONGOING FEEDBACK, ADJUSTMENT AND INTERVENTION

Trade unions and worker representatives should be granted periodic access to the system in order to monitor how management is deploying the AAMS, ensuring this is in line with previously agreed principles and to guard against 'function creep' (i.e., extension of a system into new areas or functionalities). Concerns flowing from AAMS deployment should be swiftly escalated to an appropriate body and consulted upon with worker representatives. Workers impacted by the technology should be given opportunities to voice concerns without fear of reprisals. Worker feedback should be collated and used to shape future cycles of adoption and implementation. Management should operate with the default assumption of system error, rather than worker error, when issues arise or are reported. Even in the absence of reported problems, representatives should be granted regular access to the system in order to maintain transparency and monitor how management is deploying the AAMS.

6

CONCLUSION AND RECOMMENDATIONS

This report has provided a snapshot of existing AAMS which are currently in use or being deployed in the European services sector. Rather than a comprehensive overview, it has aimed to indicate the wide range of new ways in which services workers (across diverse sectors and roles) are being subjected to management by AI and algorithmic technologies, and the consequences of these technologies. A core message is that while platform and gig economy workers are at the blunt end of AAMS, a far larger number of workers subject to such technologies work in 'ordinary' workplaces. Rather than replacing managers with 'robot bosses', AAMS are increasingly being appended to enterprise systems used by human managers to augment their managerial roles. This sometimes happens without the knowledge and/or full understanding of either workers or lower tiers of management.

While they can potentially be of benefit to both firms and employees, AAMS pose a diverse range of threats which must urgently be mitigated against. Closely monitoring workers and their private information threatens privacy norms and regulations and poses security risks. AAMS also threaten to create an information gap between managers and employees, push work pace to extreme levels, and to take on critical managerial functions like assessing productivity, determining pay, and handling hiring and firing, all with inadequate human supervision. AAMS' inherently opaque nature means they are often not fully comprehended by the managers who deploy them. As such, it is not only workers at risk. Firms also stand to lose out if they invest in 'snake oil' systems which do not deliver on their promises.

Guarding against these hazards means putting workers, their knowledge, their daily experiences at the core of technology rollouts. It also requires trade unions to be able to access specialist and independent technical knowledge about specific AAMS, which management should be encouraged to facilitate. A companion study draws on extensive survey data amongst European trade unionists to show that the appetite for collective bargaining over the wide array of AAMS is considerable. In this connection, unions should aim to (1) make themselves fully cognisant of the forms of AAMS already being used within organisations by conducting audits in partnership with management; (2) be closely involved with any purchasing decisions for AAMS; (3) partner with management and technicians in implementing such systems; and (4) continuously monitor management's usage of AAMS to guard against 'function creep'. Such systematic engagement and bargaining over AAMS in multiple steps will not be possible without strong unions, which are the only effective means of redressing the balance of power between management and the workforce.

The European policy environment is beginning to acknowledge the likely significance of AAMS for workers' rights and working conditions. Already under the GDPR, employers are to be restricted to collecting data that is 'adequate, relevant and limited to what is necessary' for the relevant purposes. Trade unions may be able to request Data Impact Assessments to challenge blanket data collection (Prospect 2020), but the laxity of definitions and poor enforcement gives employers broad scope to circumvent the spirit of the rules (Abraha 2023).[11] Furthermore, current and proposed data regulations (such as the Data Governance Act) focus solely on individuals' privacy and security. This fails to contend with how employer data-gathering across organisations often *collectively* weakens workers by appropriating large-scale data about their combined work for managerial ends. Trade union bargaining over AAMS raises the possibility of asserting collective rights over organisational data in ways which benefit workers, and could be supported by future legislation (Calacci & Stein 2023). The proposed EU AI Act will identify 'high-risk' AI systems (including systems for managing workers) through an EU-wide database, alongside a monitoring and incident reporting framework. However, it seems unlikely that every piece of enterprise software using AI or algorithmic forms of management will be designated 'high-risk'. More substantively, the proposed Platform Workers' Directive includes stipulations on regulating algorithmic management and making AAMS transparent and accountable, but may not extend to cover most workers on standard employment contracts (i.e., those outside of the platform economy).

However, future European directives are urgently needed to close major loopholes in current and proposed legislation – and to expand coverage of protections and rights AAMS far beyond platform workers (Ponce Del Castillo 2023b). The ETUC (2022) recently published a series of recommendations for a directive on AAMS.

11 See the relevant GDPR article here: https://gdpr-info.eu/art-5-gdpr/

Such a 'worker-friendly AI' directive should:

1. Define European minimum standards for the design and use of algorithmic systems in the employment context;
2. Mandate transparency and explainability for AAMS. Workers and their representatives should have the right to receive information about the used applications in plain and understandable language;
3. Guarantee the right to gain external expertise on AAMS;
4. Mandate algorithmic impact assessments for changes in working conditions, including a fundamental rights and equality impact assessment by the employer (before implementation and repeatedly)
5. Ban intrusive applications, with applications to monitor workers allowed only if their use is negotiated and agreed with trade unions and/or workers' representatives;
6. Guarantee workers' right to check and revise algorithmic decisions.

Any such directive should also (as above) grant employees extensive and collective rights to control data-gathering in the workplace.

In the meantime, trade unions will continue to act as the sole buffer between workers and risky, untested and disciplinary AAMS. Representatives urgently need to improve their understanding of these systems while exploring ways of engaging in systematic bargaining over their adoption.

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