RESEARCH REPORT

Eurofound

Working conditions and sustainable work

Algorithmic management in European workplaces



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Eurofound

European Foundation for the Improvement of Living and Working Conditions

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Authors: Cesira Urzì Brancati, Dragoş Adăscăliţei and Sara Riso

Research manager: Sara Riso

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European Foundation for the Improvement of Living and Working Conditions

Tel. (+353 1) 204 31 00
Email: information@eurofound.europa.eu
Internet: https://www.eurofound.europa.eu

Contents

	Executive summary	**1**
	Introduction	**3**
	Background to the report	3
	EU policy context	3
	Data and empirical approach	4
	Structure of the report	10
1.	**Prevalence of algorithmic management and workplace implications**	**11**
	Summary	11
	Algorithmic management and use of digital tools at work	12
	Prevalence of algorithmic management in the EU	13
	Implications of algorithmic management for work organisation	20
2.	**Relationship between algorithmic management and job demands and resources**	**25**
	Summary	25
	Mapping job demands and job resources in the EU	26
	Association between algorithmic management and job quality	30
	Variations in job demands and resources under algorithmic management	32
	Algorithmic management and health and well-being outcomes	35
3.	**Job strain and algorithmic management**	**37**
	Summary	37
	Distribution of job strain in European workplaces	38
	Health and well-being across job strain categories	42
	Differences in job strain by use of algorithmic management	43
	Job strain and well-being under algorithmic management	44
	Conclusions and policy pointers	**47**
	Conclusions	47
	Policy pointers	48
	References	**51**
	Annexes	**55**
	Annex 1: Chapter 1 full regression results	55
	Annex 2: Chapter 2 full regression results for main predictors	60
	Annex 3: Chapter 3 full regression results	61
	Annex 4: Construction and operationalisation of job demands, resources and strain indicators	63

Occupational groups

Shortened versions of the names of the International Standard Classification of Occupations 2008 (ISCO-08) occupational groups have been used in this report, as indicated in the table below.

Occupational group	Corresponding ISCO-08 group
Managers	1. Managers
Professionals	2. Professionals
Technicians	3. Technicians and associate professionals
Clerical workers	4. Clerical support workers
Services and sales workers	5. Services and sales workers
Skilled agricultural workers	6. Skilled agricultural, forestry and fishery workers
Craft workers	7. Craft and related trades workers
Plant and machine operators	8. Plant and machine operators and assemblers
Elementary occupations	9. Elementary occupations

Executive summary

Introduction

Algorithmic management is the use of digital technologies to fully or partly automate managerial functions, including the organisation, coordination, monitoring, supervision and evaluation of work. While originally associated with digital labour platforms, the term is now understood as applying more broadly across a wider range of employment settings.

Although algorithmic management can enhance efficiency and risk management and, in some sectors, such as financial services and transport, may be driven by regulatory compliance, it also presents challenges and potential drawbacks. While quantitative evidence based on representative surveys is comparatively limited, there is a growing body of research – largely based on qualitative studies – that links algorithmic management to work intensification, increased time pressure and reduced worker autonomy. Existing evidence also suggests that the effects are contingent on the job resources available to workers, such as autonomy, organisational support and skills use, which can buffer potential adverse impacts.

This report contributes to the ongoing policy debate by presenting findings from the analysis of European Working Conditions Survey 2024 data, with a focus on algorithmic management in European workplaces. In this report, algorithmic management is measured by whether employees report that computer programs are used at work to allocate their tasks, determine their working hours (scheduling) or monitor their performance. This simplified operationalisation captures three core management functions of algorithmic management but does not provide an exhaustive definition of the concept. The analysis is restricted to employees only, examining both the prevalence of algorithmic management and its relationship with working conditions and employees' health and well-being.

To investigate the combined association of algorithmic management, job resources and job demands on health and well-being outcomes, this report draws on the concept of job strain, defined as a situation in which job demands exceed job resources. Employees are distributed across a range of job-quality profiles from highly strained jobs characterised by high demands and limited resources to highly resourced jobs characterised by a more favourable balance between demands and resources.

Policy context

Following the adoption of the Platform Work Directive (Directive (EU) 2024/2831), policy attention has progressively moved beyond its original focus on algorithmic management in platform work towards its use in more conventional work settings. The classification of certain artificial intelligence (AI) systems used for work management as high-risk systems under the Artificial Intelligence Act (Regulation (EU) 2024/1689) marks an important step in the EU's approach to regulating digital technologies in the workplace and reflects growing concern about the implications of these technologies for employees.

Other EU legislative instruments that are relevant to algorithmic management include the General Data Protection Regulation (Regulation (EU) 2016/679), which establishes safeguards for the processing of workers' personal data and automated decision-making; the Information and Consultation Framework Directive (Directive 2002/14/EC), which provides for the involvement of workers' representatives in decisions affecting work organisation; and the Occupational Safety and Health Framework Directive (Council Directive 89/391/EEC), which requires employers to assess and prevent risks to workers' health and safety, including psychosocial risks.

More recently, the European Parliament, in its resolution on digitalisation, artificial intelligence and algorithmic management in the workplace (2025), recognised both the opportunities and the challenges associated with the increasing use of digitalisation, AI and algorithmic management in the workplace.

Key findings

- Algorithmic management is most prevalent among clerical workers, technicians, and plant and machine operators. In these occupations, automated task allocation and performance monitoring are the most commonly reported algorithmic management functions, while automated scheduling is considerably less prevalent. Managers, professionals, services and sales workers, craft workers, workers in elementary occupations and especially skilled agricultural workers report lower levels of algorithmic management overall. Automated scheduling is also more evenly distributed across occupations than the other two functions.

- In the sectors with the highest prevalence of algorithmic management – finance and real estate, information and communications, and transport and storage – performance monitoring and automated task allocation are consistently the most frequently reported functions, whereas automated scheduling is less widespread. By contrast, all three functions are comparatively uncommon in education, agriculture and mining, and construction.
- Out of the three algorithmic management functions, automated task allocation is the strongest predictor of job transformation, including the creation of new tasks, the removal of other tasks and greater interaction with colleagues. Automated scheduling and performance monitoring show similar but more moderate associations with job transformation.
- Use of the three algorithmic management functions is associated with higher job demands, especially quantitative demands (capturing work intensity). Employees subject to algorithmic management are also more likely to experience job strain than those who are not. Among the three functions examined, performance monitoring stands out as the one most consistently associated with poorer health and well-being outcomes, and it appears to amplify, to a small extent, the adverse effects of existing job strain in already demanding jobs.
- Whether algorithmic management mitigates or compounds these negative outcomes depends on the specific algorithmic function: automated task allocation neither mitigates nor compounds job strain; automated scheduling has a marginally significant mitigating effect for employees in strained jobs; and performance monitoring significantly compounds the negative effects of job strain, further increasing exhaustion and work–family conflict and reducing work engagement.

Policy pointers

- Algorithmic management is not evenly distributed across sectors, occupations and EU Member States, nor is it a uniform set of practices; rather, it encompasses a diverse range of managerial functions and organisational applications. While common baseline protections are essential, their implementation can be supported through social dialogue, collective bargaining, practical guidance and examples of good practice that reflect the different ways algorithmic management is used.
- Ongoing monitoring and comparisons across Member States can help strengthen evidence-based policymaking. At the same time, greater investment is needed in analysing company practices to better understand how algorithmic management functions are implemented and integrated into work organisation, including how different tools and practices interact and combine to shape workplace outcomes.
- Algorithmic management is part of the broader digital transformation of work. In this analysis, it is associated with higher job demands, especially quantitative demands and greater job strain, while its relationship with access to job resources is more mixed. As its adoption expands, attention should be paid to the implications for job quality by ensuring that its implementation is accompanied by adequate job resources, employee support and safeguards for healthy working conditions.
- Performance monitoring is the most widespread form of algorithmic management and is linked to higher demands, fewer resources and poorer health and well-being outcomes, especially for already strained workers. Safeguards should ensure transparency about what is monitored, how data are used and how decisions are made. Strong enforcement of labour and data protection laws – alongside the effective implementation of existing rights to information, consultation and collective bargaining – is essential to ensure that algorithmic performance monitoring is fair and proportionate.
- It is essential to ensure the responsible implementation and integration of algorithmic management functions within organisational processes and digital systems through governance frameworks, impact assessments and employee involvement. Where relevant risks are identified, organisations should implement appropriate safeguards in line with existing labour, data protection and AI legislation. Algorithmic management can reshape tasks and work organisation, requiring a human-centred redesign of jobs to align productivity gains with employee well-being, supported by policy guidance and consultation mechanisms.

Introduction

Background to the report

Across advanced economies, the organisation of work is being reconfigured as managerial functions are increasingly delegated to data-driven and automated or semi-automated systems. This transformation represents a broader paradigm shift from human-centred, discretionary management to data-driven systems of coordination and control. Central to this shift is the rise of algorithmic management, whereby digital technologies, embedded in workplace software systems, are used to fully or partly automate managerial functions, including the organisation, coordination, monitoring, supervision and evaluation of work. The European Commission's quality jobs roadmap refers to algorithmic management as:

> *the use of automated monitoring systems and automated decision-making systems powered by algorithms that replace functions that managers usually perform, such as allocating tasks, pricing individual assignments, determining working schedules, giving instructions, evaluating the work performed, providing incentives or applying adverse treatment.*
>
> (European Commission, 2025, p. 6)

The growing availability of work-related data in digital form combined with advances in data collection, processing and analytical capabilities has accelerated the adoption of these systems across workplaces. A previous Eurofound literature review on algorithmic management, drawing on evidence from surveys conducted at different points in time, suggests that its diffusion has been gradual and uneven across sectors, with higher prevalence observed in transport, logistics, financial and professional services, and manufacturing (Eurofound, 2025).

The existing literature – largely drawing on case studies – consistently links algorithmic management with the intensification of work, increased time pressure, reduced autonomy and privacy concerns arising from intrusive forms of digital monitoring, while also pointing to potential opportunities for improved efficiency and risk prevention when it is appropriately designed (Ball, 2021; Eurofound, 2025; Martín et al., 2025). This dual character is consistent with the broader theoretical and empirical literature, which conceptualises algorithmic management as a socio-technical system whose effects depend on its implementation context and the availability of job resources (Parent-Rocheleau et al., 2022).

Understanding how algorithmic management shapes job quality and outcomes is essential to ensure that technological innovation aligns with broader social objectives, including fair working conditions, sustainable productivity growth and inclusive labour markets.

EU policy context

The growing importance of algorithmic management has been increasingly recognised within the EU's policy agenda. Recent regulatory initiatives seek to address some of the challenges algorithmic management may pose to workers' rights and job quality.

A key milestone in this regard is the Platform Work Directive (Directive (EU) 2024/2831). It establishes rules to improve working conditions in platform work, including specific provisions on aspects of algorithmic management, such as transparency requirements, human oversight and limits on certain forms of personal data processing and automated decision-making. The directive also addresses issues related to employment status. Although formally limited to platform work in scope, some scholars have suggested its use as a blueprint for regulating algorithmic management more broadly (Adams-Prassl et al., 2023).

In parallel, the Artificial Intelligence Act (Regulation (EU) 2024/1689) introduces a cross-cutting, risk-based framework governing the use of AI systems, including those used in employment contexts. It classifies certain AI systems related to work management and recruitment as high-risk systems, subjecting providers and deployers to strict requirements on transparency, human oversight and risk management. The Artificial Intelligence Act complements the existing EU legal framework related to algorithmic management. This includes the General Data Protection Regulation (GDPR) (Regulation (EU) 2016/679), which governs the processing of workers' personal data and provides safeguards in relation to automated individual decision-making and profiling. It also operates alongside key provisions of EU labour law, notably the Information and Consultation Framework Directive (Directive 2002/14/EC), which establishes workers' rights to be informed and consulted on decisions likely to lead to substantial changes in work organisation or contractual relations, and the occupational safety and health framework established by the Occupational Safety and Health Framework Directive (Council Directive 89/391/EEC), which requires employers to assess and prevent workplace risks, including emerging psychosocial risks associated with new technologies.

In her mission letter to Roxana Mînzatu, Executive Vice-President for Social Rights and Skills, Quality Jobs and Preparedness, President von der Leyen asked her to 'focus on the impact of digitalisation in the world of work … [including] an initiative on algorithmic management' (European Commission, 2024). This commitment is reflected in the Commission's broader quality jobs agenda. The quality jobs roadmap seeks, among other objectives, to embed job quality considerations across relevant EU policies, including those related to digitalisation and AI (European Commission, 2025).

In preparation for a future quality jobs act, the Commission has launched a consultation with the European social partners to gather their views on the possible direction of EU action to further improve job quality. The consultation is also considering the challenges and opportunities associated with the use of algorithmic management and AI at work.

Alongside these policy developments, the European Parliament adopted an own-initiative resolution on digitalisation, artificial intelligence and algorithmic management in the workplace (2025). The resolution calls for greater transparency, effective human oversight, stronger protections for workers' rights, safeguards against solely automated decision-making and protections against intrusive data practices.

These developments highlight that algorithmic management is not a purely technological or business concern. It carries social, legal and rights-related implications, firmly positioning it on the agenda of the European social partners. The 2020 cross-industry framework agreement on digitalisation, while not explicitly referring to algorithmic management, established key principles for the use of digital technologies in the workplace. These include the human-in-control principle and safeguards against intrusive surveillance, aiming to protect workers' dignity, privacy and autonomy (ETUC et al., 2020).

Against this background, empirical evidence on how algorithmic management affects working conditions is crucial to inform policymaking, particularly as these systems continue to expand beyond platform work into the wider economy.

Data and empirical approach

Data sources

The main data source for the statistical analysis conducted for this research report is the 2024 wave of the European Working Conditions Survey (EWCS 2024), Eurofound's longest-running survey, conducted regularly since 1991. The EWCS 2024 covers workers aged 16–74 living in private households across 35 European countries: all 27 EU Member States, Norway, Switzerland and six Western Balkan countries. The analysis presented in this report refers exclusively to data from the Member States, with 'EU' denoting the EU-27. The survey is a representative, probability-based survey built on 36 644 face-to-face interviews conducted in 2024 in respondents' homes, with sample sizes of around 1 000 respondents per country. The EWCS provides a comprehensive and harmonised picture of working conditions and job quality in Europe, allowing for the construction of both objective and subjective indicators of job quality and supporting comparative analysis.

The EWCS is a broad, multi-topic survey focused on the quality of the working environment and the key dimensions of job quality rather than on workplace technologies per se. However, the battery of questions on workplace technologies has been progressively expanded and enriched over successive waves and now includes indicators that can be used as proxies for the presence and use of algorithmic management practices.

The analysis presented in this report is restricted to employees because it examines algorithmic management in the context of the employment relationship, where the managerial functions captured by the EWCS – that is, work allocation, scheduling and performance monitoring – are most directly applicable. This focus also avoids conflating algorithmic management with the more heterogeneous organisational arrangements characterising self-employment, where managerial authority and employment relationships are structured differently.

The results should be interpreted with caution: the findings are associations and do not establish causal effects. Additionally, algorithmic management is measured through employees' own reports, therefore the results cover only the practices employees are aware of, and prevalence may be underestimated where employees do not recognise them.

All the figures and tables in this report are based on the EWCS 2024 data.

Operationalisation of key concepts and theoretical underpinning

Algorithmic management

The empirical analysis operationalises algorithmic management using three core indicators available in the EWCS 2024, which serve as proxies for the functions of algorithmic management. These indicators capture the extent to which computer programs are used to (1) monitor work performance, (2) allocate tasks and (3) determine when to work. These three functions are labelled throughout the report as 'performance monitoring', 'automated task allocation' and 'automated scheduling', respectively.

The wording of the survey refers to the use of computer programs rather than algorithms, reflecting the need for terminology that is clear and accessible to respondents across sectors and occupations. In the workplace, such computer programs often form part of the digital systems through which algorithmic management practices are implemented. At the same time, the survey wording may encompass systems with different levels of technological sophistication, ranging from relatively simple software applications to more advanced data-driven or algorithmic systems.

The present report treats performance monitoring as a crucial component of algorithmic management, on the grounds that collecting and analysing information about workers cannot readily be separated from the use of that information to influence, direct or evaluate work (Ball, 2010, 2021).

The operationalisation adopted in this report is grounded in the literature that treats algorithmic management as the automation of managerial functions traditionally performed by human supervisors. In a widely cited framework, Kellogg et al. (2020) distinguish three core functions of management: direction, evaluation and discipline. Under this framework, direction is reflected in the automated allocation of tasks and the scheduling of work, while evaluation and discipline are primarily enacted through the monitoring of work performance.

In the empirical analysis that follows, algorithmic management is measured both through separate indicators for each core function covered in the survey and through a combined indicator of overall intensity, ranging from 0 (the employee is subject to none of the functions) to 100 (the employee is subject to all three).

Job demands and resources

Drawing on the job demands–resources (JD-R) model (Demerouti et al., 2001), this report presents a snapshot of the distribution of job demands and resources in European workplaces and uses this as a baseline for analysing their relationship with algorithmic management.

In the JD-R model, job demands are defined as aspects of work that require sustained physical or mental effort and are associated with physiological or psychological costs (such as work intensity and time pressure). Job resources are defined as aspects of work that support goal achievement and help mitigate demands (for example autonomy, social support and opportunities for skills use).

The relationships between job demands, job resources and workers' health and well-being are explained through two processes. First, the health impairment process links high job demands to burnout, which is captured in the EWCS through two indicators: physical exhaustion and emotional exhaustion. Second, the motivational process explains how job resources foster work engagement – captured in the EWCS through the three indicators vigour, absorption and dedication – and, in turn, contribute to positive work outcomes.

In this study, demands and resources are conceptualised as features of the work environment through which algorithmic management may influence workers' health and well-being. Given the richness of the EWCS 2024 data and the multidimensional nature of algorithmic management, the JD-R framework provides a particularly suitable analytical lens for this analysis.

The JD-R model builds on earlier work by Karasek and Karasek et al., who conceptualised job strain in the job demand–control model as arising from the combination of high job demands and low job control (Karasek, 1979, 1985; Karasek et al., 1990). Job demands are task requirements such as work intensity, while job control encompasses both skills discretion (the range of skills used at work) and decision authority (the ability to make decisions about work tasks and methods). The model was later extended into the job demand–control–support model, which uses social support from supervisors and colleagues as an additional factor (Karasek et al., 1990).

The conceptual framework used for this analysis also incorporates insights from the effort–reward imbalance model (Siegrist, 1996), which focuses on the imbalance between high levels of effort and insufficient rewards, particularly in terms of pay, recognition (esteem), job security and career opportunities. This perspective is particularly relevant in the context of algorithmic management, and especially digital performance monitoring, as research suggests that these practices may increase work intensity and performance pressures while reshaping how workers are evaluated and rewarded (Ball, 2021), potentially giving rise to an effort–reward imbalance.

The literature on algorithmic management reviewed by Eurofound (2025), which informed the selection of job demands and job resources used in this analysis (see Table 1), identifies a core set of demands and resources as particularly salient in the context of algorithmic management. Overall, the evidence suggests that algorithmic management is associated with a deterioration in psychosocial working conditions, primarily through the intensification of job demands.

Consistent with this, a recent systematic review found that the experience of algorithmic management was associated with higher workload, greater time pressure and elevated stress levels, particularly when digital systems were used to monitor performance or allocate tasks (Martín et al., 2025). These effects appear especially pronounced among clerical and skilled workers, who are more frequently subject to automation and monitoring.

Table 1: Potential effects of algorithmic management on job demands and resources discussed in the literature

Job demands	
Physical risks	Algorithmic management can both reduce and increase workers' exposure to physical risks, depending on how it is designed and implemented. While some systems may enhance safety by automating hazardous tasks or improving operational oversight, others may contribute to occupational risks through increased work intensity, constant monitoring and reduced worker autonomy (EU-OSHA, 2023; Cox et al., 2024a).
Physical demands	Emerging evidence from conventional workplaces suggests that high levels of algorithmic management are associated with increased physical demands, including higher prevalence of musculoskeletal pain and occupational accidents among logistics workers (Nilsson et al., 2025). In highly automated systems, workers may have limited opportunities to regulate their pace of work and modify tasks.
Social demands	Algorithmic management may adversely affect workplace social relations by increasing performance pressure, intensifying monitoring, reducing trust and autonomy, and weakening opportunities for managerial and peer support. These mechanisms may contribute to social isolation, reduced cooperation, workplace incivility and, in some cases, bullying or other counterproductive workplace behaviours, although the empirical evidence remains limited and is still emerging (Ball, 2021; Cox et al., 2024b; Reimann et al., 2024).
Quantitative demands	There is growing evidence that algorithmic management can increase quantitative demands, particularly when it encompasses goal setting, continuous monitoring and performance evaluation. These practices may intensify work by increasing work pace, tightening performance targets and placing workers under greater pressure to meet continuously monitored productivity standards (Gilbert et al., 2021; Håkansta et al., 2024; Jensen et al., 2024).
Emotional demands	In customer-facing workplaces such as retail and contact centres, algorithmic management systems increasingly incorporate customer feedback, customer satisfaction metrics and automated performance monitoring into managerial decision-making (Eurofound, 2025). The continuous monitoring and evaluation of performance can increase social and emotional demands on workers by heightening visibility, intensifying pressure to meet monitored targets and requiring greater emotional labour in interactions with customers (Ball, 2021; Doellgast et al., 2023).
Time-related demands	Empirical analysis based on EU-OSHA's 2019 Esener survey data shows that the use of data-driven management technologies – including wearable devices and other devices that determine the content or pace of work or monitor worker performance – is associated with increased time pressure and longer or more irregular working hours (Urzì Brancati et al., 2022).
Perceptions of job insecurity	Algorithmic management may contribute to feelings of job insecurity. A large-scale Nordic survey found that experience of algorithmic management was positively associated with higher levels of job insecurity, even after controlling for transparency and employee influence over technology implementation (Jensen et al., 2024). Similarly, analysis of Esener 2019 data by Urzì Brancati et al. (2022) found that the use of digital systems to monitor performance, determine the content or pace of work, and deploy wearable devices was associated with greater feelings of insecurity and stress, largely driven by increased time pressure and the fear of job loss.
Job resources	
Social support	Social support from supervisors and colleagues is a well-established buffer against work stress, burnout and psychosocial risks (Bakker et al., 2007; Nahrgang et al., 2011). Algorithmic management can reduce human managerial interaction and replace supervisory functions with automated systems, potentially limiting access to managerial and peer support (Parent-Rocheleau et al., 2022; Doellgast et al., 2023). Ball (2021) also identifies managerial support as a key factor mitigating the negative effects of monitoring.
Task discretion and autonomy	Autonomy is one of the most important job resources in both the JD-R model and the demand–control model, helping workers to manage their workload and cope with job demands. In the context of algorithmic management, control over the order, method and pace of work may help mitigate work intensification and its associated psychosocial risks. However, a growing body of research suggests that algorithmic management can weaken this resource by limiting workers' discretion over how and when tasks are performed, thereby reducing their autonomy and control over work processes (Parent-Rocheleau et al., 2022; Håkansta et al., 2024).
Flexibility of working hours	Working time flexibility can serve as an important job resource by supporting recovery and work–life balance. However, in the context of algorithmic management, this resource may be weakened when scheduling is driven by algorithmic optimisation and demand fluctuations. This suggests reduced control over the scheduling and timing of their work.
Training and learning opportunities	Training and learning opportunities are important job resources that support skills development and workers' adaptability. However, highly standardised and closely monitored forms of work may reduce opportunities for learning and skills use (Jarrahi et al., 2021; Parent-Rocheleau et al., 2022; Håkansta et al., 2024).

Job resources	
Opportunity for career advancement	Career prospects are important job resources that support motivation and organisational commitment. However, when evaluation, promotion and human resources development decisions are governed by opaque algorithmic systems, transparency, predictability and perceptions of fairness may be reduced, with the potential risk of discriminatory outcomes (Leicht-Deobald et al., 2019; Köchling et al., 2020). Consistent with this, an OECD employer survey identifies unclear accountability, limited explainability and difficulties understanding algorithmic logic as key trustworthiness concerns (Milanez et al., 2025).
Rewards	Fair rewards and recognition buffer stress and support motivation (Siegrist, 1996). However, when rewards are determined by opaque or constantly changing algorithmic metrics, workers may have difficulty understanding how outcomes are generated, potentially undermining perceptions of distributive and procedural fairness (Schweyer, 2018; Leicht-Deobald et al., 2019).
Organisational participation and workplace voice	Organisational participation and workplace voice can enhance control, fairness and trust under algorithmic management. Drawing on a laboratory experiment, Milanez (2025) found that involving workers in the design and implementation of algorithmic management systems can generate mutually beneficial outcomes by increasing acceptance, cooperation and the quality of decisions. However, when managerial decisions are embedded in opaque algorithmic processes or are difficult to challenge, opportunities for worker influence and meaningful participation may be reduced (Baiocco et al., 2022; Håkansta et al., 2024).

Notes: Esener, European Survey of Enterprises on New and Emerging Risks; EU-OSHA, European Agency for Safety and Health at Work; OECD, Organisation for Economic Co-operation and Development.
Source: Authors' own compilation of sources.

On the resources side, the literature identifies task discretion (or autonomy), social support and opportunities for worker influence as key resources that can buffer the negative effects of algorithmic management on workers' well-being (Parent-Rocheleau et al., 2022; Martín et al., 2025). However, algorithmic management can also erode these resources, weakening or even neutralising their protective role and thereby limiting their capacity to buffer the negative effects of heightened job demands. While the literature identifies potential benefits of algorithmic management, these appear to be highly contingent on participatory, transparent and worker-centred implementation (Eurofound, 2025).

In Eurofound analyses of EWCS data, job quality is typically captured through seven indices or dimensions that combine both job demands and job resources (Eurofound, 2026). By contrast, the approach followed in this report is to first separate job demands and job resources from these broader job quality dimensions and examine them separately, before combining them into one composite indicator of job strain. This approach is motivated not only by the need to better identify the distinct mechanisms through which algorithmic management influences working conditions but also by the need to estimate its net impact by assessing the balance between job demands and resources. In addition, analysing demands and resources separately makes it possible to identify which specific aspects of work are most affected, highlighting areas where job demands are intensified or resources are weakened.

Job strain

The job strain indicator follows the JD-R model (Demerouti et al., 2001; Bakker et al., 2017) and builds on the job quality index developed by Eurofound for the European Working Conditions Telephone Survey (EWCTS) 2021, which applied a methodology used by the Organisation for Economic Co-operation and Development (OECD) for measuring the quality of the working environment (Eurofound, 2022; Murtin et al., 2022). The job strain indicator was developed as a parsimonious alternative to the multidimensional job quality indices typically used in EWCS analyses. Because the questionnaire for the EWCTS 2021 had to be substantially shorter than previous EWCS questionnaires to accommodate telephone interviewing during the COVID-19 pandemic, a more limited set of job quality indicators was available. For the purposes of the present analysis, this approach is particularly useful because it provides a theoretically grounded summary measure of the overall quality of the work environment and is well suited to capturing the mechanisms through which algorithmic management is hypothesised to operate, increasing certain job demands and altering access to job resources.

The job strain indicator incorporates 14 component indicators comprising the 7 job demands and 7 job resources described in Table 2.

The construction of the job strain indicator follows three principles common to all components.

1. Each of the 14 components is built from several underlying EWCS 2024 items and reduced to a binary indicator (1 = present, 0 = absent). This standardisation ensures that no single dimension dominates the job strain score by virtue of its measurement scale and that all demands and resources are equally weighted and directly comparable.

2. Because the underlying survey items use heterogeneous response scales (seven-point frequency scales, five-point Likert agreement scales, four-point frequency scales, yes/no items and counts), the threshold rule used to dichotomise each item is calibrated to its scale. As a general convention, frequency-based indicators are counted as present when they occur for at least one quarter of working time, and attitudinal items are counted as present when the respondent expresses clear agreement.
3. Components built from several items are combined using one of two aggregation rules. Where the presence of any single element is sufficient to constitute the demand or resource, an 'at least one' rule is applied (the component is 1 if any input item is met). Where the construct is intended to capture a sustained or multifaceted condition, a 'count' rule is applied (the component is 1 only if the number of qualifying items reaches a specified threshold).

   Count-based components are paired with a validity requirement: a minimum number of constituent items must be non-missing for the component to be computed at all, preventing the indicator from being driven by item non-response. Here, the quantitative demands indicator is calculated only for employees with valid responses for at least two of its five items, the physical demands and financial and job insecurity indicators for at least two of their items, the rewards indicator for at least three of its six, and so on (see Table 2 for a full description). This prevents non-response from being interpreted as the absence of a demand or resource. Components are coded as 0 only when sufficient information is available to conclude that the threshold is not met; otherwise, they remain marked as missing.

For each employee, the level of job strain is calculated as the difference between the resource and demand counts and normalised to range from −1 (all demands present, no resources) to +1 (all resources present, no demands). Positive values denote a resource surplus, and negative values denote a demand surplus. Following the OECD operationalisation (Murtin et al., 2022), the rate is grouped into six categories: extreme strain (rate < −0.50), high strain (−0.50 ≤ rate < −0.25), moderate strain (−0.25 ≤ rate < 0), low resourced (0 ≤ rate < 0.20), moderately resourced (0.20 ≤ rate < 0.50) and highly resourced (rate ≥ 0.50). The indicator is computed for the EU sample with a validity rule requiring at least six of the seven components to be observed on each side, so that the measure is not driven by missing data.

The validity thresholds applying to both individual components and the job strain indicator are met for roughly 99.8 % of the EU sample, so the gain in robustness comes at almost no cost in coverage.

Table 2: Construction of the job strain indicator: demand and resource components, coding threshold and aggregation rules

Component	Type	Underlying items and coding threshold	Aggregation rules
Physical risks	Demand	Loud noise (a quarter of the time or more) High temperatures (a quarter of the time or more) Low temperatures (a quarter of the time or more) Breathing in smoke, fumes, powder or dust (a quarter of the time or more) Breathing in vapours (for example solvents, thinners) (a quarter of the time or more) Handling or being in skin contact with chemical products or substances (a quarter of the time or more) Handling or being in direct contact with infectious materials (a quarter of the time or more)	≥ 1 condition met
Physical demands	Demand	Tiring or painful positions (a quarter of the time or more) Lifting or moving people (a quarter of the time or more) Carrying or moving heavy loads (a quarter of the time or more) Repetitive hand or arm movements (a quarter of the time or more) Sitting for periods of at least half an hour at a time (three quarters of the time or more) Vibrations from tools or machinery (a quarter of the time or more)	≥ 2 conditions met
Social demands	Demand	Physical violence Sexual harassment Cyberbullying or harassment Bullying or harassment Verbal abuse Unwanted sexual attention Threats Humiliating behaviours Discrimination at work	≥ 1 condition met

Component	Type	Underlying items and coding threshold	Aggregation rules
Quantitative demands	Demand	Working at very high speed (three quarters of the time or more) Working to tight deadlines (three quarters of the time or more) Enough time to get the job done (rarely or never) Frequent disruptive interruptions (very or fairly often) Three or more pace determinants	≥ 2 conditions met
Emotional demands	Demand	Hiding own feelings at work (most or all of the time) Handling angry clients (three quarters of the time or more) Emotionally disturbing situations (three quarters of the time or more) Feeling lonely at work (most of the time or always)	≥ 1 condition met
Time-related demands	Demand	Long weekly working hours (48 hours or more a week) Long working days (10 hours or more per day) No recovery period (less than 11 hours between two working days in the past month) Unpredictability of working time Changes in working time arrangements (yes, the same day, or yes, the day before) Weekend work (usually working for at least one hour, at least one weekend per month) Work intruding on free time (several times per month or more) Shift work Working at night (at least one night per month)	≥ 1 condition met
Financial and job insecurity	Demand	Fear of job loss (strongly agree or tend to agree) Difficulty finding a similar job (strongly agree or tend to agree) Expected deterioration in work situation (strongly agree or tend to agree) Unpredictable earnings	≥ 2 conditions met
Social support	Resource	Split construct rule reflecting two distinct support channels: ○ support from colleagues and manager (always or most of the time); or ○ majority of leadership quality items endorsed: respect, cooperation, confidence, feedback, development and clear explanations (strongly agree or tend to agree).	Co-worker and manager support (≥ 2 of 3 support items met) or quality leadership (≥ 4 of 6 manager behaviour items met)
Autonomy	Resource	Control over task order, methods and work pace (always or often)	≥ 2 conditions met
Working time flexibility	Resource	Ability to take a break when one wishes (always or most of the time) Influence over working time arrangements (not entirely set by the organisation) Ease of taking an hour off during working time (very easy)	≥ 1 condition met
Training and learning opportunities	Resource	Employer-paid training, on-the-job training, learning new things and enough opportunities to use knowledge and skills (strongly agree)	≥ 2 conditions met
Career advancement	Resource	Good prospects for career (strongly agree)	1 condition met
Rewards	Resource	Recognition of work (strongly agree) Paid appropriately (strongly agree) Being able to apply one's own ideas (always or most of the time) Doing useful work (always or most of the time) Fair treatment (strongly agree or tend to agree) The feeling of work well done (always or most of the time)	≥ 3 conditions met
Participation and voice	Resource	Consulted before objectives are set, being involved in improving work organisation and having influence over decisions (always or most of the time)	≥ 2 conditions met

Source: Authors, based on the EWCS 2024 indicators.

A small number of survey items required additional handling. Survey codes for 'does not apply', 'refused' and 'don't know' were recoded as missing, while structural codes such as 'never' on count items were recoded as 0.

Structure of the report

Given the importance of ensuring that the development and use of algorithmic management benefits both employees and employers, this report aims to shed light on its prevalence in the EU and its associations with employees' health and well-being, taking into account the role of job demands and resources in shaping these relationships.

Chapter 1 identifies the prevalence of algorithmic management in the EU and examines its distribution across sociodemographic groups, sectors, employment characteristics and workplace characteristics. It then identifies the key drivers of the use of algorithmic management in European workplaces. The chapter also examines the relationship between the reported use of algorithmic management and a range of indicators related to task transformation, work content and pace of work.

Chapter 2 examines the relationship between algorithmic management and job demands and resources. It begins by describing the overall distribution of demands and resources among employees and then explores how these vary based on the use of different algorithmic management functions. The chapter continues by testing whether these relationships persist after accounting for sectoral, occupational and individual characteristics, distinguishing descriptive patterns from statistically robust associations. The chapter concludes by examining the association between use of algorithmic management and health and well-being outcomes.

Chapter 3 combines job demands and job resources into a summary job strain indicator. Using this measure, the chapter first establishes a baseline by examining the distribution of job strain across the employee sample, ranging from high-strain jobs characterised by high demands and limited resources to highly resourced jobs characterised by a more favourable balance between demands and resources. It then investigates the extent to which experience of algorithmic management is associated with job strain and whether algorithmic management compounds or mitigates the negative impact of job strain on health and well-being outcomes.

The report concludes with policy pointers based on the survey findings.

1 Prevalence of algorithmic management and workplace implications

Summary

Algorithmic management functions – automated task allocation, automated scheduling and performance monitoring – tend to co-occur but are only weakly correlated with other digital tools, including collaboration platforms and generative AI. This suggests that algorithmic management is not simply a by-product of general workplace digitalisation or technologically advanced work environments.

Implementation of algorithmic management is uneven across Member States, with significant differences between them in the distribution of the three functions. Northern European Member States generally show higher prevalence of algorithmic management than several southern and eastern European ones.

Occupation is a significant predictor of the use of algorithmic management, with mid-ranking occupations significantly more likely to be subject to automated task allocation and performance monitoring than all other occupations. Scores on the algorithmic management intensity index (combining all three functions) are highest among clerical workers and technicians, while significantly lower scores are observed in agricultural, elementary and craft-related occupations.

Sector is also a significant predictor of the use of algorithmic management, with substantial variation in prevalence across industries. Employees in finance and real estate, information and communications, and transport and storage are the most likely to report the use of algorithmic management functions. Among the three algorithmic management functions examined, automated scheduling is both less prevalent overall and more evenly distributed across sectors. The low prevalence of automated scheduling is probably because employees report high levels of consistency in their daily and weekly hours across most occupations: if their schedule does not change, there is no need for hours to be automatically allocated.

In terms of sociodemographic characteristics, younger male employees (under 35 years) are significantly more likely than older male employees to report that they are subject to the three algorithmic management functions. Employees with lower educational attainment are less likely to experience automated task allocation and performance monitoring, with a statistically significant difference relative to those with high educational attainment.

The use of algorithmic management is significantly higher in larger workplaces than in micro-workplaces. Employees in workplaces with formal employee representation are also significantly more likely to report the use of algorithmic management than those without such representation. A similar pattern is evident for telework arrangements: employees who telework are significantly more likely than employees who do not telework to report the use of automated task allocation and performance monitoring at work. Teleworking employees also score significantly higher on overall algorithmic management intensity; the likelihood of experiencing automated scheduling, however, does not differ significantly by telework status.

Algorithmic management is associated with job transformation: removing some tasks, introducing new ones and increasing interactions with colleagues. The strongest associations are linked to automated task allocation.

Performance monitoring and automated task allocation are associated with modest but statistically significant differences in task standardisation and complexity. Employees subject to algorithmic management are also more likely to have the pace of their work determined by performance targets or machines.

To measure algorithmic management, the EWCS 2024 asked respondents to what extent a computer program allocates their work tasks, determines the hours they work and monitors their work performance. Each question was answered on a four-point scale ranging from 'to a large extent' to 'not at all'. For the analysis, the percentages shown in the figures refer to employees reporting that a computer program undertakes the task in question to a large extent or some extent, in line with the Eurofound overview report (Eurofound, 2026). In

addition, the three algorithmic functions were combined into an indicator measuring the intensity of algorithmic management, ranging from 0 (employee not subject to any of the algorithmic functions) to 100 (employee subject to all of them).

This chapter begins by examining the extent to which each algorithmic management function is associated with the different digital tools at work covered in the survey. It then presents the prevalence of algorithmic management – measured through employees' reporting of individual algorithmic management functions and, in selected cases, the intensity of algorithmic management use overall – by Member State, sector, occupation, and sociodemographic, job and workplace characteristics.

The chapter then examines task transformation and task characteristics among employees subject to algorithmic management, focusing on how the three algorithmic management functions are associated with changes in task content. Only statistically significant predictors are discussed.

Algorithmic management and use of digital tools at work

Understanding where algorithmic management is adopted requires situating it within the broader diffusion of digital technologies at work. Different digital tools – including collaboration platforms, remote meeting software, generative AI tools, collaborative robots (cobots) and wearable devices (wearables) – may create new options for organising work. Examining how these technologies are associated with different forms of algorithmic management helps identify the technological environments in which such practices are most likely to develop.

The correlations shown in Table 3 indicate that algorithmic management represents a relatively distinct dimension of workplace digitalisation, in the sense that while the three algorithmic management functions tend to co-occur rather than existing as isolated practices, they are only weakly associated with other forms of workplace digitalisation. In particular, task allocation by a computer program is quite strongly correlated with both the automated scheduling of work (0.475) and performance monitoring (0.418), and these two are also moderately correlated with each other (0.401).

The three algorithmic management functions tend to occur together and are not simply a by-product of more digitalised workplaces.

By contrast, correlations between algorithmic management and collaborative digital technologies, such as remote meeting software and collaboration platforms, are generally low (between 0.059 and 0.160). Similarly, associations with generative AI tools are weak (between 0.065 and 0.124), suggesting that the use of generative AI does not strongly overlap with algorithmic management practices in workplaces. Correlations with cobots and wearables are also very low (between 0.085 and 0.139), indicating that physical automation technologies are largely independent of systems of digital managerial control. These findings reinforce the distinction between algorithmic management and broader workplace digitalisation, suggesting that the adoption of digital technologies does not automatically entail the use of algorithmic management.

Table 3: Correlations between algorithmic management functions and other digital tools in the workplace

	Automated task allocation	Automated scheduling	Performance monitoring	Generative AI	Remote meeting software	Collaboration platforms	Cobots	Wearables
Automated task allocation	1	0.475	0.418	0.124	0.160	0.158	0.085	0.127
Automated scheduling	0.475	1	0.401	0.065	0.059	0.070	0.086	0.112
Performance monitoring	0.418	0.401	1	0.083	0.131	0.135	0.139	0.122
Generative AI	0.124	0.065	0.083	1	0.375	0.348	0.096	0.127
Remote meeting software	0.160	0.059	0.131	0.375	1	0.609	0.018	0.125
Collaboration platforms	0.158	0.070	0.135	0.348	0.609	1	0.059	0.109
Cobots	0.085	0.086	0.139	0.096	0.018	0.059	1	0.076
Wearables	0.127	0.112	0.122	0.127	0.125	0.109	0.076	1

Notes: The values represent pairwise correlation coefficients ranging from –1 to +1. Higher positive values indicate that two technologies are more likely to be used together, while values closer to 0 indicate little or no association. The diagonal values equal 1 because each technology is perfectly correlated with itself. Green cells highlight the strongest positive correlations in the matrix, indicating the pairs of technologies that are most frequently associated with one another.
Source: Authors' calculations.

Prevalence of algorithmic management in the EU

According to the EWCS 2024, 19 % of employees in the EU report that a computer program monitors their work performance to a large or some extent, 18 % report that computer programs are used to allocate their work tasks and 10 % say that a computer program determines when they have to work. Among employees who report that some aspects of their work are decided by a computer program, 57 % state that there is a clear procedure for raising issues in the event of a disagreement with automated decisions.

It should be noted that employees may not always be aware that computer programs that monitor performance, allocate tasks or set working time are operating in their workplace, particularly where decisions are mediated by managers or embedded in scheduling and human resources tools that are not visibly labelled as automated. For this reason, prevalence rates may understate the actual diffusion of algorithmic management practices.

Patterns in the use of algorithmic management across Member States, sectors, occupations, sociodemographic characteristics and workplace characteristics indicate whether its use is concentrated or broadly diffused.

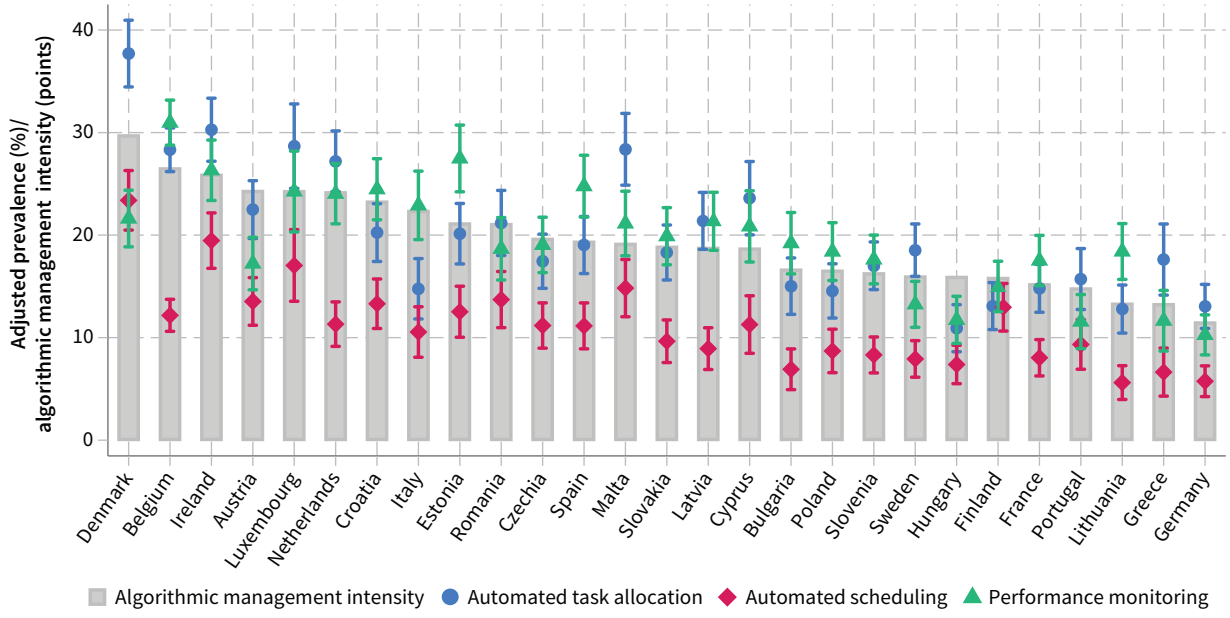
Member State differences

Differences in national prevalence rates, as shown in the EWCS overview report (Eurofound, 2026), may reflect differences in workforce composition in terms of occupation, sector and employment structures as much as genuine national factors such as regulations, industrial relations systems, management cultures and the pace of technology adoption. The estimates presented below are therefore adjusted for these compositional differences, isolating variation that is more plausibly attributable to Member State-specific institutions and practices.

Algorithmic management is generally more prevalent in northern European Member States, which are characterised by high levels of digitalisation.

Figure 1 summarises the adjusted prevalence of the three algorithmic management functions (coloured markers) and the overall algorithmic management intensity index (grey columns) across the EU. The chart shows substantial variation within the EU, both in the

Figure 1: Adjusted prevalence of algorithmic management functions and algorithmic management intensity score, by Member State



Notes: The figure shows the adjusted prevalence (predictive margins in percentage points for binary outcomes, represented by dots) and predicted mean score (for algorithmic management intensity, represented by bars), by Member State, estimated using probit models with robust standard errors, presented with 95 % confidence intervals. Member States are sorted by algorithmic management intensity. All models control for sociodemographic characteristics (gender, age and education) and employment characteristics (contract type, occupation, sector, workplace size, telework and trade union presence).
Source: Authors' calculations.

overall prevalence of algorithmic management and in the specific forms it takes. Denmark has the highest overall algorithmic management intensity, followed by Belgium and Ireland, while Germany, Greece, Lithuania and Portugal exhibit the lowest intensity and also comparatively lower prevalence across all three indicators.

Automated task allocation is especially widespread in Denmark, where an estimated 38 % of employees are subject to this practice, while markedly lower prevalence is observed in Hungary (11 %), Lithuania (13 %), Germany (13 %) and Finland (13 %). A similar pattern emerges for automated scheduling, which is most common in Denmark (23 %) and Ireland (20 %) but far less prevalent in Hungary (7 %), Greece (7 %), Lithuania (6 %) and Germany (6 %). Performance monitoring also varies considerably between Member States: prevalence is highest in Belgium (31 %), Estonia (28 %) and Ireland (26 %), whereas employees in Germany (10 %), Portugal (12 %), Greece (12 %) and Hungary (12 %) report substantially lower levels. The relatively narrow confidence intervals – the error bars shown as thin lines at the top and bottom of each point estimate – suggest that the estimated prevalence rates are measured with a high degree of precision.

Most of the differences among the Member States shown in the chart are statistically significant (see Table A2 in Annex 1). Compared with Denmark (selected as the reference category because it scores highest on the algorithmic management intensity index), every other Member State shows lower prevalence of automated task allocation and scheduling. Meanwhile, differences in performance monitoring go in both directions: Belgium, Estonia, Ireland and Spain show significantly higher prevalence than Denmark, while Germany, Greece, Hungary and Portugal show significantly lower prevalence. It should, however, be noted that the explanatory power of the model is modest, suggesting that the observed characteristics included in the model explain only part of the variation in the use of algorithmic management, with other factors not included in the model playing an important role.

Occupational and sectoral patterns

As with Member State, occupation and sector emerge from the empirical analysis as significant predictors of the use of algorithmic management.

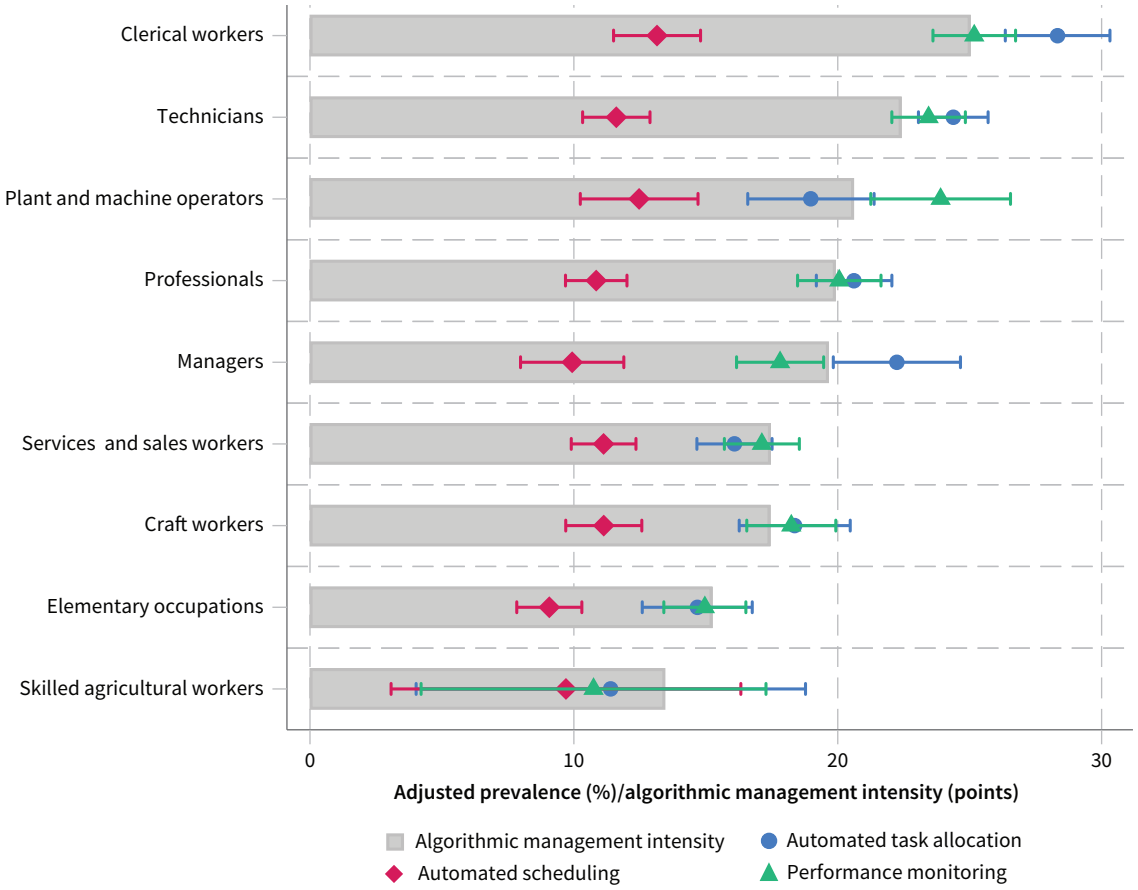
Algorithmic management is most prevalent among employees in clerical and technical occupations and in the finance and real estate, information and communications, and transport and storage sectors.

Reported use of algorithmic management is unevenly distributed across occupations, with the highest levels concentrated among clerical workers, technicians [1], and plant and machine operators (Figure 2). Clerical workers have the highest adjusted prevalence across all three functions (28 % for automated task allocation, 13 % for automated scheduling and 25 % for performance monitoring) and score highest on overall algorithmic management intensity (25). Technicians show high adjusted prevalence rates, particularly for automated task allocation (24 %) and performance monitoring (23 %), as do plant and machine operators, especially for performance monitoring (24 %) and automated scheduling (13 %). Managers and professionals occupy an intermediate position, while services and sales workers, craft workers, elementary occupations and, in particular, skilled agricultural workers consistently report lower levels. A notable pattern is that automated scheduling is less prevalent and more evenly distributed than the other two functions, with a comparatively small range of use between occupations (ranging from 9 % to 13 %).

Turning to sectors (which in this report are based on a modified version of the general industrial classification of economic activities within the EU (NACE) Rev. 2), differences are wider than across occupations and follow a clear pattern: the adjusted prevalence of algorithmic management is highest among employees

[1] In the International Standard Classification of Occupations 2008 (ISCO-08), technicians and associate professionals (major group 3) are workers who 'perform technical and related tasks connected with research and the application of scientific or artistic concepts and operational methods'. This category includes science and engineering associate professionals (code 31), health associate professionals (code 32), business and administration associate professionals (code 33), legal, social, cultural and related associate professionals (code 34) and information and communications technicians (code 35). For brevity in this report, they are referred to as technicians.

Figure 2: Adjusted prevalence of algorithmic management functions and algorithmic management intensity, by occupation



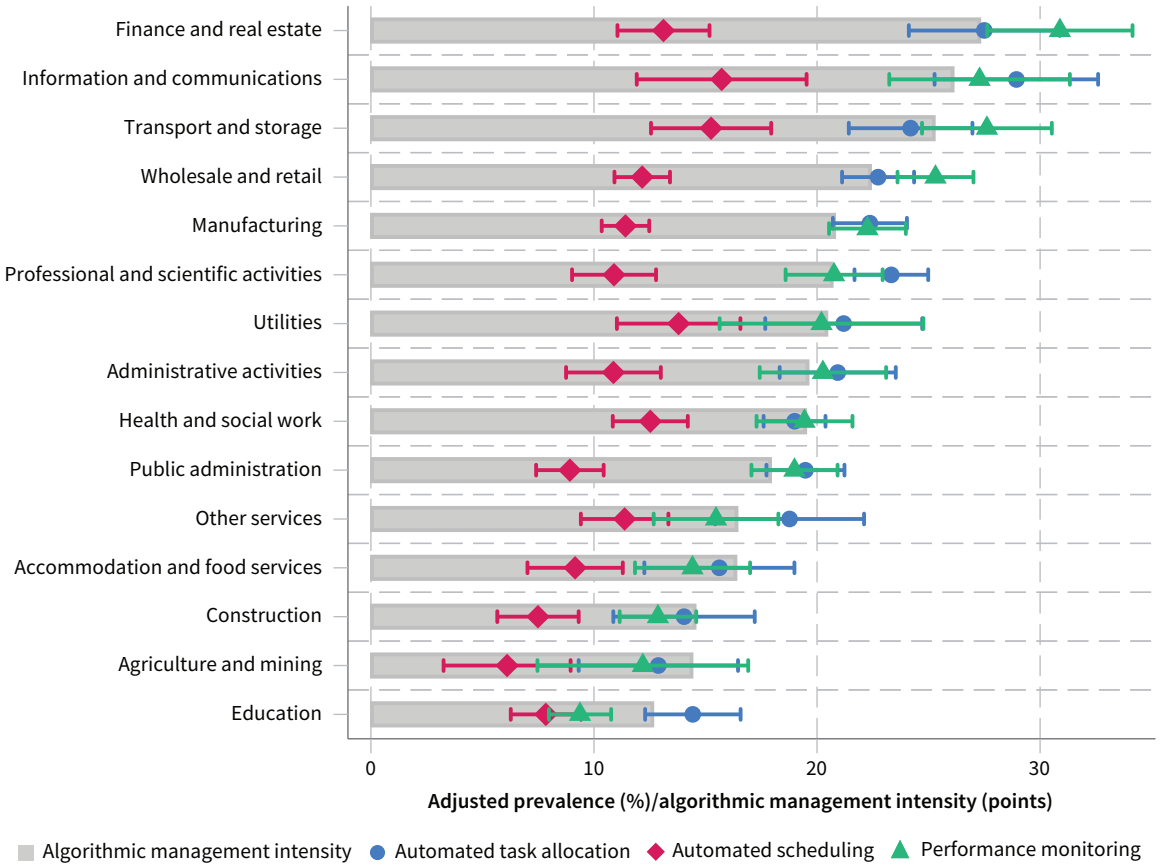
Notes: International Standard Classification of Occupations 2008 (ISCO-08) one-digit occupational groups. The figure shows the adjusted prevalence (predictive margins in percentage points for binary outcomes, represented by dots) and predicted mean score (for algorithmic management intensity, represented by bars), by occupation, estimated using probit models with robust standard errors, presented with 95 % confidence intervals. All models control for sociodemographic characteristics (gender, age and education), employment characteristics (contract type, sector, workplace size, telework and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

in finance and real estate, information and communications, and transport and storage, while it is lowest among those in construction, agriculture and mining, and education (Figure 3). Sectoral differences are statistically significant in most cases and reinforce the descriptive pattern presented in the EWCS overview report (Eurofound, 2026).

Employees in finance and real estate have the highest overall score on algorithmic management intensity (27/100) and relatively high prevalence across the three algorithmic management functions: 28 % for automated task allocation, 13 % for automated scheduling and 31 % for performance monitoring. Employees in most other sectors report significantly lower prevalence for one or more algorithmic management functions. Education stands out, with the lowest adjusted prevalence of performance monitoring (9 %) and consistently low prevalence across the other functions.

For transport and storage (24 % automated task allocation, 15 % automated scheduling and 28 % performance monitoring) and information and communications (29 % automated task allocation, 16 % automated scheduling and 27 % performance monitoring), estimated prevalence rates are also comparatively high and not much different from those of finance and real estate (see Table A2 in Annex 1). By contrast, agriculture and mining, construction, accommodation and food services, and education show consistently large and statistically significant negative differences across all three functions and on the overall intensity measure compared with finance and real estate (the baseline sector). The manufacturing, wholesale and retail, professional and scientific activities, public administration, and health and social work sectors also report significantly lower prevalence of algorithmic management, although the differences are more moderate.

Figure 3: Adjusted prevalence of algorithmic management functions and algorithmic management intensity, by economic sector



Notes: The figure shows the adjusted prevalence (predictive margins in percentage points for binary outcomes, represented by dots) and predicted mean score (for algorithmic management intensity, represented by bars), by economic sector, estimated using probit/linear regression models with robust standard errors clustered at Member State level, presented with 95 % confidence intervals. All models control for sociodemographic characteristics (gender, age and education), employment characteristics (contract type, occupation, workplace size, telework and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

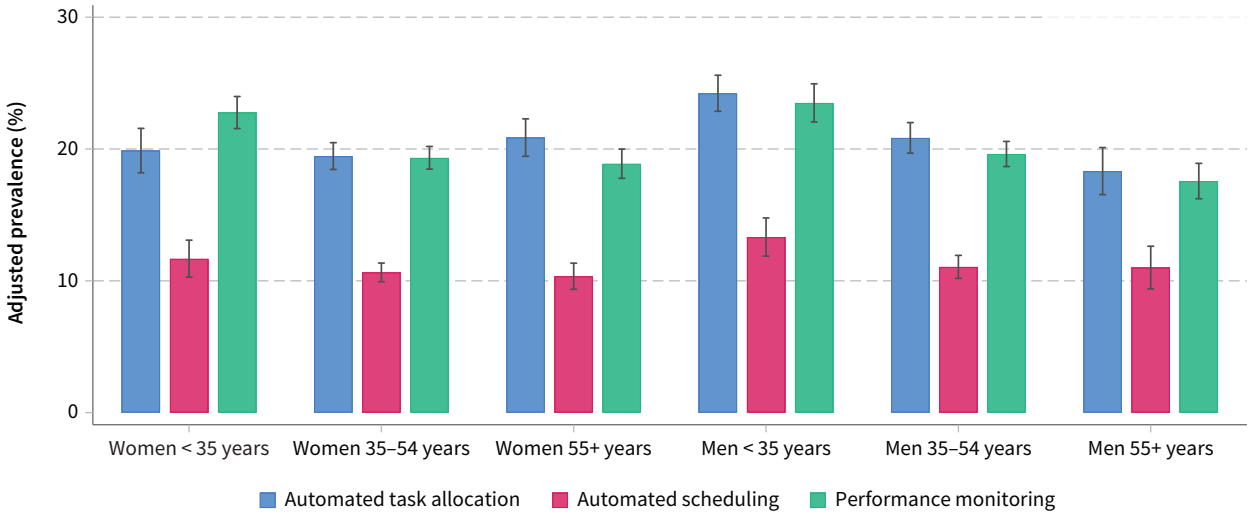
A broader pattern is that performance monitoring has the most widespread sectoral variation, with prevalence significantly lower than in finance and real estate in nearly every other sector. Automated scheduling shows fewer statistically significant differences, suggesting more limited sectoral differentiation for this algorithmic management function.

Sociodemographic characteristics

Examining sociodemographic differences helps identify whether the use of algorithmic management is concentrated among particular groups of employees, which is relevant for targeting policy responses.

Figure 4 shows that employees under 35 years of age, particularly younger men, are generally more likely than older workers to report being subject to the three forms of algorithmic management covered in the survey. This pattern is most evident for automated task allocation and performance monitoring, with prevalence significantly higher among younger men (around 3–4 percentage points above that among men aged 35–54) and significantly lower among older men. For women, differences across age groups are smaller and largely not statistically significant, except for the higher prevalence of performance monitoring among those under 35.

Figure 4: Adjusted prevalence of algorithmic management functions, by age group and gender (%)

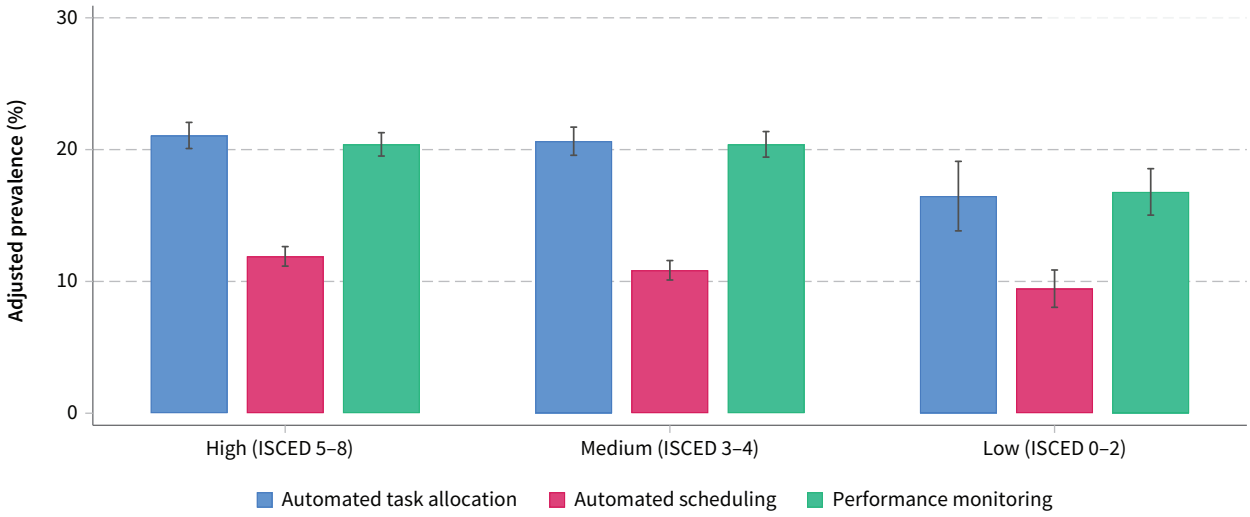


Notes: The figure shows the predicted probability of experiencing each form of algorithmic management, by gender and age group, estimated using probit models with robust standard errors, presented with 95 % confidence intervals. All models control for education, employment characteristics (contract type, occupation, sector, workplace size, telework and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

Automated scheduling is less common overall, with smaller differences across gender and age groups. The differences between the middle and older age groups appear less pronounced and not statistically significant.

Figure 5 shows small differences in the reported experience of algorithmic management by educational attainment. Employees with high and medium levels of education experience very similar levels of automated task allocation and performance monitoring, and the differences between them do not appear to be statistically significant. By contrast, employees with lower levels of education are somewhat less likely to report experiencing automated task allocation and performance monitoring, and these differences are statistically significant, particularly when compared with employees with high educational attainment. Automated scheduling remains the least common form of algorithmic management experienced across all educational groups, with negligible differences by education level.

Figure 5: Adjusted prevalence of algorithmic management functions, by educational attainment (%)



Notes: ISCED, International Standard Classification of Education. The figure shows the predicted probability of experiencing each form of algorithmic management, by educational attainment, estimated using probit models with robust standard errors, presented with 95 % confidence intervals. All models control for sociodemographic characteristics (gender and age), employment characteristics (contract type, occupation, sector, workplace size, telework and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

Differences by contract type were also examined, but after controlling for other variables, they were no longer statistically significant and are therefore not presented here. The full results are available in Annex 1.

Workplace characteristics

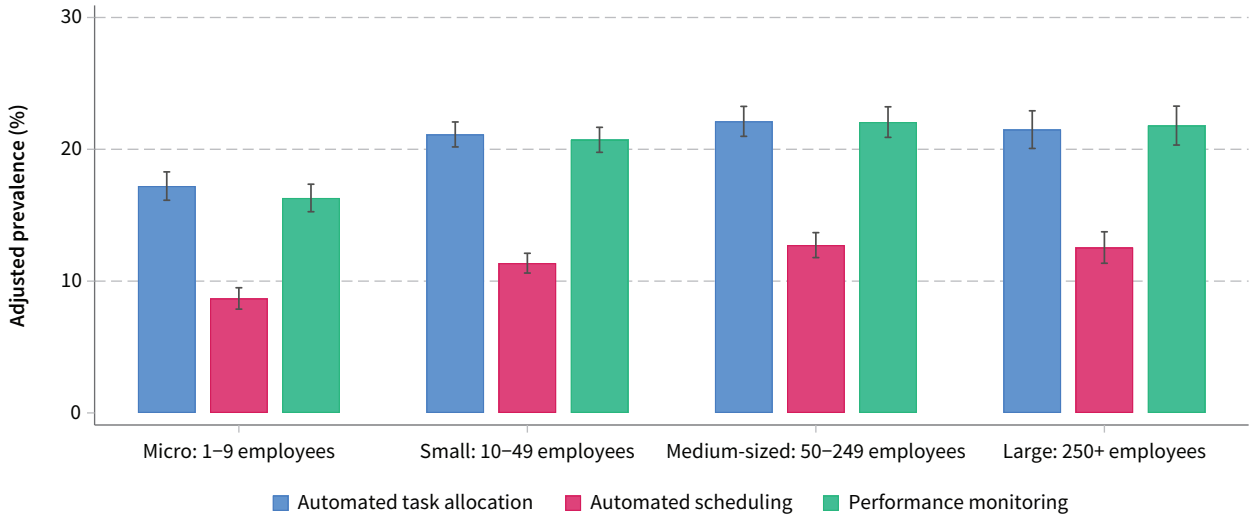
The analysis points to clear and statistically significant differences in the reported experience of algorithmic management by workplace size, trade union presence and telework arrangements.

Algorithmic management is more prevalent in larger workplaces, among teleworkers and in workplaces with established employee representation.

By establishment size, prevalence is lowest in micro-workplaces (1–9 employees), where 17 % report being subject to automated task allocation, 9 % to automated scheduling and 16 % to performance monitoring (Figure 6). Prevalence rises significantly with workplace size: among employees of small workplaces (10–49 employees) 21 % experience automated task allocation, 11 % experience automated scheduling and 21 % experience performance monitoring. These employees are significantly more likely than employees of micro-workplaces to be subject to all three functions and to score significantly higher on the algorithmic management intensity index. Prevalence is highest overall among employees of medium-sized workplaces (50–249 employees) (automated task allocation, 22 %; automated scheduling, 13 %; and performance monitoring, 22 %). Large workplaces (250+ employees) display similarly elevated levels (automated task allocation, 21 %; automated scheduling, 12 %; and performance monitoring, 22 %), with all differences likewise being statistically significant.

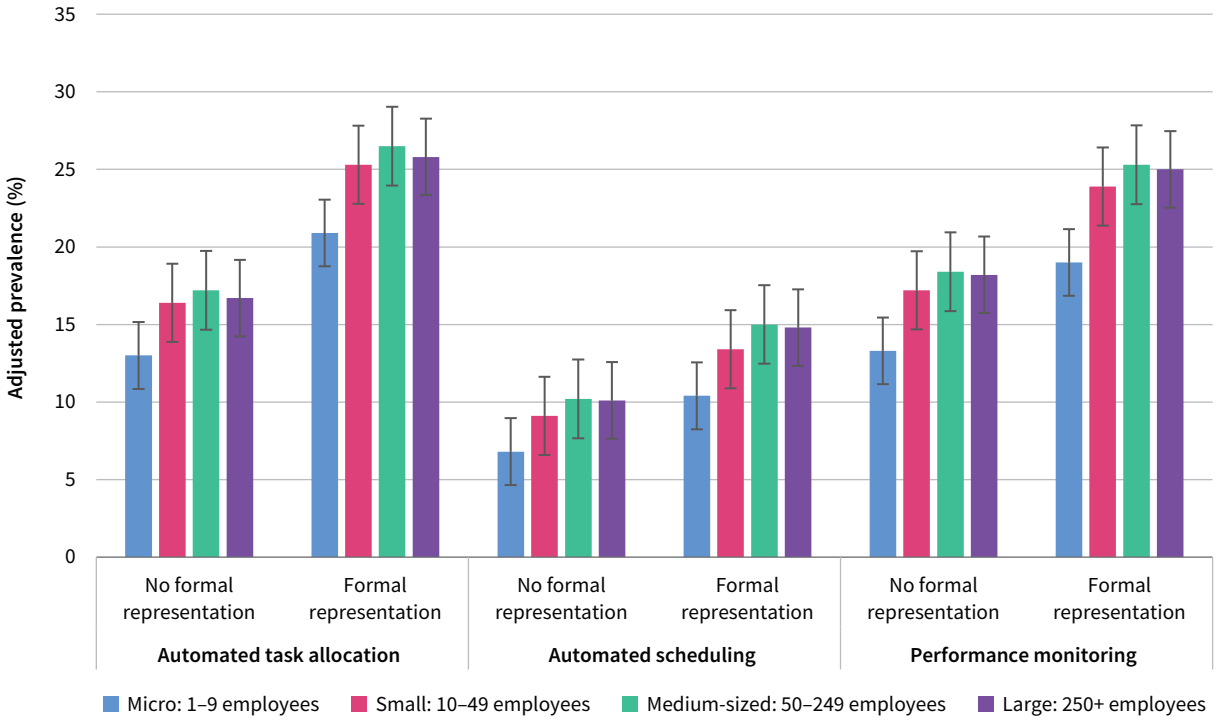
The presence of formal employee representation (a trade union, works council or similar employee representation) is also strongly associated with employees being more likely to report the use of algorithmic management in their workplace. Since the presence of formal employee representation in turn is linked to workplace size, Figure 7 combines workplace size with employee representation to show how both dimensions jointly relate to the prevalence of algorithmic management. Across all workplace sizes, adjusted prevalence is consistently higher in workplaces with formal employee representation than in workplaces without it for each of the three algorithmic management functions.

Figure 6: Adjusted prevalence of algorithmic management functions, by workplace size (%)



Notes: The figure shows the predicted probability of experiencing each form of algorithmic management, by workplace size, estimated using probit models with robust standard errors, presented with 95 % confidence intervals. All models control for sociodemographic characteristics (gender, age and education), employment characteristics (contract type, occupation, sector, telework and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

Figure 7: Adjusted prevalence of algorithmic management functions by presence of formal employee representation and workplace size (%)



Notes: The figure shows the predicted probability of experiencing each form of algorithmic management, by workplace size combined with formal employee representation, estimated using probit models with robust standard errors, presented with 95 % confidence intervals. Controls include age and gender, education, permanent contract, occupation, sector, telework and Member State.
Source: Authors' calculations.

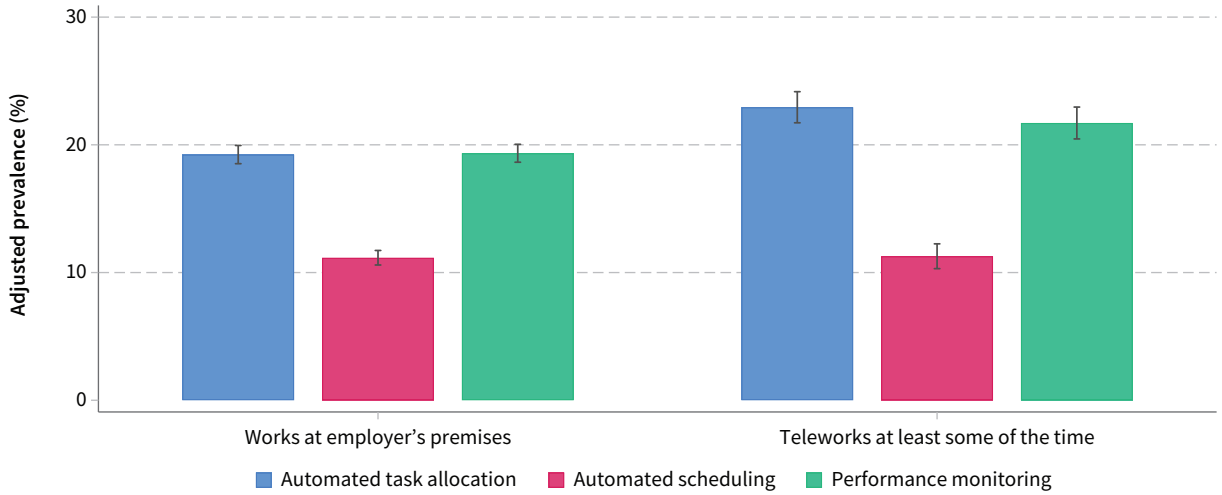
Because these estimates account for workplace size, sector and other characteristics, the positive association cannot simply be explained by the greater presence of formal employee representation in larger organisations. Employees in workplaces with formal employee representation may be more aware of the technologies used to organise and monitor work and may be more likely to identify and report the presence of algorithmic management. The higher reported prevalence in these workplaces may therefore partly reflect greater awareness rather than the more widespread use of these systems.

Complementary evidence from EU-OSHA provides additional context on worker consultation in relation to the implementation of digital technologies in the workplace, drawing on the agency's European Survey of Enterprises on New and Emerging Risks (Esener) 2024, a representative EU-wide survey of more than 41 000 establishments across 30 European countries, based on interviews with the person most knowledgeable about occupational safety and health in each workplace.

EU-OSHA reports that consultation with workers on the occupational safety and health implications of digital technologies increased from 24 % in 2019 to 35 % in 2024 among establishments using at least one digital technology (EU-OSHA, 2025). In addition, EU-OSHA's qualitative case study research on AI-based worker management systems documents how worker participation and representation can help identify, prevent and mitigate the psychosocial risks linked to these systems, including through consultation and oversight during implementation (EU-OSHA, 2024).

A similar pattern to that of formal employee representation emerges for telework (Figure 8). Adjusted prevalence is higher among teleworkers for automated task allocation (23 % versus 19 % for non-teleworkers) and performance monitoring (22 % versus 19 % for non-teleworkers), with both differences being statistically significant. Automated scheduling, by contrast, is similar in both groups (around 11 %) and not significantly different.

Figure 8: Adjusted prevalence of algorithmic management functions, by telework arrangement (%)



Notes: The figure shows the predicted probability of experiencing each form of algorithmic management, by telework arrangement, estimated using probit models with robust standard errors, presented with 95 % confidence intervals. All models control for sociodemographic characteristics (gender, age and education), employment characteristics (contract type, occupation, sector, workplace size and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

Implications of algorithmic management for work organisation

Reshaping tasks and influencing task content

If the evidence suggests that algorithmic management has entered more conventional workplaces, an important question is the extent to which it is associated with task transformation. Figure 9 illustrates the probability of respondents answering that technology removed tasks, increased tasks or increased interaction, controlling for employee and workplace characteristics (including age, education, occupation, sector, workplace size, union presence, telework and Member State). The results show that employees who report algorithmic management at work are more likely to report more technology-driven task change than those who do not report algorithmic management.

Algorithmic management is associated with changes in job tasks and with somewhat more standardised, target-driven and machine-paced work, especially in the case of performance monitoring.

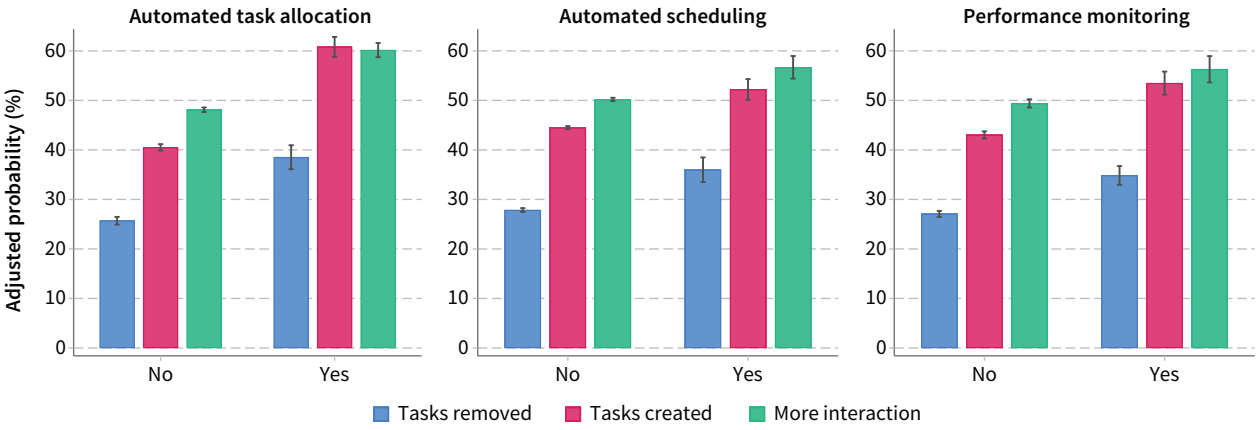
Across all three algorithmic management functions – automated task allocation, automated scheduling and performance monitoring – respondents were more likely to say that technology has removed tasks, created new tasks and increased interaction with their colleagues. The specific types of tasks that are created or removed fall outside the scope of the present report and will be explored in a follow-up project on the impact of technology on task content using EWCS 2024 data.

The biggest differences relate to automated task allocation: 38 % of employees who experience automated task allocation report tasks being removed versus 26 % of those who do not experience it; 61 % of employees who experience automated task allocation report new tasks being created versus 40 % of those who do not experience it; and finally, 60 % of employees who experience automated task allocation report more interaction with colleagues versus 48 % of those who do not experience it.

Similar but slightly smaller gaps in task transformation are evident for employees who experience automated scheduling and performance monitoring. For automated scheduling, 36 % of employees who experience it in their workplace report tasks being removed versus 28 % of those who do not experience it; 52 % of employees who experience it report that new tasks are created versus 44 % of employees who do not; and 57 % of employees who experience it report increased interaction with colleagues versus 50 % of those who do not experience it. For performance monitoring, the pattern is comparable: 35 % for tasks removed among those who report their performance is monitored versus 27 % of those whose performance is not; 53 % for tasks created versus 43 %; and 56 % for increased interaction with colleagues versus 49 %. The differences in task transformation between workplaces where each of the algorithmic management functions is used and those where it is not are statistically significant.

It is worth noting that, while the increase in the proportion of employees reporting that technology has removed tasks is relatively similar across the three

Figure 9: Impact of technology on tasks, by algorithmic management function (%)



Notes: The figure shows the average predicted probabilities from probit regression analyses of technology-driven task change according to the use of each algorithmic management function. All models control for sociodemographic characteristics (gender, age and education), employment characteristics (contract type, occupation, sector, workplace size, telework and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

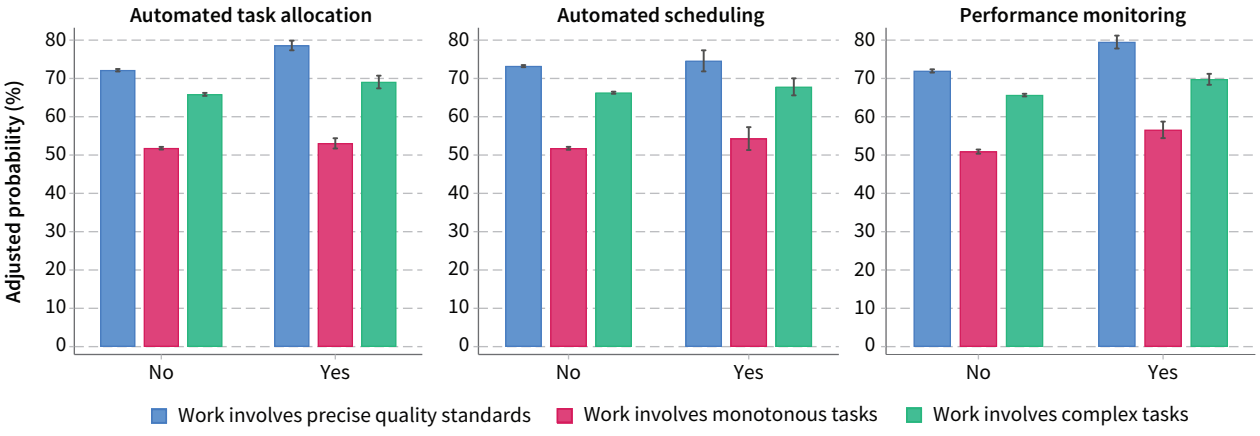
algorithmic management functions, automated task allocation is associated with a greater increase in the proportion reporting that technology has created new tasks than either automated scheduling or performance monitoring. This pattern may reflect the more direct role of automated task allocation in reshaping the organisation of work compared with the other two algorithmic management functions. If these new tasks are not accompanied by a corresponding reduction in existing work, this may point to a process of work intensification.

Differences in reported interaction with colleagues are comparatively similar across the three functions.

The analysis does not allow for causal inferences and therefore does not permit conclusions to be drawn about the direction of the relationship between experience of algorithmic management and increased interaction with colleagues. One possible explanation is that algorithmic management is more likely to be adopted in workplaces where work is already highly interconnected or digitally mediated. This interpretation is consistent with the finding that, as measured in the survey, algorithmic management is more prevalent among clerical workers and technicians and associate professionals; in sectors such as finance, information and communications, and transport; and in larger workplaces. These work environments typically rely on highly coordinated, digitally mediated and interdependent workflows. Consequently, the higher levels of interaction with colleagues reported by employees subject to algorithmic management may reflect the organisational characteristics of these workplaces, rather than being a direct consequence of algorithmic management itself.

Algorithmic management may also have an impact on task content. To check whether this is the case, Figure 10 plots the probability of respondents answering that

Figure 10: Task content, by algorithmic management function (%)



Notes: The figure shows the average predicted probabilities from probit regressions of change in task content according to the use of each algorithmic management function. All models control for sociodemographic characteristics (gender, age and education), employment characteristics (contract type, occupation, sector, workplace size, telework and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

their job requires precise quality standards to be met (standardisation), involves monotonous tasks (routine) or involves complex tasks (complexity), controlling for the standard sociodemographic, sector, occupation and Member State variables. The results vary by type of algorithmic management function and task content. Performance monitoring is significantly associated with jobs involving precise quality standards, task monotony and task complexity. Employees subject to automated task allocation are also significantly more likely to report having to meet precise quality standards and perform complex tasks, although not to perform monotonous tasks. By contrast, employees subject to automated scheduling do not report significantly different task content on any of the three dimensions (standardisation, routine and complexity) from employees not subject to it. Regardless of the significance of the statistical associations, the magnitude of all coefficients is relatively modest. The estimated marginal effects generally range between 3 and 8 percentage points, indicating measurable but not substantial differences between employees who report the use of computer programs for work scheduling, task allocation and performance monitoring and those who do not. This suggests that algorithmic management is not confined to a specific type of job or task profile.

The analysis does not explain the organisational processes underlying these associations; nevertheless, the findings point to some parallels with earlier research on highly standardised forms of work organisation. Studies of lean production, for example, have highlighted how standardised work processes, close performance monitoring and quality requirements can increase work demands and reduce workers' discretion (Landsbergis et al., 1999; Hasle et al., 2012).

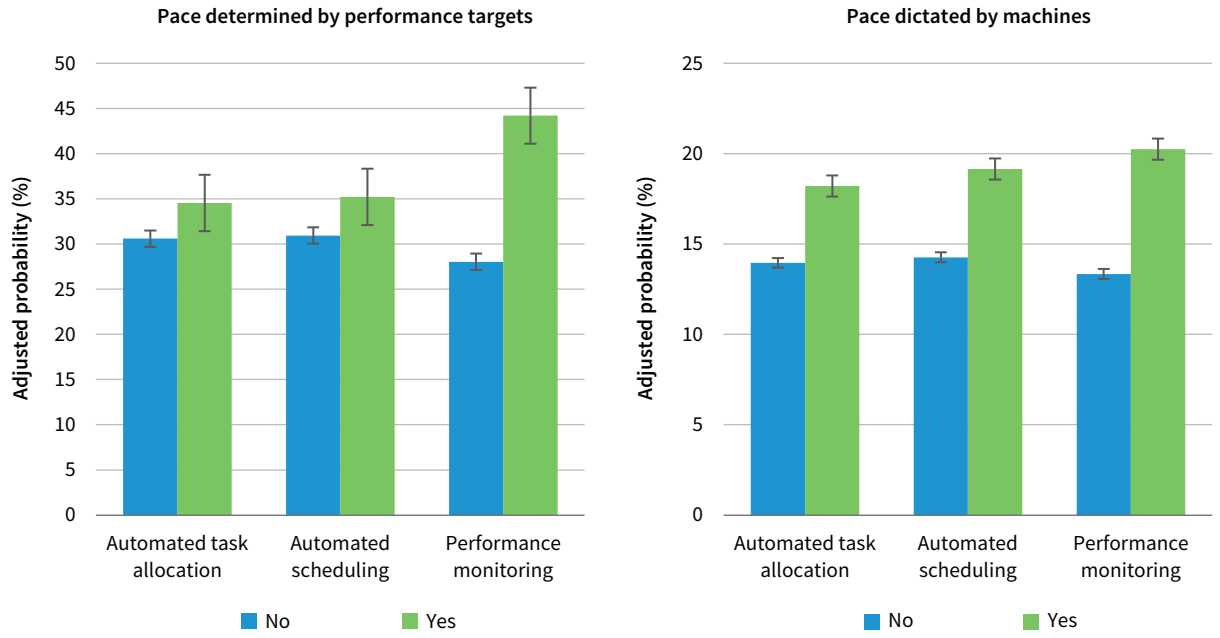
These findings are consistent with broader evidence on the digitalisation of work organisation. Previous research has shown that digital technologies tend to standardise and routinise work processes by codifying tasks, procedures and performance requirements, while at the same time increasing the overall complexity of many jobs (Fernández-Macías et al., 2025).

Using machines and performance targets as pacemakers

Beyond task content, algorithmic management tends to be related to the organisation of work itself, particularly the pace at which work is carried out. A long-standing EWCS question asks respondents whether the pace of their work is dependent on machines or on numerical production or performance targets. The variable 'pace determined by machines' refers to the speed of work being dictated by technical equipment, automated processes or the rhythm of a machine (such as a conveyor belt or digital system). It suggests lower levels of autonomy over the temporal aspect of work, as employees must synchronise their physical or mental actions with the speed of a machine. The variable 'pace determined by targets' refers to the speed of work being dictated by quantitative outputs or performance goals set by management (for example, the number of calls handled per hour or the units produced per shift). These measures capture important dimensions of externally determined work intensity and control.

The results of the analysis presented in Figure 11 show that employees subject to each of the three algorithmic

Figure 11: Pace determinants, by algorithmic management function (%)



Notes: The figure shows the average predicted probabilities from probit regressions of pace determinants according to the use of each algorithmic management function. All models control for sociodemographic characteristics (gender, age and education), employment characteristics (contract type, occupation, sector, workplace size, telework and trade union presence) and Member State fixed effects.
Source: Authors' calculations.

management functions are more likely to report a pace dictated by performance targets or by machines. This pattern is consistent with work intensification, as an externally determined pace of work may reduce workers' control over the speed at which they carry out their tasks. The gap is largest for performance monitoring: 44 % of monitored workers report a target-driven pace of work, against 28 % of unmonitored workers. Machine pacing is less common overall but shows the same pattern across all three functions, rising from 13–14 % to 18–20 % for those subject to each function.

Chapter 1 key takeaways

- The prevalence of algorithmic management is uneven across Member States, sectors, occupations and workforce groups. It is particularly high in finance and real estate, information and communications, and transport and storage, and also among clerical workers, technicians, employees in larger workplaces and younger employees (under 35 years of age). Monitoring efforts should pay particular attention to these contexts in tracking developments in the use of algorithmic management and its implications for working conditions over time.
- Algorithmic management is associated with the creation of new tasks, the removal of others, increased interaction with colleagues and greater reliance on machine-paced work and numerical performance targets. Performance monitoring and automated task allocation are linked to task standardisation and task complexity. These findings suggest that digital technologies are reshaping the nature and organisation of work.

2 Relationship between algorithmic management and job demands and resources

Summary

Of the job demands included in the EWCS, time-related demands are the most common in the EU, while social support is the most prevalent job resource. However, both the experience of job demands and access to job resources vary across sectors and occupations.

Employees in physically intensive industries report higher levels of physical demands and financial and job insecurity, while in service-oriented sectors emotional and social demands dominate. Office-based sectors generally display more favourable job demand profiles across most domains. In terms of job resources, workers in public administration, education and utilities report better resource availability. The opposite pattern is observed in manufacturing, accommodation and food services, and transport and storage, where resources are scarcer.

In terms of occupation, employees in manual occupations experience the highest levels of physical risks and demands, while services and sales roles involve greater emotional, social and time-related demands. By contrast, employees in higher-skilled occupations generally report lower overall job demands. Job resources are concentrated in higher-skilled occupations, particularly among managers and professionals, whereas employees in lower-skilled and manual occupations report more limited access to these resources.

Employees subject to algorithmic management report higher job demands across almost all dimensions than employees who are not subject to it. The largest differences are concentrated in quantitative, time-related and emotional demands. A regression analysis confirmed this pattern, showing that reported use of algorithmic management is significantly associated with higher job demands, particularly quantitative demands. By contrast, associations with job resources are more mixed: some functions, especially performance monitoring, are linked to lower access to job resources like working time flexibility, rewards and autonomy, while automated task allocation appears to be associated – albeit weakly – with higher levels of enabling resources, such as autonomy and employee participation. This pattern should not be interpreted as evidence that automated task allocation enhances the availability of these job resources. Rather, it may reflect the organisational characteristics of workplaces in which automated task allocation is more commonly used. These workplaces may combine digitally coordinated forms of work with relatively higher levels of employee autonomy and participation. In addition, the autonomy indicator measures employees' control over the order of tasks, methods and speed of work, which is compatible with both automated task allocation and scheduling: once the task or schedule is allocated, the employee may decide how and when to perform the work.

The relationship between algorithmic management and health and well-being outcomes appears to be complex and not uniformly adverse. For instance, automated task allocation is positively associated with engagement. However, performance monitoring stands out as the algorithmic management function most likely to be associated with lower scores on health and well-being measures.

This chapter presents an empirical analysis of job quality among employees, distinguishing between job demands and job resources, operationalised using the EWCS 2024 data. This analysis uses the JD-R model as its theoretical framework (Bakker et al., 2007), which conceptualises job quality in terms of the balance between job demands and job resources. The JD-R model highlights how high demands can contribute to strain and adverse outcomes, while adequate resources at work can buffer these pressures and support motivation, engagement and well-being.

The suitability of the JD-R framework for this analysis is supported by the existing literature on algorithmic management (Eurofound, 2025). Parent-Rocheleau et al. (2022) conceptualise algorithmic management as a form of work design by drawing on the JD-R model. Based on their review of empirical and descriptive studies, they argue that algorithmic management acts as a 'work designer' by reshaping both job resources and job demands. Similarly, Lippert et al. (2023) employ the JD-R framework to identify algorithmic-management-specific demands and resources, while Martín et al. (2025) apply the framework to interpret

occupational health and safety risks and opportunities associated with algorithmic management.

The chapter begins by examining the distribution of job demands and job resources across the employee sample. It then turns to sectoral and occupational differences, building on the previous chapter's findings that these are important predictors of reported use of algorithmic management. Having mapped these distributions, the analysis focuses on variation by use of individual algorithmic management functions, examining the share of employees reporting specific job demands and job resources based on whether they are subject to each function. The chapter continues with regression analyses examining the association between job demands and resources and algorithmic management while controlling for sectoral, occupational and individual characteristics. The chapter concludes with regression analyses examining whether the algorithmic management functions considered in this report are associated with health and well-being outcomes.

Mapping job demands and job resources in the EU

Before examining the association between job demands, job resources and algorithmic management, it is useful to establish as a baseline the distribution of these indicators – specifically measures of job demands (time-related demands, physical demands, quantitative demands, emotional demands, physical risks, social demands, and financial and job insecurity) and job resources (social support, rewards, training and learning opportunities, working time flexibility, autonomy, participation and employee voice, and career advancement) – across the employee workforce in the EU as a whole, and also across sectors and occupations. Meta-analytic evidence shows that higher job demands are associated with higher levels of burnout, while more job resources are associated with lower burnout and higher work engagement levels (Crawford et al., 2010).

Nearly 7 in 10 employees experience time-related demands, making them the most widespread job demands in European workplaces.

Figure 12 shows the prevalence of the seven job demands and seven job resources indicators across the EU. On the demands side, time-related demands are the most widespread, affecting 68 % of employees, followed by physical demands (49 %), quantitative demands (43 %) and emotional demands (40 %). Physical risks are reported by 37 % of employees and social demands – including exposure to adverse social behaviour or discrimination – affect 20 % of employees. Drawing on data from previous waves of the EWCS, past Eurofound research has identified physical risks, emotional demands, quantitative demands and adverse social behaviour as key job demands, each being directly associated with poorer health and well-being (Eurofound, 2019).

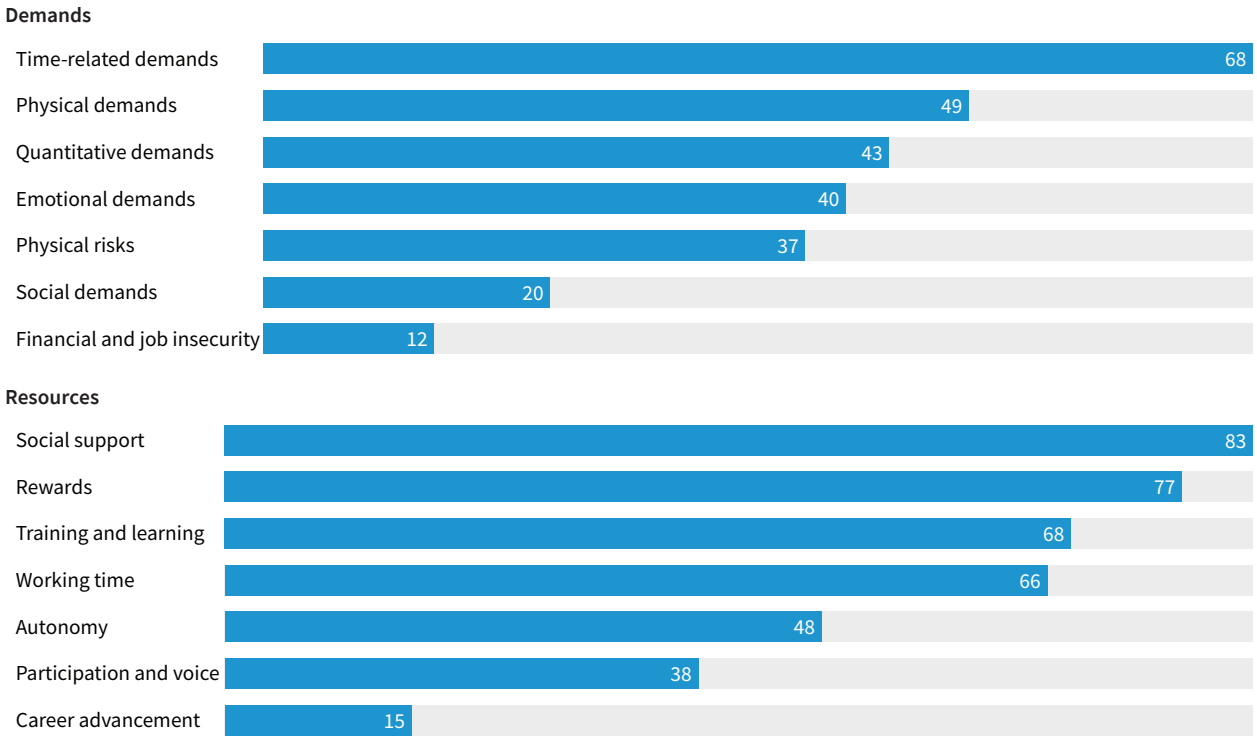
Social support, rewards, and training and learning opportunities are among the most widespread job resources, each accessible to at least two thirds of EU employees.

Perceptions of financial and job insecurity are the least prevalent, reported by 12 % of employees, most likely because the sample does not include the self-employed. The literature consistently identifies job insecurity as an important psychosocial stressor. Longitudinal meta-analysis finds that workers experiencing job insecurity have significantly higher odds of poorer mental health over time (Rönnblad et al., 2019), and broader review evidence links job insecurity to depression, burnout and poorer self-rated health (Llosa et al., 2018; Niedhammer et al., 2021).

In terms of resources, social support is the most widespread, accessible to 83 % of employees, followed by rewards (77 %), training and learning opportunities (68 %) and working time flexibility (66 %). Autonomy over the order, methods or pace of work is available to less than half of employees (48 %), while organisational participation and workplace voice is reported by 38 %. In the literature, both autonomy and participation are linked to better well-being and can mitigate the negative effects of demanding work (Demerouti et al., 2001; Crawford et al., 2010; De Spiegelaere et al., 2019; Bakker et al., 2023). Evidence also shows that social support from colleagues and managers can protect against the negative effects of demanding working conditions on mental well-being (Eurofound, 2023).

Opportunities for career advancement are the least prevalent resource, reported by only 15 % of employees. Career advancement prospects are, however, widely recognised as an important job resource and a core element of rewards at work, alongside recognition and job security (Siegrist, 1996). Review evidence confirms that rewards, including promotion prospects, are consistently linked to workers' health and well-being (van Vegchel et al., 2005).

Figure 12: Distribution of job demands and job resources (%)



Source: Authors' calculations.

When interpreting these figures, it should be noted that the absolute prevalence of each indicator partly depends on its construction (see Table 2 in the Introduction for details). All else being equal, binary indicators, awarded a score of 1 whenever at least one of the many subindices is present (for example, time-related demands or physical risks), are more likely to be triggered than indicators that require several subindices to be present concurrently (for example, financial and job insecurity or quantitative demands) or that rest on a single subindex (for example, career advancement). Prevalence also reflects the underlying frequency of the constituent items. Social demands, for instance, uses an 'at least one' rule but remains comparatively rare because its component experiences (violence, harassment and discrimination) are themselves uncommon.

The aggregate prevalence rates presented in Figure 12 provide a useful overview but may conceal substantial heterogeneity across the economy, particularly across economic sectors or occupations. Since sector and occupation are also important determinants of experience of algorithmic management, it is worth examining them more closely, especially given the focus of the analysis on algorithmic management.

Sectoral distribution

The distribution of both job demands and resources varies across sectors (Figure 13). With regard to job demands, employees in manual and labour-intensive sectors such as agriculture and mining, construction and manufacturing report the highest levels of physical risks and to a lesser extent physical demands, whereas those in office-based or knowledge-intensive sectors, including information and communications, finance and real estate, professional and scientific services, and public administration, generally report lower levels of physical risk. In contrast, employees in health and social work and education experience comparatively high levels of emotional and social demands, reflecting the interpersonal nature of their roles. Time-related demands are particularly high in agriculture and mining and in accommodation and food services. Financial and job insecurity is also particularly pronounced in agriculture and mining and comparatively lower in professional and public sector occupations.

Job demands and resources differ markedly across sectors and occupations, with physically intensive and lower-skilled work facing higher demands and fewer resources.

Figure 13: Distribution of job demands across economic sectors (z-scores)



Notes: Positive values are highlighted in red and negative in green to indicate that a lower score on job demands is favourable (green) whereas a higher score is unfavourable (red). To allow for comparison across both sectors and individual indicators, the values in the figure are standardised and expressed as z-scores: each cell shows how far a sector deviates from the EU average with regard to a given demand, in standard deviation units. Positive values indicate above-average exposure; negative values indicate below-average exposure.
Source: Authors' calculations.

Several sectors demonstrate favourable resource profiles across multiple dimensions, particularly in regard to autonomy, working time flexibility, training and learning opportunities, and career advancement (Figure 14). In public administration, education and utilities most visibly, employees consistently report greater resource availability. In contrast, employees in manufacturing, accommodation and food services, and transport and storage tend to have more negative scores across several indicators, suggesting comparatively lower access to key job resources.

Figure 14: Distribution of job resources across economic sectors (z-scores)



Notes: In contrast to Figure 13, here higher positive scores are highlighted in green and negative scores are highlighted in red because higher scores on resources are favourable. To allow for comparison across both sectors and individual indicators, the values in the figure are standardised and expressed as z-scores: each cell shows how far a sector deviates from the EU average with regard to a given resource, in standard deviation units. Positive values indicate above-average exposure; negative values indicate below-average exposure.
Source: Authors' calculations.

Occupational distribution

Figures 15 and 16 show the differences in job demands and job resources, respectively, across occupational groups.

Managers, professionals, technicians and clerical workers generally report lower levels of physical risks and physical demands, and they also show little variation in levels of social and emotional demands. In contrast, manual and lower-skilled occupations, especially skilled agricultural workers, craft workers, plant and machine operators, and workers in elementary occupations, experience the highest levels of physical risks and physical demands, with the largest positive values concentrated in agriculture and trades. Services and sales workers stand out for having comparatively higher levels of emotional demands, social demands and time-related demands, reflecting the interpersonal and time-pressured nature of this work. Clerical workers appear to experience notably less time pressure than most occupations. Financial and job insecurity is relatively low across most occupations but is somewhat higher among plant and machine operators and those in elementary occupations.

The variation in job resources across occupations shows a clear advantage for higher-skilled roles (Figure 16). Managers, professionals and technicians report the greatest access to resources overall, particularly autonomy, working time flexibility, training and learning opportunities, career advancement, rewards, and participation and voice. Managers stand out most, with especially high scores for participation and voice, working time flexibility and autonomy, reflecting greater control and influence at work. Clerical workers are closer to the average, with moderate access to most resources but having less of an advantage than the managerial and professional groups. By contrast, for most job resources, services and sales workers, craft workers, plant and machine operators, and workers in elementary occupations report consistently lower access to resources. The largest gaps are in training and learning opportunities, participation and voice, and

Figure 15: Distribution of job demands across occupational groups (z-scores)

	Physical risks	Physical demands	Quantitative demands	Emotional demands	Social demands	Time-related demands	Financial and job insecurity
Managers	-0.41	-0.27	0.12	-0.03	-0.04	0.17	-0.07
Professionals	-0.28	-0.11	-0.02	0.06	-0.01	-0.08	-0.04
Technicians	-0.13	-0.09	0.06	0.09	0.01	-0.09	-0.04
Clerical support workers	-0.47	0.08	-0.06	-0.05	0.00	-0.45	-0.02
Services and sales workers	0.01	-0.15	-0.03	0.27	0.15	0.41	0.04
Skilled agricultural workers	0.89	0.22	-0.38	-0.43	0.01	0.21	-0.01
Craft workers	0.69	0.28	0.09	-0.31	-0.16	-0.07	-0.04
Plant and machine operators	0.45	0.45	0.06	-0.12	-0.11	0.20	0.10
Elementary occupations	0.41	0.05	-0.09	-0.22	0.02	-0.05	0.15

Notes: Positive values are highlighted in red and negative values are highlighted in green to indicate that a lower score on job demands is favourable (green) whereas a higher score is unfavourable (red). To allow for comparison across both occupations and individual indicators, the values in the figure are standardised and expressed as z-scores: each cell shows how far an occupational group deviates from the EU average with regard to a given demand, in standard deviation units. Positive values indicate above-average exposure; negative values indicate below-average exposure.
Source: Authors' calculations.

Figure 16: Distribution of job resources across occupational groups (z-scores)

	Social support	Autonomy	Working time flexibility	Training and learning	Career advancement	Rewards	Participation and voice
Managers	0.06	0.33	0.46	0.32	0.32	0.22	0.71
Professionals	0.10	0.24	0.11	0.34	0.15	0.18	0.30
Technicians	0.05	0.16	0.19	0.24	0.15	0.11	0.15
Clerical support workers	0.00	0.06	0.13	0.04	-0.14	-0.07	-0.13
Services and sales workers	0.02	-0.18	-0.16	-0.21	-0.11	-0.09	-0.22
Skilled agricultural workers	-0.25	-0.06	0.45	-0.71	-0.24	0.20	-0.37
Craft workers	-0.02	-0.21	-0.23	-0.10	-0.11	-0.14	-0.16
Plant and machine operators	-0.09	-0.44	-0.22	-0.24	-0.15	-0.16	-0.31
Elementary occupations	-0.27	-0.14	-0.30	-0.78	-0.23	-0.29	-0.35

Notes: Unlike Figure 15, here higher positive scores are highlighted in green and negative scores are highlighted in red because higher scores on resources are favourable. To allow for comparison across both occupations and individual indicators, the values are standardised and expressed as z-scores: each cell shows how far an occupational group deviates from the EU average with regard to a given resource, in standard deviation units. Positive values indicate above-average exposure; negative values indicate below-average exposure.
Source: Authors' calculations.

working time flexibility, particularly among workers in elementary occupations. Skilled agricultural workers show a more mixed profile, with relatively high working time flexibility but lower social support and fewer opportunities for training and learning and participation and voice.

Association between algorithmic management and job quality

Algorithmic management and job demands

Table 4 shows the prevalence of each of the seven job demands among employees subject and not subject to the three core algorithmic management functions identified in the previous chapter: automated task allocation, automated scheduling and performance monitoring.

Employees subject to algorithmic management report higher levels of job demands across nearly all dimensions, with the largest differences observed for quantitative demands.

The first thing to note is that employees who are subject to algorithmic management functions in their workplace report higher levels of job demands across nearly all dimensions. The gap between them and employees not subject to algorithmic management is particularly pronounced for **quantitative demands**, where for automated task allocation, there is an 18-percentage-point difference (58 % among those who report this function in their workplace versus 40 % among those who do not) and a 22-percentage-point difference for automated scheduling (63 % versus 41 %). Performance monitoring is associated with a 25-percentage-point difference in prevalence (63 % among employees who report it versus 38 % among those who do not). These findings are consistent with the literature, which links algorithmic management to work intensification (Eurofound, 2025; Martín et al., 2025).

Substantial gaps between the two groups of employees are also observed for **emotional demands** (between 8 and 14 percentage points across the three functions), **time-related demands** (3 to 10 percentage points) and, to a lesser extent, **financial and job insecurity** (4 to 7 percentage points), with employees subject to each function experiencing higher levels of these demands. These patterns somewhat align with findings from Esener 2024. The survey found that establishments using machine systems or computers to monitor work performance or determine the content or pace of work are more likely to report psychosocial risks – including time pressure, poor communication or cooperation, job insecurity, and long or irregular working hours – than establishments where such technologies are not in use (EU-OSHA, 2025).

The relationship between algorithmic management and **physical demands** is weaker than for some other demands but remains consistently positive, with differences between the two employee groups ranging from 5 to 9 percentage points. For **physical risks**, the pattern is more mixed: automated task allocation is associated with a slightly lower likelihood (–3 percentage points) of employees reporting physical risks, while automated scheduling is associated with a higher likelihood (6 percentage points), as is performance monitoring, but of lower magnitude (2 percentage points).

Table 4: Share of employees reporting job demands, by algorithmic management function (%)

	Automated task allocation (%)		Automated scheduling (%)		Performance monitoring (%)	
	No	Yes	No	Yes	No	Yes
Physical risks	38	35 ⇓	37	43 ⇑	37	39 ⇑
Physical demands	48	53 ⇑	48	55 ⇑	47	56 ⇑
Quantitative demands	**40**	**58** ⇑	**41**	**63** ⇑	**38**	**63** ⇑
Emotional demands	39	47 ⇑	**39**	**53** ⇑	**38**	**50** ⇑
Social demands	19	24 ⇑	19	26 ⇑	19	23 ⇑
Time-related demands	68	71 ⇑	**67**	**77** ⇑	67	74 ⇑
Financial and job insecurity	11	15 ⇑	11	18 ⇑	11	15 ⇑

Note: An upward arrow indicates higher prevalence and a downward arrow indicates lower prevalence of a job demand among employees subject to the algorithmic management function in question. The darker shading highlights the wider gaps. All differences are statistically significant.
Source: Authors' calculations.

Algorithmic management and job resources

Table 5 shows the prevalence of each of the seven job resources among employees who report and do not report the use of the three algorithmic management functions examined in this report.

Compared with the findings on job demands, the relationship between algorithmic management and job resources appears more mixed, with some job resources reported more frequently by employees who also report the use of algorithmic management, while others are reported equally or less. For instance, employees who experience algorithmic management at work are more likely to report having access to **training and learning opportunities**, measured through a composite indicator capturing employer-paid training, on-the-job training, opportunities to learn new things and opportunities to improve skills, where at least two of these conditions are met. The prevalence of training and learning opportunities is 14 percentage points higher for employees who report the use of automated task allocation (79 %) than among those who do not (65 %). The corresponding difference for automated scheduling is 7 percentage points (74 % versus 67 %) and 10 percentage points for performance monitoring (76 % versus 66 %). Percentages are also moderately higher for employees who report use of algorithmic management in relation to **career advancement** opportunities, ranging from 2 to 5 percentage points (19 % versus 14 % for automated task allocation; 17 % versus 15 % for automated scheduling; and 18 % versus 15 % for performance monitoring).

While somewhat counter-intuitive given the dominant focus on control in the literature, these findings align with the argument advanced by Parent-Rocheleau et al. (2022) that algorithmic systems may strengthen knowledge-related job resources by providing workers with real-time information, structured feedback and clearer performance guidance. Similarly, Meijerink et al. (2023) develop the concept of the 'duality of algorithmic management', arguing that algorithmic systems can both constrain and enable employees. In their framework, algorithmic tools may create value for employees through non-monetary benefits such as learning, access to information and task support, even where they also intensify demands. The positive associations found in this analysis may reflect the characteristics of workplaces that are more likely to adopt algorithmic management, such as being more digitally advanced or offering higher-quality jobs, rather than the effects of algorithmic management itself.

The relationship with **working time flexibility** is generally positive but weaker. There is virtually no difference in access to this resource between employees subject to performance monitoring and those not subject to it (67 % versus 66 %, respectively). By contrast, working time flexibility is more common among those who report the use of automated task allocation (71 %) than those who do not (65 %), while automated scheduling is also associated with a higher prevalence, although the difference is smaller (68 % versus 66 %). Although this pattern may appear counter-intuitive, it does not necessarily imply that algorithmic management increases working time flexibility. Rather, it may reflect work settings in which digital systems are used to coordinate flexible working arrangements, for example by coordinating shift allocation or workers' availability. Given the cross-sectional nature of the data, these associations should not be interpreted as causal effects.

Table 5: Share of employees reporting job resources, by algorithmic management function (%)

	Automated task allocation (%)		Automated scheduling (%)		Performance monitoring (%)	
	No	Yes	No	Yes	No	Yes
Social support	82	85	82	84	83	82
Autonomy	47	51 ⇑	48	45 ⇓	48	46
Working time flexibility	65	71 ⇑	66	68	66	67
Training and learning opportunities	65	79 ⇑	67	74 ⇑	66	76 ⇑
Career advancement	14	19 ⇑	15	17	15	18
Rewards	77	76	**78**	**68 ⇓**	**78**	**70 ⇓**
Participation and voice	37	44 ⇑	38	39	38	37

Note: An upward arrow indicates higher prevalence and a downward arrow indicates lower prevalence of a job resource among employees subject to the algorithmic management function in question. Shading indicates statistically significant differences, and darker shading highlights the wider gaps. Green indicates instances of higher prevalence of a resource among employees subject to the algorithmic management function in question, while orange indicates lower prevalence.
Source: Authors' calculations.

For **social support**, differences between the two groups of employees are minimal. Social support is moderately more prevalent among employees who report automated task allocation (85 % versus 82 %) and automated scheduling (84 % versus 82 %). However, performance monitoring is associated with a slightly lower prevalence (82 % versus 83 %). A similarly mixed pattern is evident for **participation and voice**: levels are similar where scheduling is automated (39 %, versus 38 % where it is not) and performance is monitored (37 % versus 38 %), but where tasks are automatically allocated, the prevalence of this resource is substantially higher (44 % versus 37 %). This finding resonates with recent work suggesting that the effects of algorithmic management vary across functions. Whereas automated scheduling and performance monitoring are often experienced as direct forms of control, automated task allocation may be perceived more as a coordination tool, particularly where workers retain discretion over how tasks are completed. Parent-Rocheleau et al. (2024) highlight that algorithmic management should not be reduced to surveillance alone and that coordination-oriented uses may coexist with worker agency and more participatory forms of workflow organisation.

By contrast, **rewards** has the clearest negative relationship with at least two algorithmic management functions. While the difference in prevalence of rewards is marginal for automated task allocation (accessible to 76 % of employees who are subject to it versus 77 % of those who are not), automated scheduling is associated with the largest difference in rewards (68 % of those who are subject to it versus 78 % of those who are not). For performance monitoring, the prevalence of rewards is 8 percentage points lower among employees who experience it (70 % versus 78 %).

Autonomy follows a more uneven pattern: it is associated with slightly lower prevalence among employees subject to automated scheduling (45 % versus 48 %) and performance monitoring (46 % versus 48 %), but somewhat higher prevalence among those subject to automated task allocation (51 % versus 47 %).

These findings align more closely with the dominant literature on algorithmic management, which frequently links monitoring and scheduling to reduced worker discretion, information asymmetries, and weaker perceptions of fairness and recognition (Eurofound, 2025). They are also consistent with the effort–reward imbalance model (Siegrist, 2017), according to which increased demands combined with lower recognition or perceived rewards are likely to generate strain and undermine well-being.

Statistical tests

To assess whether the descriptive differences in the experience of job demands and access to job resources between employees subject and not subject to algorithmic management (shown in Tables 4 and 5) are statistically significant, a series of statistical tests (*t*-tests) were conducted (results not included in the report but available on request). Almost all confirmed significant associations between algorithmic management and the job demands and resources considered. A few exceptions stand out: social support shows no significant difference related to automated scheduling or performance monitoring, rewards do not differ related to automated task allocation, and physical risks and working time flexibility show no significant differences related to performance monitoring and automated scheduling.

Variations in job demands and resources under algorithmic management

Job demands

The results of a regression analysis presented in simplified form in Table 6 show that algorithmic management functions and higher overall algorithmic management intensity are significantly (and positively) associated with job demands. In particular, employees who are subject to automated task allocation, automated scheduling and performance monitoring and who score higher on algorithmic management intensity are more likely to report quantitative, emotional and social demands. In addition, employees subject to automated scheduling, performance monitoring and who experience higher overall algorithmic management intensity are also more likely to report physical risks, time-related demands, and financial and job insecurity. These findings are in line with recent research showing that algorithmic management is commonly associated with more demanding working conditions (Eurofound, 2025).

Algorithmic management functions are significantly associated with higher job demands, but the relationship with job resources is more mixed.

Table 6: Summary of regression analysis results for the associations between algorithmic management functions and intensity, and job demands and resources

	Automated task allocation	Automated scheduling	Performance monitoring	Algorithmic management intensity
Job demands				
Physical risks	NS	+	+	+
Physical demands	+	NS	+	+
Quantitative demands	+	+	+	+
Emotional demands	+	+	+	+
Social demands	+	+	+	+
Time-related demands	NS	+	+	+
Financial and job insecurity	NS	+	+	+
Job resources				
Social support	NS	NS	–	NS
Autonomy	+	NS	–	NS
Working time flexibility	+	NS	–	–
Training and learning opportunities	+	NS	+	+
Career advancement	+	NS	+	+
Rewards	NS	–	–	–
Participation and voice	+	NS	NS	+

Notes: '+' denotes a statistically significant positive coefficient, '–' denotes a statistically significant negative coefficient and 'NS' indicates a coefficient that is not statistically significant. Signs reflect the direction of the association between the algorithmic management function or algorithmic management intensity and the job demand or resource.
Source: Authors' calculations.

Job resources

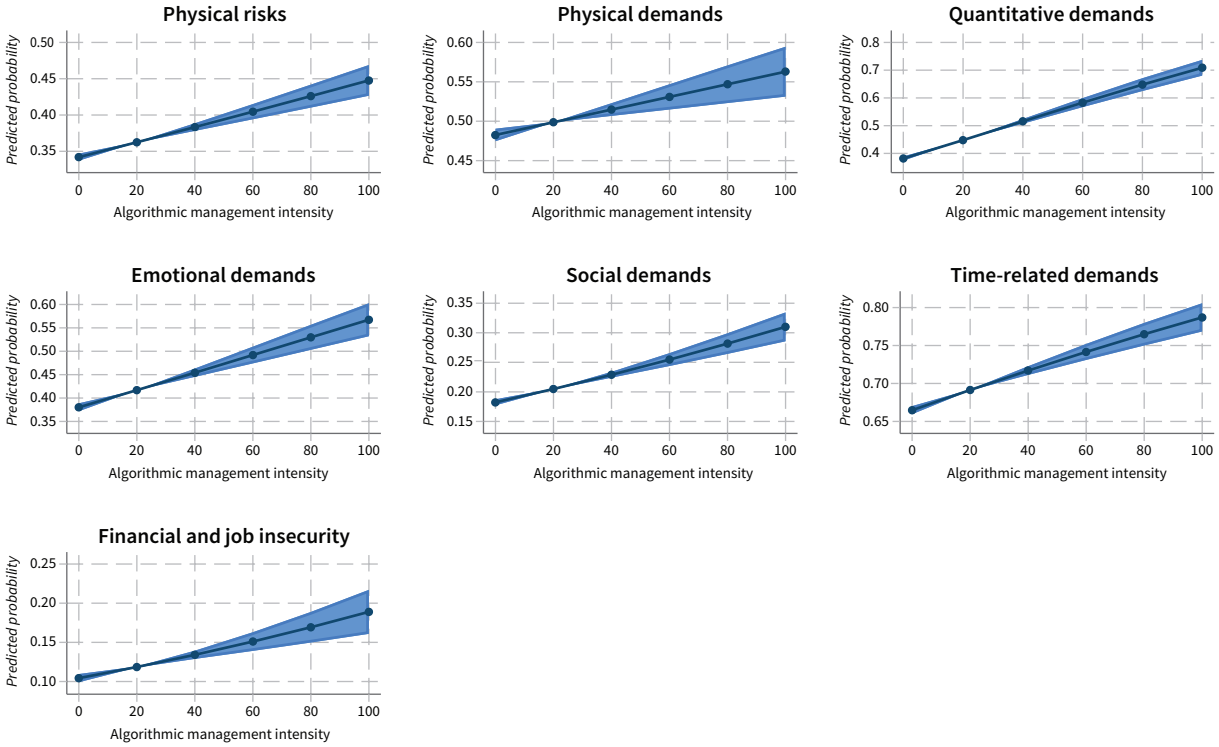
The associations with job resources are more mixed. Employees who report the use of some algorithmic management functions are more likely to report access to training and learning opportunities, career advancement, and participation and voice, particularly in relation to performance monitoring, automated task allocation and overall algorithmic management intensity. By contrast, working time flexibility, rewards and social support are less likely to be reported among employees subject to certain algorithmic management functions, especially performance monitoring.

Autonomy shows a contrasting pattern: employees subject to automated task allocation are more likely to report autonomy, whereas those subject to performance monitoring are less likely to report it, suggesting that different algorithmic management functions may be associated with different levels of control over work. This mixed pattern reflects the distinction highlighted by Noponen et al. (2023) between more controlling and more enabling uses of algorithmic management. While performance monitoring appears to be more closely associated with reduced access to some job resources and lower autonomy, automated task allocation may, in some workplaces, function in a more enabling or empowering way by helping employees organise work more efficiently and streamline work processes without requiring close supervision.

Algorithmic management intensity

Figures 17 and 18 show the predicted probability of employees reporting job demands and job resources across increasing levels of algorithmic management intensity, after controlling for other factors. In each panel, the dark blue line shows the predicted probability of reporting a given job demand or job resource as algorithmic management intensity increases from low to high. The light blue shaded area around the line represents the confidence interval, indicating the degree of statistical uncertainty around the estimate: narrower bands indicate more precise estimates, while wider bands suggest greater uncertainty.

Figure 17: Summary of regression results for the association between job demands and algorithmic management intensity



Source: Authors' calculations.

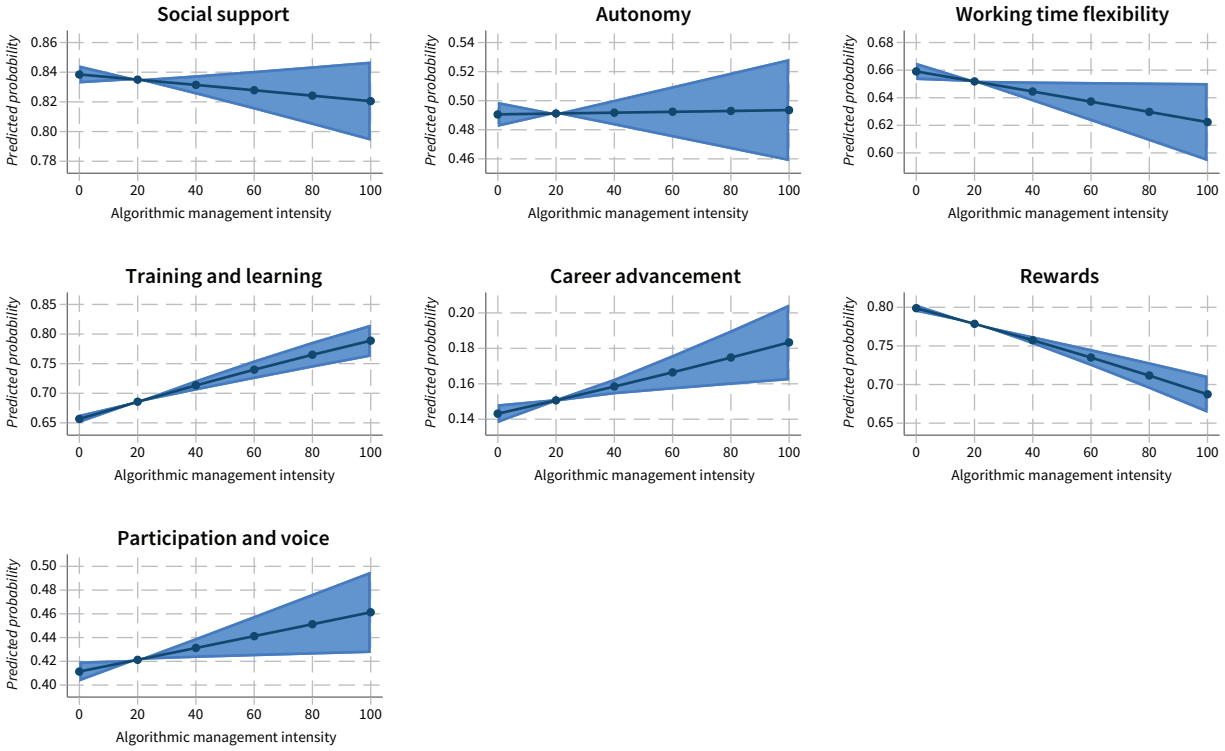
Figure 17 shows that, as algorithmic management intensity increases, employees become more likely to report job demands across all seven dimensions. In practical terms, this means that employees subject to more intensive forms of algorithmic management are more likely to experience more demanding and potentially less favourable working conditions, including heavier workload, tighter time pressure, greater emotional strain, higher levels of physical demands and risks, and increased financial and job insecurity. The biggest increases are observed for quantitative demands, time-related demands and emotional demands, suggesting that these aspects of work become particularly more common with the greater use of algorithmic management.

The estimates are more precise for quantitative demands, where the confidence intervals remain relatively narrow across the range of algorithmic management intensity. By contrast, there is greater uncertainty around the estimates for financial and job insecurity and physical demands, particularly at higher levels of algorithmic management intensity, where the confidence intervals widen.

The relationship between algorithmic management intensity and job resources is more mixed (Figure 18). As the intensity of algorithmic management increases, employees are more likely to report access to training and learning opportunities, career advancement, and participation and voice, suggesting that some forms of algorithmic management may coexist with opportunities for development and involvement in work processes. By contrast, higher algorithmic management intensity is associated with a lower likelihood of reporting rewards and working time flexibility, while social support also shows a slight downward trend. Autonomy remains broadly stable across the range of algorithmic management intensity values.

The estimates are comparatively more precise for rewards, and training and learning opportunities. By contrast, there is greater uncertainty around the estimates for the other job resources, particularly at higher levels of algorithmic management intensity, where the confidence intervals widen.

Figure 18: Summary of regression results for the association between job resources and algorithmic management intensity



Source: Authors' calculations.

Algorithmic management and health and well-being outcomes

Having established that algorithmic management is associated with differences in job demands and job resources, and given that job demands and job resources affect health and well-being outcomes, the next step is to examine the relationship between algorithmic management and those outcomes. Building on this analysis, Chapter 3 will examine how the use of algorithmic management influences the relationship between job strain – a summary indicator that combines job demands and job resources – and health and well-being outcomes.

Table 7 indicates whether each algorithmic management function is significantly associated with four selected health and well-being outcomes. Statistically significant associations are marked with asterisks. The well-being outcomes in Table 7 are derived from individual survey items scored on a scale from 0 to 100, where 0 represents the most negative outcome and 100 represents the most positive outcome. A negative sign indicates a negative association between the algorithmic management function and the health and well-being outcome, while a positive sign indicates a positive one. In the case of exhaustion, a negative sign denotes a lower score, which means higher exhaustion. The four outcomes analysed here are as follows.

- **Well-being**, which captures positive aspects of mental health, in line with the World Health Organization's core dimensions. It covers five items assessing individuals' interest in everyday activities, vitality and overall positive affect (for example, feeling happy or being in a good mood). The average score in the sample is 69.2.
- **Engagement**, which has three dimensions: vigour ('at my work I feel full of energy'), dedication ('I am enthusiastic about my job') and absorption ('time flies when I am working'). The average score in the sample is 70.6.
- **Exhaustion**, which is measured using two components: physical exhaustion ('I feel physically exhausted at the end of the working day') and emotional exhaustion ('I feel emotionally drained by my work'). These are some of the symptoms of burnout. Because the exhaustion scale is reverse-coded, higher scores on the exhaustion index indicate lower levels of exhaustion. The average score in the sample is 59.6.
- **Work–family conflict**, which combines three survey items: worrying about work when not working, which reflects stress and mental workload; feeling too tired after work to complete household tasks, which indicates physical or mental exhaustion; and work preventing sufficient time with family, signalling an imbalance between professional and personal life. Higher scores on the index indicate lower levels of work–family conflict. The average score in the sample is 65.2.

The regression results shown in Table 7 indicate that the three algorithmic management functions are associated with slightly different patterns of employee well-being, but with generally more negative than positive relationships. Performance monitoring stands out as the most consistently detrimental practice, showing significantly negative associations across all observed outcomes: lower overall well-being and engagement, and higher levels of exhaustion and work–family conflict.

Of the three algorithmic management functions, performance monitoring stands out as the one most significantly associated with poorer health and well-being outcomes.

Automated scheduling is also associated with significantly lower scores on both the exhaustion index and the work–family conflict index, indicating higher levels of exhaustion and work–family conflict. However, no significant association is observed between automated scheduling and well-being or engagement.

Automated task allocation presents a more mixed picture. While it is associated with higher levels of work–family conflict, it is also positively linked to engagement and shows no significant relationship with well-being or exhaustion. This suggests that some forms of algorithmic management may enhance aspects of employee engagement, while still putting pressure on employees' time and work–life boundaries. It should also be noted that most of the effects are rather small, with between 1.2 and 4.0 points of difference on a 0–100 scale.

Table 7: Associations between algorithmic management functions and health and well-being outcomes

	Well-being	Engagement	Exhaustion	Work–family conflict
Automated task allocation	NS	1.209*** (0.391)	NS	–1.743*** (0.496)
Automated scheduling	NS	NS	–4.035*** (0.996)	–2.839*** (0.688)
Performance monitoring	–1.532*** (0.481)	–1.256** (0.474)	–3.724*** (0.688)	–3.875*** (0.661)

Notes: The table presents the results from a linear regression model, controlling for gender–age group, education, permanent contract, occupation, sector, workplace size, presence of formal employee representation, telework and Member State. Asterisks indicate the level of statistical significance: * marginally significant ($p < 0.10$); ** significant ($p < 0.05$); and *** highly significant ($p < 0.01$). 'NS' denotes results that are not significant. Because the exhaustion scale is coded as 0 = high exhaustion and 100 = low exhaustion, a negative coefficient means a higher level of exhaustion (a worse outcome).
Source: Authors' calculations.

Chapter 2 key takeaways

- The prevalence of job demands and job resources varies substantially across sectors and occupations, with manual and lower-skilled employees experiencing the highest demands and the lowest access to resources. The association between algorithmic management and higher job demands suggests that digital management practices may interact with and, depending on the specific algorithmic management function involved, potentially reinforce existing inequalities in working conditions.
- While algorithmic management is associated with higher job demands, particularly quantitative demands, its relationship with job resources is more mixed. Performance monitoring tends to be linked to lower levels of autonomy, flexibility and rewards, whereas automated task allocation is more often associated with better access to resources such as autonomy and employee participation. This suggests that algorithmic management should not be viewed as a single, uniform phenomenon, but rather as a set of practices with potentially different implications for employees.
- Compared with the other two algorithmic management functions (automated task allocation and automated scheduling), performance monitoring stands out as the most problematic practice, being associated with lower well-being and work engagement and higher levels of exhaustion and work–family conflict.

3 Job strain and algorithmic management

Summary

About a quarter (24 %) of EU employees experience job strain, working in jobs with high demands that are not adequately offset by the available job resources. Nearly half of EU employees, however, are in relatively well-resourced jobs, although this varies widely across Member States. The most favourable conditions are found in northern and western–continental European Member States, whereas southern European Member States, especially Greece, have the highest levels of strain and the lowest levels of job resources.

Job strain differs more by sector than by Member State, being lowest in knowledge-intensive fields and highest in labour-intensive, customer-facing sectors. It also follows a clear occupational gradient, with employees in lower-skilled roles experiencing much higher job strain. Age slightly reduces strain, and gender differences are modest overall.

Higher levels of job strain are significantly associated with poorer outcomes across the four selected health and well-being indicators. A clear gradient is observed, with progressively lower well-being and engagement, higher work–family conflict and poorer exhaustion outcomes as job strain increases.

Employees subject to algorithmic management generally report higher levels of job strain than those not subject to it, although the strength of this association varies across the three functions. The relationship is weakest for automated task allocation but more pronounced for automated scheduling and performance monitoring.

The combined impact of algorithmic management and job strain on health and well-being outcomes is mixed. The association between automated task allocation and health and well-being outcomes does not differ between strained and non-strained employees. By contrast, the combination of performance monitoring and job strain is associated with higher levels of exhaustion and work–family conflict and lower levels of engagement than would be expected from either factor alone. Somewhat surprisingly, the negative associations observed between automated scheduling and exhaustion and work–family conflict appear to be attenuated for employees in already strained jobs. However, these interaction effects are weak and should be interpreted with caution.

The previous chapter presented findings showing associations between algorithmic management and higher job demands, particularly quantitative, time-related and emotional demands. Its relationship with job resources is more mixed. However, examining job demands and job resources separately provides only a partial picture of job quality. High job demands do not necessarily translate into adverse outcomes if workers have access to sufficient resources – such as autonomy, participation, support or flexibility – to help them cope with these pressures. Even moderate demands may become problematic when resources are lacking. It is therefore important to consider job demands and job resources together and to examine the balance between them.

This balance is captured by the concept of 'job strain', which refers to situations where workers experience high job demands that are not adequately offset by the available job resources. The job strain indicator, as discussed in the Introduction, summarises, for each employee, the difference between seven job demands and seven job resources, with negative values indicating that demands exceed resources. Examining job strain therefore allows for a more exhaustive analysis of whether algorithmic management is associated with poorer job quality than that possible when considering demands or resources in isolation.

Job strain is highly relevant from a policy perspective because it is closely linked to workers' health and well-being, labour market participation and retention, and organisational performance (Schaufeli et al., 2014; Saint-Martin et al., 2018; Murtin et al., 2022). This chapter therefore adopts a job strain perspective to examine how job demands and job resources combine within jobs. It begins by establishing a baseline picture of the workforce showing the distribution of workers across the range of job quality profiles, from high-strain jobs characterised by high demands and limited resources to highly resourced jobs where demands are balanced by higher levels of support. The chapter then investigates the extent to which algorithmic management is associated with job strain and whether it affects the relationship between job strain and employees' health and well-being.

Distribution of job strain in European workplaces

Around a quarter of employees in the EU (24 %) hold strained jobs: extreme and high strain together account for 15 % of employees, the more acute end of the distribution, with the remaining 10 % in jobs with moderate strain (Figure 19). By contrast, close to half of employees have well-resourced jobs: 29 % are in moderately resourced and 20 % are in highly resourced jobs, while the remaining 26 % are in low resourced jobs. These EU averages conceal wide variation across Member States, and that variation is widest at the top of the resourced-jobs distribution: the strained share ranges from 12 % in the Netherlands to 41 % in Greece, while the highly resourced share ranges from 3 % in Greece to 36 % in Denmark.

Member State

The most favourable job profiles cluster in the northern and western–continental European Member States. The Netherlands and Denmark stand clearly apart: only 7 % and 8 % of the employees in these countries, respectively, are in jobs with acute strain (extreme and high strain combined), the smallest shares in the EU, while the shares of employees in highly resourced jobs (35 % and 36 %, respectively) are the largest in the EU. Austria has the third largest share of employees in highly resourced jobs (29 %), while Belgium, Finland, Ireland, Luxembourg and Sweden each have a quarter or more of their employees in the top resourced-jobs band. Germany presents a distinctive pattern: it has the largest share of employees in moderately resourced jobs (34 %), alongside a more modest share in highly resourced jobs (23 %). The share of employees in jobs

Figure 19: Distribution of job strain, by Member State (%)



Note: Figures are rounded to the nearest whole number; as a result, totals may not sum to exactly 100 %.
Source: Authors' calculations.

with acute strain is well below the EU average in Austria, Germany, Finland, Ireland and Luxembourg, ranging between 9 % and 12 %. Sweden is a partial exception to this trend: its share of employees in highly resourced jobs sits at 26 %, while its share of employees in jobs with acute strain reaches 16 %. This latter value is well above those of the rest of the group and is explained by Sweden having one of the larger extreme-strain shares (5 %), pointing to a more polarised distribution of job quality.

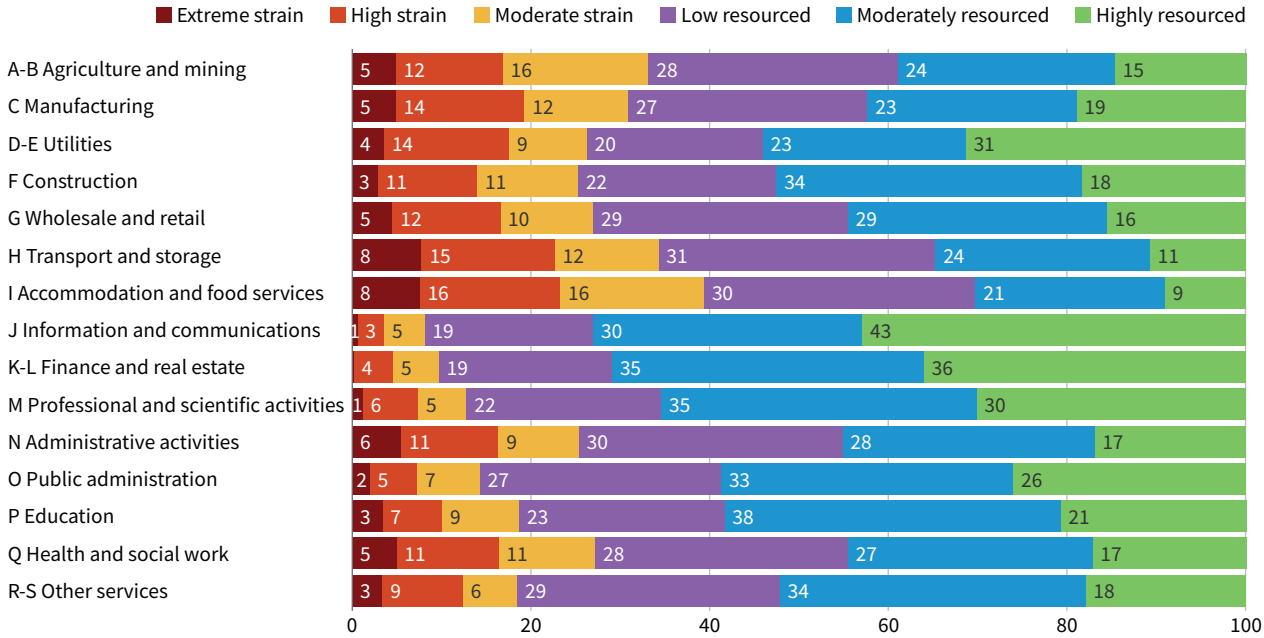
The largest shares of employees in strained jobs are concentrated in the southern European Member States. In this group, Greece stands out: 24 % of its employees are in jobs with acute strain, the largest such share in the EU, reinforced by an almost equally large moderate-strain band (17 %). At the same time, only 3 % of employees in Greece are in the top resourced-jobs band, the smallest share in the EU. Cyprus (23 % in jobs with acute strain and 12 % in highly resourced jobs), Spain (20 % and 16 %), Portugal (19 % and 11 %) and Italy (18 % and 16 %) follow the same pattern: a large acute-strain base and a compressed share in the top resourced-jobs band, with none of these Member States having more than 1 in 6 employees in highly resourced jobs. Malta is the exception, with acute strain totalling 14 %, below the EU average, and just over half of its employees in moderately or highly resourced jobs (51 %).

Central and eastern European Member States form a more heterogeneous group. At one end, Croatia and Romania rank just behind Greece on the share of employees holding acute-strain jobs (22 %, compared with 24 % for Greece). Croatia's position is driven by the joint largest share of employees with extreme-strain jobs in the EU (8 %), while Romania combines large shares of acute-strain jobs with the second smallest group of highly resourced jobs in the EU (8 %). Czechia (21 %) and Hungary (16 %) also have above-average shares of acute-strain jobs. At the other end, the distribution of jobs in Estonia and Slovenia resembles those of western–continental Member States: small shares of acute-strain jobs (both 12 %) and larger shares of highly resourced jobs (26 % and 25 %, respectively). Slovakia has the clearest case of employment polarisation, pairing a slightly above-average share of acute-strain jobs (15 %) with one of the largest highly resourced groups in the EU (26 %), which indicates a wide internal dispersion of job quality. Estonia, Latvia and Slovenia sit closer to the continental core than to the other central and eastern European economies with which they are often grouped, while Lithuania, with its above-average acute-strain share (17 %) and relatively large share of highly resourced jobs (21 %), occupies a more mixed middle position.

Sector

Job strain varies more across sectors than across Member States (Figure 20). The share of employees in strained jobs ranges from 8 % in information and communications to 40 % in accommodation and food services, an almost fivefold difference. Sector therefore differentiates the distribution of strained jobs more strongly than Member State of employment does. Acute strain (combining extreme and high strain) is lowest in knowledge-intensive and public sector services, where work is cognitively demanding but also autonomous and well rewarded, and highest in labour-intensive,

Figure 20: Distribution of job strain, by sector (%)



Note: Figures are rounded to the nearest whole number; as a result, totals may not sum to exactly 100 %.
Source: Authors' calculations.

customer-facing and physically demanding sectors, where high demands are combined with limited resources.

The most favourable conditions are found in knowledge-intensive services. Information and communications has the lowest acute strain of any sector (4 %) and the largest share of employees holding highly resourced jobs (43 %). Finance and real estate (5 % acute strain, 36 % highly resourced), professional and scientific activities (7 % and 30 %) and public administration (7 % and 26 %) follow, while the education sector combines a small share of acutely strained jobs (10 %) with a larger share of highly resourced jobs (21 %). Extreme strain is almost absent in these sectors, at 0.2 % in finance and real estate and 0.7 % in information and communications, against an EU average of 4 %.

The opposite pattern is found in the contact-intensive and physically demanding sectors. Accommodation and food services has the largest share of acute-strain jobs (24 %, including 8 % extreme strain) and the smallest highly resourced group (9 %). Transport and storage follows closely behind, with a combined 23 % of jobs in the acute-strain category, the joint largest extreme-strain share of any sector (8 %) and a highly resourced share of 11 %. Manufacturing and agriculture and mining (19 % and 17 % of employees, respectively, in acutely strained jobs) come next, although the composition of the extreme- and high-strain shares in these two sectors differs: agriculture and mining has the larger total strained share (33 %, against 31 % in manufacturing) but with strain concentrated in the moderate band, whereas manufacturing has a larger share of jobs in the high-strain category. Highly resourced shares in these four sectors lie between 9 % and 19 %, and total moderately and highly resourced shares between 30 % and 42 %, roughly half the levels observed in the knowledge-intensive services.

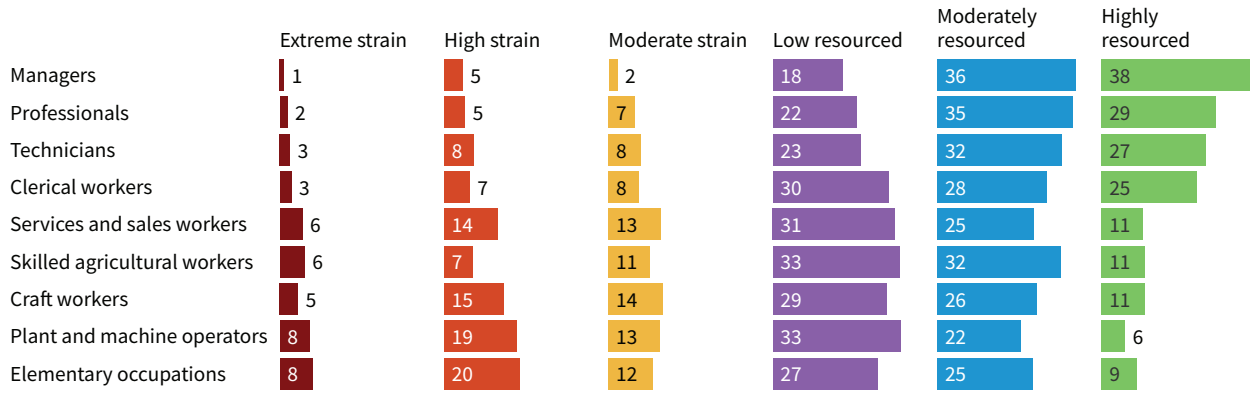
Several sectors occupy an intermediate position. Health and social work has above-average employment shares in acute-strain jobs (16 %, of which 5 % are extreme-strain jobs) and a below-average highly resourced share (17 %), reflecting care-related demands that are only partly offset by the resources available. Construction lies just below the EU average on acute-strain jobs (14 %), has the lowest extreme-strain rate among the more demanding sectors (3 %) and has the majority of its jobs falling into the resourced category. Utilities is the most polarised sector, combining an above-average acute-strain share (18 %) with the third largest highly resourced group in the EU (31 %). Administrative services combines an above-average acute-strain share (16 %) and elevated extreme-strain rate (5 %) with a below-average highly resourced share (17 %).

Occupation

Job strain follows a clear occupational gradient (Figure 21). Acute strain rises steadily moving down the skills ladder: from 6 % among managers and 7 % among professionals, both well below the EU average of 15 %, to 27 % among plant and machine operators and peaking at 28 % among elementary occupations. Technicians (11 %) and clerical workers (10 %) are also below the average, while services and sales workers (20 %) and craft workers (20 %) sit clearly above it.

While one in four EU employees is in a strained job, the burden falls disproportionately on lower-skilled employees and those in labour-intensive sectors.

Figure 21: Distribution of job strain, by occupation (%)



Note: Figures are rounded to the nearest whole number; as a result, totals may not sum to exactly 100 %.
Source: Authors' calculations.

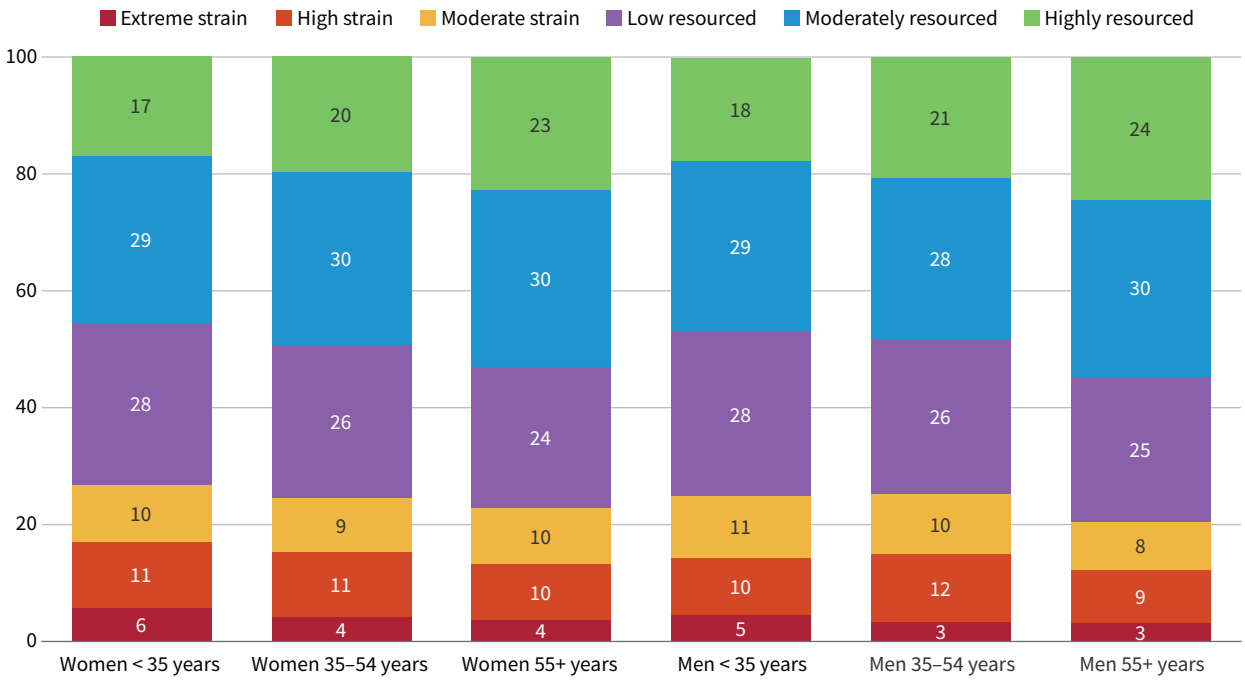
The distribution of resourced jobs mirrors this ordering: the highly resourced share falls from 38 % among managers to 6 % among plant and machine operators, and moderately and highly resourced shares combined fall from 74 % to 28 % between the same two groups. The majority of professionals, technicians and clerical workers are moderately or highly resourced (64 %, 59 % and 53 %, respectively), whereas the shares for manual and lower-skilled service occupations all fall below 45 %.

Age group and gender

Job strain is lower among older workers, while job resources tend to be higher. The age gradient in job strain is more pronounced among women than among men (Figure 22). These differences may reflect age-related patterns in working conditions, selection into different jobs or the selective retention of workers in less strained jobs. The combined moderately and highly resourced share rises steadily for both women and men with age, from around 46 % of employees under 35 years of age for both to 53 % for women and 54 % for men aged 55 years or over. The highly resourced share rises from about 17 % of employees under 35 for both to 23 % for women and 24 % for men aged 55 or over. Acute strain moves in the opposite direction: among women it falls monotonically with age, from 17 % for those under 35 to 15 % for those in the prime-age group (35–54 years) and then to 14 % for those aged 55 or over, whereas among men it is broadly flat across the youngest and prime-age bands (15 % and 15 %) before dropping to 12 % for those aged 55 or over.

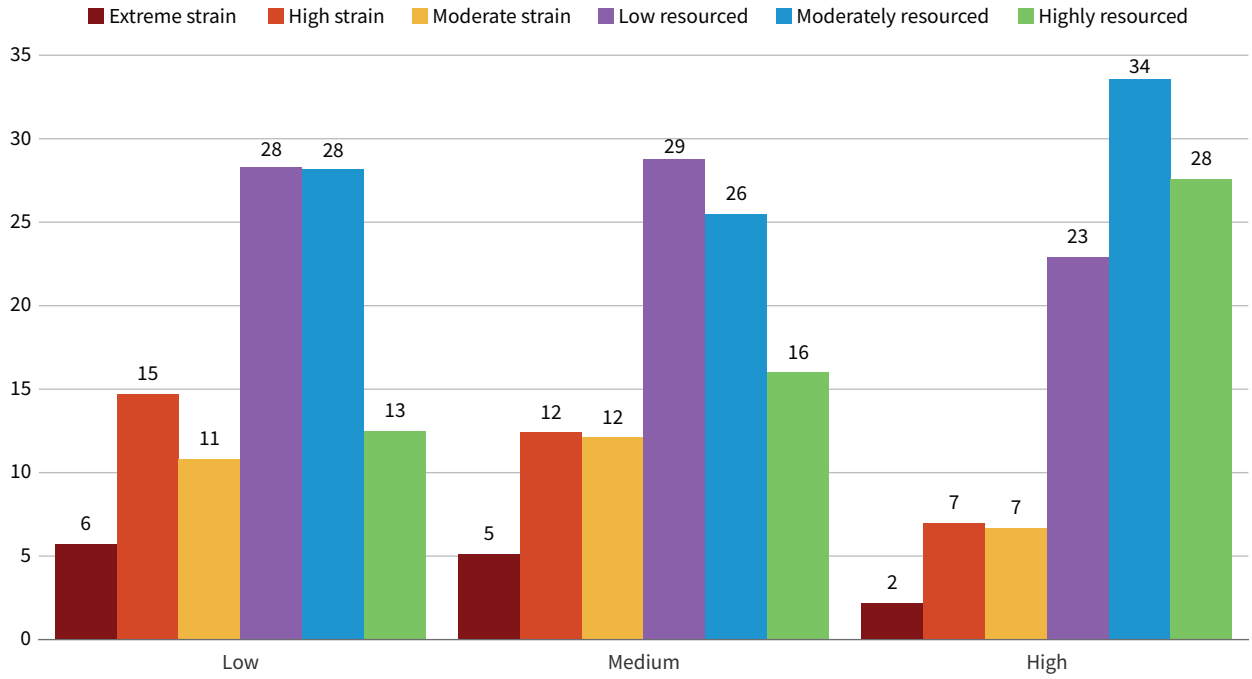
Differences by gender are smaller and do not move consistently in one direction. Looking at the share of acute-strain jobs, women are marginally more strained at work at every age, with the widest gap among those under 35 years (17 %, versus 15 % of men). However, when looking at the broader strained job category, this reverses in the prime-age band (men, 25 %; women, 24 %), reflecting a larger moderate-strain band among prime-age men. Young women stand out as the least resourced and most acutely strained of the six groups, with the smallest highly resourced share (17 %) and the largest extreme-strain share (6 %), an outcome that likely reflects their concentration in entry-level and less-resourced service roles early in their careers. However, gender differences are modest in absolute terms: across the six age-by-gender groups, the shares of acutely strained jobs range from 12 % to 17 % and the highly resourced shares range from 17 % to 24 %. Therefore, age and gender together differentiate job strain far less than sector or occupation does.

Figure 22: Distribution of job strain, by gender and age group (%)



Note: Figures are rounded to the nearest whole number; as a result, totals may not sum to exactly 100 %.
Source: Authors' calculations.

Figure 23: Distribution of job strain, by level of education (%)



Note: Figures are rounded to the nearest whole number; as a result, totals may not sum to exactly 100 %.
Source: Authors' calculations.

Educational attainment

Job strain varies considerably by educational level (Figure 23). The combined acute-strain share stands at 9 % among those with high education levels, well below the EU average of 15 %, but climbs to 17 % among those with medium education levels and 21 % among those with low education levels. The groups with low and medium education levels are otherwise broadly alike, with relatively similar total strained shares (32 % and 29 %, respectively) and combined moderately and highly resourced shares (41 % and 42 %, respectively), although the group with a low education level has a larger share of acute-strain employment.

The resourced side widens that divide: those with high levels of education show high and moderate resource levels at 62 %, against around 42 % for both other groups, and their highly resourced share, at 28 %, is more than double the 13 % recorded among those with low education levels. Extreme strain follows the inverse pattern, affecting 6 % of employees with low education levels but only 2 % of those with high education levels. Much of this protective effect operates indirectly, since education governs access to the autonomous, well-rewarded managerial and professional roles identified in the occupational breakdown above, while those with lower qualification levels remain concentrated in manual and lower-skilled service jobs where high demands meet scant resources. Consistent with that mechanism, education differentiates job strain more strongly than age or gender does but less than occupation or sector does.

Health and well-being across job strain categories

The next step is to examine the impact of job strain on employees' health and well-being, based on the four selected indicators introduced in Chapter 2. The results of a regression analysis, presented in Table 8, indicate a strong and significant association between job strain and all the selected health and well-being indicators. Relative to employees in highly resourced jobs (the reference category), those in highly strained jobs fare significantly worse on all indicators, even after accounting for a range of demographic, employment, workplace and Member State characteristics.

A clear gradient is evident for all outcomes: moving down the table from extremely strained jobs to moderately resourced jobs, the magnitude of the negative coefficients decreases steadily. This pattern suggests that higher levels of job strain are systematically associated with poorer outcomes across all indicators examined.

Table 8: Impact of job strain on selected health and well-being indicators

	Well-being	Engagement	Exhaustion	Work–family conflict
Highly resourced = baseline				
Extreme strain	–31.573*** (1.035)	–28.172*** (1.144)	–38.971*** (1.347)	–33.819*** (0.866)
High strain	–21.308*** (0.713)	–19.685*** (0.822)	–28.702*** (1.065)	–25.092*** (0.889)
Moderate strain	–15.998*** (0.718)	–14.079*** (0.745)	–21.844*** (1.023)	–18.992*** (0.745)
Low resourced	–10.725*** (0.396)	–9.652*** (0.537)	–16.449*** (0.748)	–14.173*** (0.568)
Moderately resourced	–5.587*** (0.307)	–4.508*** (0.337)	–8.859*** (0.571)	–7.798*** (0.413)

Notes: The table presents the results from a linear regression model, controlling for gender–age group, education, permanent contract, occupation, sector, workplace size, presence of formal employee representation, telework and Member State. Indicators are scored on a scale from 0 to 100, where 0 represents the least favourable outcome and 100 represents the most favourable outcome. The values indicate the score for each job-strain category compared with the score of the highly resourced category; the values in parentheses indicate the standard errors. Asterisks indicate the level of statistical significance: * marginally significant ($p < 0.10$); ** significant ($p < 0.05$); and *** highly significant ($p < 0.01$).
Source: Authors' calculations.

The strongest associations are observed for exhaustion. Compared with employees in highly resourced jobs, those experiencing extreme strain have exhaustion scores that are nearly 39 points lower, while employees in high-strain jobs score approximately 29 points lower. Similar gradients are observed for work–family conflict, where extreme strain is associated with scores that are nearly 34 points lower than those of employees in highly resourced jobs.

Well-being and engagement follow comparable patterns. Employees in extreme-strain jobs have well-being scores approximately 32 points lower and engagement scores around 28 points lower than those in highly resourced jobs. Although the magnitude of the association is somewhat smaller for engagement than for exhaustion and work–family conflict, the differences remain substantial.

All estimated coefficients are statistically significant at the 1 % level, indicating that the observed associations are highly unlikely to reflect random variation. The relatively small standard errors suggest that the estimates are precise.

Differences in job strain by use of algorithmic management

This section develops the investigation by examining the relationship between job strain and the use of algorithmic management. The results in Figure 24 show the six job strain categories into which employees fall, distinguishing between those who report the use or absence of each algorithmic management function examined in this report.

The mean job strain is significantly higher among employees subject to all three algorithmic management functions, with larger differences across performance monitoring and automated scheduling than automated task allocation ([2]).

Job strain is significantly and strongly associated with poorer health and well-being outcomes. Employees subject to algorithmic management are more likely to experience job strain.

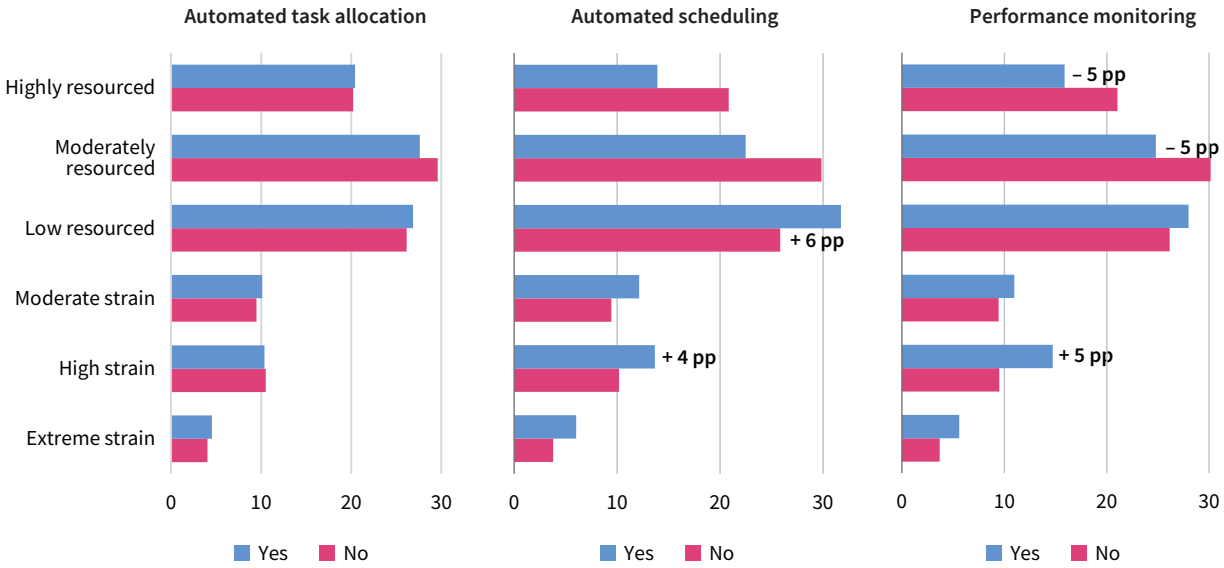
The strain categories give a more nuanced picture (Figure 24). Although the distribution of these categories varies based on whether employees report the use of each algorithmic management function, these differences are relatively small ([3]).

For automated task allocation, the share of employees in the extreme-strain category is 1 percentage point higher for those reporting its use than for those not reporting its use, while the share of highly strained employees is 1 percentage point lower and the share of moderately strained employees is the same. A similar pattern is observed across the resourced-job categories. For automated scheduling, 32 % of employees reporting its use fall into the three strain categories (extreme, high or moderate), compared with 23 % of those not reporting its use; the share of highly resourced employees is 14 % among those reporting automated scheduling and 21 % among those not reporting it.

([2]) The differences in the means between the groups were evaluated using a two-tailed Student's *t*-test.

([3]) Statistical significance was determined using Pearson's chi-squared (χ^2) tests of independence to evaluate the distributional differences between the groups.

Figure 24: Distribution of job strain, by algorithmic management function (%)



Note: pp, percentage points.
Source: Authors' calculations.

Performance monitoring shows a similar pattern: 31 % of monitored employees fall into the three strain categories, compared with 23 % of those not monitored, and 16 % of those reporting performance monitoring are highly resourced, compared with 21 % of those not reporting it.

It should be noted that the low resourced category follows the same pattern as the strain categories: employees subject to algorithmic management are more likely to fall into this category than those who are not. This concentration is highest for automated scheduling, where 32 % of employees reporting the use of this algorithmic management function are classified as low resourced, compared with 26 % of employees not reporting the use of automated scheduling. A similar difference occurs for performance monitoring, at 28 % versus 26 %.

Job strain and well-being under algorithmic management

The final stage of this investigation is to examine whether the relationship between the three algorithmic management functions and health and well-being outcomes differs based on levels of job strain. To this end, linear regression models were estimated that included interaction terms between each algorithmic management function and job strain. In a regression model, an interaction term tests whether the association between one independent variable and an outcome depends on the level of another independent variable. In the case of the current analysis, this shows whether algorithmic management strengthens or weakens the negative effects of job strain on employees' health and well-being.

Table 9 shows the regression results of the combined impact of job strain and the three algorithmic management functions on health and well-being outcomes. Job strain is measured as a binary variable, taking the value 1 for workers whose demands exceed the resources available to them and 0 otherwise. The first row shows the impact of job strain on each health and well-being outcome when all algorithmic management functions are absent (equal to 0). The next rows show, for each algorithmic management function (automated task allocation, automated scheduling and performance monitoring), first the impact on employees who are not strained and then (in the rows highlighted in orange) an interaction term that captures whether the main effect changes when strain is present.

To interpret the interaction correctly, it is necessary to first interpret the primary associations between job strain and the health and well-being outcomes, and the associations between the algorithmic management functions and the health and well-being outcomes. If the primary associations share the same direction as the interaction (either all positive or all negative), then the effects compound; if the associations point opposite ways, the two partly cancel out, so that their combination produces a smaller change than the sum of the two individual associations.

Table 9: Impact of the interaction between algorithmic management functions and job strain on health and well-being outcomes

	Well-being	Engagement	Exhaustion	Work–family conflict
Strained job (0/1)	–13.981*** (0.587)	–12.797*** (0.636)	–16.909*** (1.079)	–14.624*** (0.766)
Automated task allocation	NS	1.193*** (0.342)	NS	–1.599*** (0.473)
Automated task allocation x Strained	NS	NS	NS	NS
Automated scheduling	NS	NS	–3.902*** (0.969)	–2.696*** (0.645)
Automated scheduling x Strained	2.148* (1.258)	2.560** (1.118)	2.514* (1.291)	2.029* (1.080)
Performance monitoring	NS	NS	–2.368*** (0.579)	–2.544*** (0.554)
Performance monitoring x Strained	NS	–2.154** (0.827)	–1.429** (0.693)	–1.702* (0.834)

Notes: The table presents the results from a linear regression model, controlling for gender–age group, education, permanent contract, occupation, sector, workplace size, presence of formal employee representation, telework and Member State. Indicators are scored on a scale from 0 to 100, where 0 represents the least favourable outcome and 100 represents the most favourable outcome. Asterisks indicate the level of statistical significance: * marginally significant ($p < 0.10$); ** significant ($p < 0.05$); and *** highly significant ($p < 0.01$). The abbreviation 'NS' denotes that the coefficient is not statistically significant and was therefore omitted.
Source: Authors' calculations.

The impact of job strain in the absence of any of the three algorithmic management functions is straightforward: negative and highly statistically significant on all outcomes. The impact of the three algorithmic management functions in the absence of job strain is mixed: automated task allocation has no statistically significant association with well-being and exhaustion, it is negatively associated with work–family conflict (–1.6 points) and positively associated with work engagement (1.2 points). When combined with job strain, the associations remain unchanged (because the interaction is not significant).

The influence of automated scheduling in the absence of job strain also varies across the four outcomes: while automated scheduling is not significantly associated with well-being and engagement, it is negatively associated with exhaustion (–3.9 points) and work–family conflict (–2.7 points). However, the combined effect is one of attenuation, in that the interaction between automated scheduling and job strain is positive, although the statistical significance is very low. Similarly, when looking at well-being and engagement, the positive interaction coefficient may suggest that automated scheduling somewhat mitigates the negative impact of job strain.

This means that, while automated scheduling is negatively associated with health and well-being outcomes overall, the negative relationship tends to be less severe for workers in strained jobs than for workers in non-strained jobs.

While there is evidence suggesting that automated scheduling may facilitate unstable scheduling practices (Nguyen, 2021), it may also be the case that in already strained workplaces automated scheduling introduces an element of predictability to scheduling itself; it is also worth mentioning that any element of predictability associated with automated scheduling is likely to reflect regulatory constraints on working time and advance notice of shifts rather than a property of the technology itself. Harknett et al. (2021) found that reducing schedule uncertainty improves worker well-being and economic security. While their study acknowledges that workforce management algorithms often contribute to scheduling unpredictability, the findings also suggest that, when automated scheduling is implemented in ways that enhance schedule predictability, it may help attenuate some of the adverse effects associated with job strain.

Among the three algorithmic management functions, performance monitoring is associated with stronger negative health and well-being outcomes for employees already experiencing job strain.

The penultimate rows show first the impact of performance monitoring in the absence of job strain and then the interaction effect (the combined impact with job strain). Overall, performance monitoring has a negative association with scores for the exhaustion (–2.4 points) and work–family conflict (–2.5 points) outcomes, while its associations with overall well-being and engagement are not statistically significant. When combined with strain, performance monitoring associations are negative across all four outcomes and statistically significant for three of them: exhaustion (–1.4 points), work–family conflict (–1.7 points) and engagement (–2.2 points). This means that, for employees who are both monitored and strained, the negative impact of each compounds: their combination is associated with higher exhaustion and work–family conflict (reflected in the lower index scores for these

outcomes indicated by the values in Table 9) than the separate associations of monitoring or strain alone would produce. The combination is also associated with lower work engagement, although monitoring on its own has no significant association with engagement.

Performance monitoring appears to amplify the negative association between job strain and health and well-being outcomes by adding an additional layer of surveillance and evaluative pressure to already demanding work environments. Rather than merely providing feedback, performance monitoring can increase perceptions of continuous evaluation, work intensity and reduced autonomy, thereby exacerbating the psychological burden associated with high job demands. From a JD-R perspective, these features can be understood as additional job demands that further deplete employees' coping resources and intensify the adverse effects of job strain. These mechanisms are consistent with the observed interaction effects, although the data do not directly test the underlying processes through which monitoring may exacerbate the consequences of job strain.

This interpretation is supported by Glavin et al. (2024), who, using structural equation modelling on data from a large cross-sectional survey of over 3 500 Canadian workers, found that workplace surveillance was associated with higher job pressures, reduced autonomy and more privacy violations, which in turn were linked to greater psychological distress and lower job satisfaction. It is also consistent with Ball's (2021) systematic literature review on employee monitoring, which concluded that workplace surveillance often extends beyond the monitoring of task performance and may be perceived as intrusive, contributing to a blurring of the boundaries between work and private life.

Chapter 3 key takeaways

- Job strain affects nearly one in four EU employees and is driven more by sectoral and occupational characteristics than by Member State-level differences. Employees in lower-skilled, labour-intensive and customer-facing jobs experience the highest levels of strain, whereas those in knowledge-intensive occupations tend to benefit from more favourable working conditions. This is particularly important given the strong association between job strain and lower levels of well-being and engagement and higher levels of exhaustion and work–family conflict. The effects of algorithmic management should be considered within this broader context.
- All three algorithmic management functions are associated with higher levels of job strain, although the association is stronger for performance monitoring and automated scheduling than for automated task allocation.
- Performance monitoring warrants more scrutiny than the other algorithmic management functions, particularly in jobs characterised by job strain, for which the negative effects of performance monitoring on employee health and well-being appear to be compounded.

Conclusions and policy pointers

Conclusions

This report examined the prevalence of algorithmic management in European workplaces and analysed its impact on working conditions and employees' health and well-being. The analysis was operationalised through three algorithmic management functions: automated task allocation, automated scheduling and performance monitoring, and an algorithmic management intensity indicator.

The research findings show that algorithmic management has moved beyond platform work and entered conventional workplaces. It is concentrated in digitally intensive sectors – such as finance and real estate, and information and communications – but has also been implemented in sectors characterised by more standardised and tightly coordinated work processes, notably transport and storage. The use of algorithmic management is greatest among medium-skilled occupations, particularly clerical workers and technicians.

The findings suggest that the use of algorithmic management is associated not only with differences in prevalence across sectors and occupations but also with differences in work organisation. Employees subject to its use at work are more likely to report changes in task composition, including the removal of some tasks, the creation of new ones and greater interaction with colleagues. They also report a stronger reliance on numerical production or performance targets and machine-paced work. Performance monitoring and automated task allocation are associated with greater task standardisation, but this is not necessarily linked to more monotonous work. Both of these algorithmic management functions are associated with task complexity, suggesting that algorithmic management may standardise work processes without necessarily leading to deskilling.

One important finding is that algorithmic management is associated with higher job demands, especially quantitative demands, which constitute a key component of the work intensity dimension in Eurofound's EWCS job quality framework and have consistently been linked in the literature to adverse health and well-being outcomes (Eurofound, 2026). Employees who are managed by an algorithm are also more likely to experience job strain than those who are not subject to it. Moreover, among employees already experiencing job strain, performance monitoring appears to strengthen the negative associations with exhaustion, work–family conflict and engagement, suggesting that its negative impact on job quality may be particularly pronounced in already demanding work environments.

The findings indicate that algorithmic management should be considered not only as a technological innovation or a means of improving operational efficiency but also in relation to job design and job quality, particularly with respect to worker autonomy, opportunities for skills use and development, and work intensity. The results presented in this report suggest that the implications of algorithmic management for job quality depend on the specific functions through which it is implemented and their interaction with existing working conditions, particularly the balance between job demands and job resources.

Algorithmic management is unlikely to operate as a stand-alone workplace practice. Rather, it interacts with existing management practices, forms of work organisation and systems of employee representation. Understanding these interactions is important for explaining why similar technologies may be associated with different outcomes across workplaces and sectors. Greater use of qualitative and case-study research, particularly in sectors with a high prevalence of algorithmic management, would complement existing survey evidence and provide a richer understanding of how algorithmic management is implemented in practice, how employees perceive and experience these technologies, and the extent to which they are viewed as supportive, intrusive or fair. Such evidence would contribute to ongoing policy discussions on how the digital transformation of work can support the objective of creating and sustaining high-quality jobs in Europe.

Policy pointers

Supporting context-specific implementation

The findings highlight that algorithmic management is not confined to platform work, low-skilled occupations or sectors traditionally associated with poorer job quality. At the same time, its distribution is uneven across Member States, sectors, occupations and workplace settings. Algorithmic management is more common among medium-skilled occupational groups, including clerical workers, technicians, and plant and machine operators, while prevalence is also high in finance and real estate, and information and communications. These findings suggest that, while common baseline protections should apply across all workplaces, their implementation can be supported by practical guidance and examples that reflect the different organisational contexts in which algorithmic management is used. In addition to regulatory guidance, the development and dissemination of company- and sector-level good practices could support organisations in implementing algorithmic management systems in ways that protect job quality and workers' well-being.

Safeguarding job quality

Algorithmic management is associated with higher job demands, particularly quantitative demands. While this may partly reflect its adoption in already demanding work environments, it may also reinforce existing pressures if implemented without adequate safeguards, especially in jobs that are already highly demanding. Employees subject to algorithmic management are also more likely to experience an unfavourable balance between job demands and resources. These findings suggest that the use of algorithmic management can have significant implications for job quality. They highlight the importance of having appropriate safeguards that not only address work intensity and pace but also ensure that employees have the resources and support needed to cope with job demands.

Safeguarding against the heightened risks of performance monitoring

Performance monitoring stands out as the most widespread form of algorithmic management, and it is significantly associated with higher job demands and lower access to resources. It is also negatively associated with health and well-being outcomes. These adverse associations are stronger among employees experiencing job strain, suggesting that performance monitoring may amplify the effects of demanding work conditions. This highlights the importance of considering digital monitoring within the broader psychosocial work environment, particularly in settings characterised by high demands and limited resources. Safeguards around digital monitoring should include clear information on what is tracked, how data are used, how performance is assessed and how monitoring informs decisions. The effective enforcement of labour and data protection rules, alongside stronger information, consultation and collective bargaining rights, can help ensure that workers are able to understand, question and shape these systems.

Addressing employer responsibility and governance

At the organisational level, employers play a central role in ensuring the responsible deployment of algorithmic management tools, whether these are AI based or not, and protecting the safety, health and welfare of employees at work as part of their duty of care. This includes establishing clear governance, assessing impacts on working conditions and well-being, and involving employees and their representatives in consultations before introducing or modifying algorithmic systems in workplaces. Given the higher uptake of algorithmic management in larger workplaces, particular attention may be needed to ensure its responsible deployment and use in large organisations. Where relevant risks are identified, existing obligations and safeguards under labour, data protection and AI legislation should be applied effectively.

Supporting small and medium-sized enterprises

Given that the use of algorithmic management remains concentrated in particular sectors, occupations and larger workplaces, policy support should be proportionate to organisations' needs. Many small and medium-sized enterprises are more likely to acquire commercially available digital work management tools than develop their own systems. Practical guidance, training and capacity building can help smaller firms understand how these tools operate, identify potential risks and biases, comply with existing legal obligations, and introduce the tools responsibly while engaging constructively with employees and their representatives.

Enabling a human-centred redesign of jobs in the digital workplace

By removing, introducing and reshaping tasks and interactions, algorithmic management changes both job content and the organisation of work. The research findings suggest that it can also influence the pace of work through machine-driven monitoring and performance targets, with potential implications for work intensity and employee well-being. This points to the need for a human-centred redesign of jobs when algorithmic management tools are introduced. Policymakers could support employers in this process by providing guidance and promoting task-level impact assessments and employee consultation. Beyond task

automation, the central challenge lies in how work is redesigned to ensure that productivity gains are achieved without undermining job quality and employee well-being.

Harnessing the potential of algorithmic management

Policy should not only address the potential risks of algorithmic management but also support a better understanding of the conditions under which it can contribute positively to job quality. The positive associations observed for automated task allocation and automated scheduling suggest that some forms of algorithmic management can be implemented in ways that support job resources and employee well-being. Understanding the organisational conditions, design choices, and technological and managerial practices associated with these positive outcomes can help inform guidance, identify good practices and support the responsible design and implementation of algorithmic management systems.

Strengthening the evidence base

Continued investment in producing comparative evidence at national and EU levels, ongoing monitoring and in-depth investigation of company practices can strengthen the evidence base for policymaking on algorithmic management. Better understanding how algorithmic management is implemented in practice, how employees experience and understand it, and how it is embedded in work organisation, work practices and digital systems can help identify effective safeguards, support convergence in employee protections and ensure that digitalisation enhances job quality.

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Annexes

Annex 1: Chapter 1 full regression results

Table A1: Algorithmic management functions: probit and ordinary least squares regression results (predicted probabilities with 95 % confidence intervals)

	Automated task allocation	Automated scheduling	Performance monitoring	Algorithmic management intensity
Gender and age				
Female: < 35	0.199 [0.182, 0.216]	0.117 [0.103, 0.131]	0.228 [0.216, 0.240]	20.590 [19.456, 21.724]
Female: 35–54	0.195 [0.185, 0.205]	0.106 [0.099, 0.113]	0.193 [0.185, 0.202]	18.461 [17.778, 19.143]
Female: 55+	0.209 [0.195, 0.223]	0.103 [0.094, 0.113]	0.189 [0.178, 0.200]	18.322 [17.437, 19.207]
Male: < 35	0.242 [0.229, 0.256]	0.133 [0.119, 0.148]	0.235 [0.221, 0.249]	23.034 [21.597, 24.471]
Male: 35–54	0.208 [0.197, 0.220]	0.111 [0.102, 0.119]	0.111 [0.102, 0.119]	20.086 [19.204, 20.968]
Male: 55+	0.183 [0.165, 0.201]	0.110 [0.094, 0.126]	0.176 [0.162, 0.189]	18.345 [16.928, 19.761]
Education level				
High education level	0.211 [0.201, 0.221]	0.119 [0.112, 0.126]	0.204 [0.195, 0.213]	20.018 [19.320, 20.717]
Medium education level	0.206 [0.196, 0.217]	0.108 [0.101, 0.116]	0.204 [0.194, 0.214]	19.822 [18.954, 20.690]
Low education level	0.165 [0.138, 0.191]	0.095 [0.080, 0.109]	0.168 [0.150, 0.186]	16.925 [15.246, 18.603]
Contract				
No permanent contract	0.197 [0.177, 0.217]	0.114 [0.096, 0.131]	0.205 [0.182, 0.228]	18.958 [17.352, 20.563]
Permanent contract	0.205 [0.203, 0.208]	0.112 [0.110, 0.114]	0.200 [0.197, 0.203]	19.692 [19.480, 19.904]
Occupational group				
Managers	0.222 [0.198, 0.247]	0.099 [0.080, 0.119]	0.178 [0.162, 0.195]	19.648 [17.666, 21.631]
Professionals	0.206 [0.192, 0.221]	0.108 [0.097, 0.120]	0.201 [0.185, 0.216]	19.913 [18.539, 21.288]
Technicians	0.244 [0.231, 0.257]	0.116 [0.103, 0.129]	0.234 [0.221, 0.248]	22.406 [21.513, 23.299]
Clerical workers	0.283 [0.264, 0.303]	0.132 [0.115, 0.148]	0.252 [0.236, 0.267]	25.023 [23.512, 26.533]
Service and sales workers	0.161 [0.147, 0.175]	0.111 [0.099, 0.124]	0.171 [0.157, 0.185]	17.452 [16.458, 18.447]
Skilled agricultural workers	0.114 [0.040, 0.188]	0.097 [0.031, 0.163]	0.107 [0.042, 0.173]	13.452 [8.849, 18.055]
Craft workers	0.184 [0.163, 0.205]	0.111 [0.097, 0.126]	0.182 [0.166, 0.199]	17.434 [15.919, 18.948]
Plant and machine operators	0.190 [0.166, 0.214]	0.125 [0.102, 0.147]	0.239 [0.213, 0.265]	20.604 [18.465, 22.742]
Elementary occupations	0.147 [0.126, 0.168]	0.091 [0.078, 0.103]	0.150 [0.134, 0.165]	15.239 [13.942, 16.535]
Sector				
A–B – Agriculture and mining	0.129 [0.093, 0.165]	0.061 [0.033, 0.090]	0.122 [0.075, 0.169]	14.418 [11.704, 17.133]
C – Manufacturing	0.224 [0.207, 0.240]	0.114 [0.103, 0.125]	0.223 [0.205, 0.240]	20.814 [19.710, 21.919]
D–E – Utilities	0.212 [0.177, 0.247]	0.138 [0.110, 0.166]	0.202 [0.156, 0.248]	20.465 [17.545, 23.385]
F – Construction	0.140 [0.109, 0.172]	0.075 [0.057, 0.093]	0.129 [0.112, 0.146]	14.558 [12.723, 16.392]
G – Wholesale and retail	0.227 [0.211, 0.244]	0.122 [0.109, 0.134]	0.253 [0.236, 0.270]	22.422 [21.569, 23.276]
H – Transport and storage	0.242 [0.214, 0.270]	0.153 [0.126, 0.179]	0.276 [0.247, 0.305]	25.279 [22.829, 27.730]
I – Accommodation and food services	0.156 [0.123, 0.190]	0.092 [0.070, 0.113]	0.144 [0.118, 0.170]	16.388 [14.001, 18.774]
J – Information and communications	0.289 [0.253, 0.326]	0.157 [0.119, 0.195]	0.273 [0.232, 0.313]	26.125 [22.772, 29.478]
K–L – Finance and real estate	0.275 [0.241, 0.309]	0.131 [0.111, 0.152]	0.309 [0.276, 0.341]	27.320 [24.650, 29.990]
M – Professional and scientific activities	0.233 [0.217, 0.250]	0.109 [0.090, 0.128]	0.208 [0.186, 0.229]	20.706 [19.144, 22.268]
N – Administrative	0.209 [0.183, 0.235]	0.109 [0.088, 0.130]	0.203 [0.174, 0.231]	19.621 [17.657, 21.586]
O – Public administration	0.195 [0.177, 0.212]	0.089 [0.074, 0.104]	0.190 [0.171, 0.209]	17.941 [16.448, 19.434]

	Automated task allocation	Automated scheduling	Performance monitoring	Algorithmic management intensity
Sector				
P – Education	0.144 [0.123, 0.166]	0.144 [0.123, 0.166]	0.094 [0.080, 0.108]	12.662 [11.244, 14.081]
Q – Health and social work	0.190 [0.176, 0.204]	0.125 [0.108, 0.142]	0.194 [0.173, 0.216]	19.517 [17.944, 21.091]
R–S – Other services	0.188 [0.154, 0.221]	0.114 [0.094, 0.133]	0.155 [0.127, 0.183]	16.438 [14.494, 18.381]
Workplace size				
Micro: 1–9	0.172 [0.163, 0.181]	0.087 [0.077, 0.097]	0.163 [0.151, 0.175]	16.716 [15.982, 17.451]
Small: 10–49	0.211 [0.205, 0.217]	0.114 [0.107, 0.120]	0.207 [0.199, 0.216]	20.292 [19.732, 20.853]
Medium: 50–249	0.221 [0.211, 0.231]	0.127 [0.119, 0.136]	0.221 [0.210, 0.231]	21.326 [20.749, 21.903]
Large: 250+	0.215 [0.201, 0.229]	0.125 [0.112, 0.139]	0.218 [0.199, 0.237]	20.962 [19.639, 22.285]
Employee representation				
No formal employee representation	0.171 [0.163, 0.178]	0.091 [0.084, 0.098]	0.168 [0.160, 0.176]	16.807 [16.123, 17.491]
Formal employee representation present	0.231 [0.224, 0.237]	0.129 [0.122, 0.135]	0.228 [0.221, 0.236]	22.116 [21.503, 22.730]
Telework status				
Works at employer's premises	0.192 [0.185, 0.200]	0.112 [0.106, 0.117]	0.193 [0.188, 0.199]	18.598 [18.132, 19.065]
Teleworks	0.229 [0.214, 0.245]	0.113 [0.100, 0.125]	0.217 [0.204, 0.230]	22.159 [20.978, 23.340]
Member State				
Austria	0.225 [0.219, 0.231]	0.135 [0.130, 0.141]	0.172 [0.168, 0.177]	24.324 [23.898, 24.749]
Belgium	0.283 [0.279, 0.288]	0.122 [0.118, 0.126]	0.310 [0.303, 0.316]	26.527 [26.099, 26.956]
Bulgaria	0.150 [0.144, 0.156]	0.069 [0.064, 0.074]	0.192 [0.185, 0.200]	16.650 [16.049, 17.251]
Croatia	0.202 [0.194, 0.211]	0.133 [0.127, 0.139]	0.245 [0.235, 0.254]	23.284 [22.711, 23.856]
Cyprus	0.236 [0.228, 0.245]	0.113 [0.105, 0.120]	0.209 [0.201, 0.216]	18.705 [18.188, 19.222]
Czechia	0.175 [0.170, 0.179]	0.112 [0.107, 0.117]	0.190 [0.185, 0.196]	19.656 [19.263, 20.049]
Denmark	0.377 [0.369, 0.385]	0.234 [0.226, 0.242]	0.216 [0.212, 0.220]	29.744 [29.245, 30.243]
Estonia	0.201 [0.195, 0.208]	0.125 [0.119, 0.132]	0.275 [0.267, 0.283]	21.157 [20.636, 21.678]
Finland	0.131 [0.127, 0.135]	0.130 [0.122, 0.137]	0.150 [0.146, 0.154]	15.841 [15.293, 16.388]
France	0.148 [0.145, 0.151]	0.080 [0.078, 0.083]	0.175 [0.171, 0.179]	15.222 [14.900, 15.544]
Germany	0.130 [0.123, 0.138]	0.057 [0.054, 0.061]	0.103 [0.098, 0.108]	11.498 [10.907, 12.089]
Greece	0.176 [0.168, 0.184]	0.066 [0.062, 0.071]	0.117 [0.112, 0.121]	13.283 [12.797, 13.770]
Hungary	0.109 [0.103, 0.115]	0.074 [0.069, 0.079]	0.117 [0.112, 0.123]	15.941 [15.326, 16.556]
Ireland	0.303 [0.296, 0.309]	0.195 [0.190, 0.199]	0.263 [0.257, 0.270]	25.909 [25.455, 26.362]
Italy	0.148 [0.141, 0.154]	0.106 [0.100, 0.111]	0.229 [0.221, 0.237]	22.371 [21.812, 22.929]
Latvia	0.214 [0.210, 0.218]	0.089 [0.086, 0.092]	0.213 [0.209, 0.218]	18.776 [18.448, 19.103]
Lithuania	0.128 [0.124, 0.132]	0.056 [0.053, 0.059]	0.184 [0.179, 0.189]	13.330 [12.917, 13.743]
Luxembourg	0.287 [0.280, 0.294]	0.170 [0.164, 0.177]	0.243 [0.234, 0.251]	24.311 [23.760, 24.862]
Malta	0.284 [0.276, 0.291]	0.148 [0.142, 0.154]	0.211 [0.205, 0.217]	19.171 [18.682, 19.660]
Netherlands	0.272 [0.263, 0.281]	0.113 [0.108, 0.118]	0.240 [0.233, 0.248]	24.192 [23.687, 24.698]
Poland	0.146 [0.141, 0.150]	0.087 [0.083, 0.091]	0.184 [0.179, 0.189]	16.548 [16.162, 16.934]
Portugal	0.157 [0.151, 0.164]	0.093 [0.087, 0.100]	0.116 [0.109, 0.122]	14.810 [14.042, 15.578]
Romania	0.212 [0.203, 0.221]	0.137 [0.129, 0.145]	0.187 [0.178, 0.196]	21.091 [20.445, 21.738]
Slovakia	0.183 [0.177, 0.189]	0.096 [0.093, 0.100]	0.199 [0.193, 0.205]	18.882 [18.492, 19.272]
Slovenia	0.170 [0.166, 0.174]	0.083 [0.080, 0.086]	0.176 [0.172, 0.181]	16.290 [15.935, 16.645]
Spain	0.190 [0.187, 0.193]	0.112 [0.109, 0.114]	0.248 [0.244, 0.252]	19.374 [19.169, 19.580]
Sweden	0.185 [0.178, 0.193]	0.079 [0.073, 0.085]	0.132 [0.127, 0.138]	15.981 [15.113, 16.849]
Observations *(n)*	20 600	20 609	20 453	20 238

Notes: Columns 2–4 report adjusted prevalence (predicted probabilities) from probit models of experience of each form of algorithmic management. Column 5 reports predicted values from a linear regression of the algorithmic management intensity index (0–100). Probit is used for the three binary outcomes to account for the 0/1 nature of the dependent variables. 95 % confidence intervals are provided in square brackets, based on standard errors clustered at the Member State level.
Source: Authors' calculations based on EWCS 2024.

Table A2: Associations between algorithmic management functions and socioeconomic variables (average marginal effects)

	Automated task allocation	Automated scheduling	Performance monitoring	Algorithmic management intensity
Gender and age (Male: 35–54 = baseline)				
Female: < 35	−0.010 (0.012)	0.006 (0.008)	0.031*** (0.010)	0.504 (0.829)
Female: 35–54	−0.014 (0.009)	−0.004 (0.007)	−0.003 (0.007)	−1.626** (0.626)
Female: 55+	0.000 (0.011)	−0.007 (0.007)	−0.007 (0.008)	−1.764** (0.711)
Male: < 35	0.034*** (0.009)	0.023** (0.009)	0.039*** (0.010)	2.948*** (0.856)
Male: 55+	−0.025** (0.012)	−0.001 (0.010)	−0.021** (0.009)	−1.742** (0.837)
Education level (Medium = baseline)				
Low	−0.042** (0.017)	−0.014 (0.009)	−0.036*** (0.011)	−2.898** (1.085)
High	0.004 (0.010)	0.011 (0.007)	−0.000 (0.009)	0.196 (0.739)
Contract (No permanent contract = baseline)				
Has permanent contract	0.009 (0.011)	−0.002 (0.010)	−0.005 (0.013)	0.735 (0.884)
Occupation (Technicians = baseline)				
Managers	−0.021 (0.015)	−0.017 (0.013)	−0.056*** (0.011)	−2.757** (1.203)
Professionals	−0.038*** (0.010)	−0.008 (0.008)	−0.034*** (0.012)	−2.493*** (0.794)
Clerical workers	0.040*** (0.012)	0.015 (0.011)	0.017 (0.011)	2.617*** (0.806)
Services and sales workers	−0.083*** (0.011)	−0.005 (0.010)	−0.063*** (0.011)	−4.954*** (0.662)
Skilled agricultural workers	−0.130*** (0.040)	−0.019 (0.032)	−0.127*** (0.032)	−8.954*** (2.202)
Craft workers	−0.060*** (0.013)	−0.005 (0.011)	−0.052*** (0.012)	−4.972*** (0.870)
Plant and machine operators	−0.054*** (0.016)	0.009 (0.015)	0.005 (0.015)	−1.802 (1.271)
Elementary occupations	−0.097*** (0.013)	−0.025*** (0.009)	−0.085*** (0.012)	−7.167*** (0.839)
Economic sector (K–L – Finance and real estate = baseline)				
A–B – Agriculture and mining	−0.146*** (0.028)	−0.070*** (0.019)	−0.187*** (0.033)	−12.902*** (1.994)
C – Manufacturing	−0.051** (0.020)	−0.017 (0.013)	−0.086*** (0.016)	−6.506*** (1.460)
D–E – Utilities	−0.063** (0.026)	0.007 (0.017)	−0.107*** (0.026)	−6.855*** (1.979)
F – Construction	−0.135*** (0.025)	−0.056*** (0.014)	−0.180*** (0.019)	−12.763*** (1.572)
G – Wholesale and retail	−0.048** (0.020)	−0.010 (0.012)	−0.056*** (0.021)	−4.898*** (1.370)
H – Transport and storage	−0.033 (0.022)	0.021 (0.020)	−0.033 (0.024)	−2.041 (1.895)
I – Accommodation and food services	−0.119*** (0.024)	−0.040** (0.016)	−0.165*** (0.025)	−10.933*** (1.834)
J – Information and communications	0.014 (0.022)	0.026 (0.019)	−0.036 (0.025)	−1.195 (1.624)
M – Professional and scientific activities	−0.042** (0.020)	−0.022* (0.012)	−0.101*** (0.017)	−6.614*** (1.469)
N – Administrative	−0.066*** (0.024)	−0.022 (0.014)	−0.106*** (0.024)	−7.699*** (1.697)
O – Public administration	−0.080*** (0.021)	−0.042*** (0.013)	−0.119*** (0.020)	−9.379*** (1.523)
P – Education	−0.131*** (0.020)	−0.053*** (0.014)	−0.215*** (0.017)	−14.658*** (1.453)
Q – Health and social work	−0.085*** (0.019)	−0.006 (0.014)	−0.115*** (0.023)	−7.803*** (1.660)
R–S – Other services	−0.087*** (0.025)	−0.017 (0.016)	−0.154*** (0.022)	−10.883*** (1.844)
Workplace size (Micro: 1–9 = baseline)				
Small: 10–49	0.039*** (0.006)	0.027*** (0.007)	0.044*** (0.008)	3.576*** (0.490)
Medium: 50–249	0.049*** (0.008)	0.040*** (0.008)	0.058*** (0.009)	4.609*** (0.533)
Large: 250+	0.043*** (0.010)	0.039*** (0.010)	0.055*** (0.015)	4.246*** (0.910)
Employee representation (No formal employee representation = baseline)				
Formal employee representation present	0.060*** (0.007)	0.038*** (0.007)	0.060*** (0.008)	5.309*** (0.631)

	Automated task allocation	Automated scheduling	Performance monitoring	Algorithmic management intensity
Telework status (Works at employer's premises = baseline)				
Telework	0.037*** (0.012)	0.001 (0.009)	0.024**(0.009)	3.561*** (0.801)
Member State (Denmark = baseline)				
Austria	−0.152*** (0.006)	−0.099*** (0.005)	−0.044*** (0.004)	−5.421*** (0.336)
Belgium	−0.094*** (0.003)	−0.112*** (0.003)	0.094*** (0.002)	−3.217*** (0.189)
Bulgaria	−0.227*** (0.007)	−0.165*** (0.006)	−0.024*** (0.006)	−13.095*** (0.510)
Croatia	−0.175*** (0.008)	−0.101*** (0.007)	0.029*** (0.007)	−6.461*** (0.475)
Cyprus	−0.141*** (0.007)	−0.121*** (0.007)	−0.008 (0.005)	−11.040*** (0.434)
Czechia	−0.203*** (0.005)	−0.122*** (0.005)	−0.026*** (0.003)	−11.040*** (0.434)
Estonia	−0.176*** (0.005)	−0.109*** (0.006)	0.059*** (0.005)	−8.587*** (0.349)
Finland	−0.246*** (0.003)	−0.104*** (0.002)	−0.066*** (0.002)	−13.903*** (0.115)
France	−0.229*** (0.004)	−0.154*** (0.004)	−0.041*** (0.003)	−14.522*** (0.241)
Germany	−0.247*** (0.004)	−0.176*** (0.004)	−0.113*** (0.002)	−18.246*** (0.302)
Greece	−0.201*** (0.008)	−0.168*** (0.006)	−0.100*** (0.004)	−16.461*** (0.426)
Hungary	−0.268*** (0.007)	−0.160*** (0.006)	−0.099*** (0.005)	−13.803*** (0.527)
Ireland	−0.074*** (0.004)	−0.074*** (0.004)	0.047*** (0.003)	−3.836*** (0.256)
Italy	−0.229*** (0.007)	−0.128*** (0.006)	0.013** (0.006)	−7.374*** (0.472)
Latvia	−0.163*** (0.005)	−0.145*** (0.005)	−0.003 (0.004)	−10.969*** (0.351)
Lithuania	−0.249*** (0.005)	−0.178*** (0.005)	−0.032*** (0.004)	−16.414*** (0.382)
Luxembourg	−0.090*** (0.003)	−0.064*** (0.004)	0.026*** (0.003)	−5.433*** (0.212)
Malta	−0.093*** (0.005)	−0.086*** (0.006)	−0.005* (0.003)	−10.573*** (0.312)
Netherlands	−0.105*** (0.004)	−0.121*** (0.003)	0.024*** (0.003)	−5.552*** (0.165)
Poland	−0.231*** (0.006)	−0.147*** (0.006)	−0.032*** (0.004)	−13.196*** (0.387)
Portugal	−0.220*** (0.007)	−0.141*** (0.007)	−0.101*** (0.005)	−14.934*** (0.574)
Romania	−0.165*** (0.008)	−0.097*** (0.008)	−0.029*** (0.006)	−8.653*** (0.508)
Slovakia	−0.194*** (0.006)	−0.137*** (0.005)	−0.017*** (0.005)	−10.862*** (0.389)
Slovenia	−0.207*** (0.005)	−0.151*** (0.004)	−0.040*** (0.004)	−13.454*** (0.274)
Spain	−0.187*** (0.005)	−0.122*** (0.005)	0.032*** (0.004)	−10.370*** (0.272)
Sweden	−0.192*** (0.002)	−0.155*** (0.002)	−0.084*** (0.002)	−13.763*** (0.216)
Constant				33.606*** (1.841)
Observations (*n*)	20 600	20 609	20 453	20 238
Pseudo R^2 / R^2	0.083	0.052	0.076	0.110

Notes: Columns 2–4 report the average marginal effects from probit models, estimating the change in the probability of the experience of each form of algorithmic management associated with each covariate. Column 5 reports coefficients from a linear regression of the algorithmic management intensity index (0–100). Probit is used for the three binary outcomes to account for the 0/1 nature of the dependent variables. Standard errors clustered at the Member State level are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations based on EWCS 2024.

Table A3: Associations between exposure to automated task allocation, automated scheduling and performance monitoring and task transformation (average marginal effects)

	Tasks removed	Tasks created	More interaction
Automated task allocation	0.128*** (0.010)	0.203*** (0.010)	0.121*** (0.010)
Automated scheduling	0.081*** (0.013)	0.077*** (0.013)	0.065*** (0.013)
Performance monitoring	0.078*** (0.010)	0.105*** (0.010)	0.069*** (0.010)
Observations (*n*)	15 817	15 828	15 792
Pseudo R^2	0.092	0.130	0.133

Notes: Table shows the average marginal effects from probit models; robust standard errors clustered at the Member State level are presented in parentheses. All models control for sociodemographic characteristics (gender, age, education), employment characteristics (contract type, occupation, sector, workplace size, telework, trade union presence) and Member State fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations based on EWCS 2024.

Table A4: Associations between exposure to automated task allocation, automated scheduling and performance monitoring and task content (average marginal effects)

	Quality standards	Monotonous tasks	Complex tasks
Automated task allocation	0.065*** (0.008)	0.013 (0.009)	0.032*** (0.010)
Automated scheduling	0.014 (0.015)	0.025 (0.017)	0.015 (0.013)
Performance monitoring	0.075*** (0.011)	0.057*** (0.014)	0.041*** (0.009)
Observations (*n*)	19 967	20 078	20 056
Pseudo R^2	0.095	0.092	0.194

Notes: Table shows the average marginal effects from probit models; robust standard errors clustered at the Member State level are presented in parentheses. All models control for sociodemographic characteristics (gender, age, education), employment characteristics (contract type, occupation, sector, workplace size, telework, trade union presence) and Member State fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations based on EWCS 2024.

Annex 2: Chapter 2 full regression results for main predictors

Table A5: Associations between exposure to automated task allocation, automated scheduling and performance monitoring, and algorithmic management intensity and selected job demands (average marginal effects)

	Physical risks	Physical demands	Quantitative demands	Emotional demands	Social demands	Time-related demands	Financial and job insecurity
Automated task allocation	0.001 (0.010)	0.031*** (0.012)	0.079*** (0.010)	0.036*** (0.014)	0.027*** (0.009)	0.011 (0.011)	0.004 (0.009)
Automated scheduling	0.042*** (0.014)	0.011 (0.015)	0.060*** (0.015)	0.072*** (0.014)	0.026*** (0.010)	0.063*** (0.015)	0.029*** (0.010)
Performance monitoring	0.051*** (0.011)	0.044*** (0.015)	0.134*** (0.011)	0.078*** (0.014)	0.048*** (0.008)	0.038*** (0.010)	0.027*** (0.008)
Algorithmic management intensity (0–100)	0.001*** (0.000)	0.001*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Observations (*n*)	20 238	20 238	20 238	20 237	20 237	20 238	19 977

Notes: Table shows the average marginal effects of the experience of each algorithmic management function, and also algorithmic management intensity, on job demand outcomes, from probit models with standard errors clustered at the Member State level. All models control for sociodemographic characteristics (gender, age, education), employment characteristics (contract type, occupation, sector, workplace size, telework, trade union presence) and Member State fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations based on EWCS 2024.

Table A6: Associations between exposure to automated task allocation, automated scheduling, performance monitoring and algorithmic management intensity and selected job resources (average marginal effects)

	Social support	Autonomy	Working time flexibility	Training and learning	Career advancement	Rewards	Participation and voice
Automated task allocation	0.015 (0.011)	0.044*** (0.013)	0.029*** (0.011)	0.057*** (0.010)	0.019*** (0.006)	–0.004 (0.011)	0.054*** (0.010)
Automated scheduling	0.004 (0.010)	–0.006 (0.018)	–0.017 (0.017)	0.005 (0.015)	–0.002 (0.008)	–0.039*** (0.010)	0.008 (0.010)
Performance monitoring	–0.026*** (0.008)	–0.023* (0.012)	–0.039*** (0.013)	0.040*** (0.012)	0.014* (0.008)	–0.036*** (0.010)	–0.011 (0.013)
Algorithmic management intensity (0–100)	-0.000 (0.000)	0.000 (0.000)	-0.000** (0.000)	0.001*** (0.000)	0.000*** (0.000)	-0.001*** (0.000)	0.000** (0.000)
Observations (*n*)	20 113	20 225	20 238	20 238	20 035	20 036	20 093

Notes: Table shows the average marginal effects of the experience of each algorithmic management function, and also algorithmic management intensity, on job resource outcomes, from probit models with standard errors clustered at the Member State level. All models control for sociodemographic characteristics (gender, age, education), employment characteristics (contract type, occupation, sector, workplace size, telework, trade union presence) and Member State fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations based on EWCS 2024.

Annex 3: Chapter 3 full regression results

Table A7: Associations between algorithmic management functions' interactions with job strain on well-being indicators (average marginal effects)

	Well-being	Exhaustion	Work–family conflict	Engagement
Strained	−13.981*** (0.586)	−16.909*** (1.079)	−14.624*** (0.766)	−12.797*** (0.636)
Automated task allocation	0.818 (0.598)	−0.599 (0.930)	−1.599*** (0.473)	1.193*** (0.342)
Automated task allocation*Strained	−0.571 (1.331)	−0.387 (1.567)	−0.428 (1.065)	0.115 (0.829)
Automated scheduling	0.678 (0.576)	−3.902*** (0.969)	−2.696*** (0.645)	−0.517 (0.448)
Automated scheduling*Strained	2.148* (1.258)	2.514* (1.291)	2.029* (1.080)	2.560** (1.118)
Performance monitoring	−0.242 (0.492)	−2.368*** (0.579)	−2.544*** (0.554)	0.045 (0.409)
Performance monitoring*Strained	−1.750 (1.104)	−1.429** (0.693)	−1.702* (0.834)	−2.154** (0.827)
Gender and age (Male: 35–54 = baseline)				
Female: < 35	−0.001 (0.776)	−2.309*** (0.573)	−1.064 (0.687)	−1.280* (0.679)
Female: 35–54	−2.442*** (0.469)	−3.853*** (0.555)	−2.998*** (0.512)	−0.094 (0.413)
Female: 55+	−2.056*** (0.733)	−2.496*** (0.728)	−0.431 (0.580)	1.785** (0.659)
Male: < 35	2.777*** (0.559)	2.100*** (0.657)	2.789*** (0.592)	−0.721 (0.484)
Male: 55+	0.817 (0.768)	2.406*** (0.696)	3.817*** (0.541)	0.707 (0.530)
Education (Medium = baseline)				
Low	−0.751 (0.789)	−0.632 (0.847)	1.569** (0.720)	−0.368 (0.816)
High	−0.443 (0.417)	0.269 (0.493)	2.005*** (0.564)	−0.160 (0.385)
Contract (No permanent contract = baseline)				
Permanent contract	−0.705 (0.559)	−1.753** (0.645)	−2.366*** (0.620)	−0.464 (0.474)
Occupation (3. Technicians = baseline)				
1. Managers	0.039 (0.563)	−0.628 (0.839)	−3.784*** (0.757)	0.457 (0.551)
2. Professionals	−0.357 (0.580)	−0.631 (0.717)	−1.568** (0.712)	−0.488 (0.513)
4. Clerical workers	−0.892* (0.490)	3.259*** (0.828)	2.897*** (0.726)	−2.827*** (0.551)
5. Services and sales workers	0.379 (0.482)	−0.946 (0.721)	−0.089 (0.838)	−1.528** (0.582)
6. Skilled agricultural workers	1.521 (1.337)	−2.240 (2.068)	−4.181** (1.988)	−0.451 (1.636)
7. Craft workers	−0.420 (0.884)	−1.156 (0.818)	−1.294 (1.064)	−1.005 (0.730)
8. Plant and machine operators	1.435** (0.611)	0.944 (0.983)	1.645 (1.011)	−0.631 (0.640)
9. Elementary occupations	−0.356 (0.649)	0.185 (0.931)	2.152** (0.811)	−3.210*** (0.635)
Sector (K–L – Finance and real estate = baseline)				
A–B – Agriculture and mining	0.723 (1.333)	−1.147 (1.881)	−2.706* (1.533)	2.517 (1.539)
C – Manufacturing	−1.280 (0.908)	0.668 (1.185)	−0.363 (0.874)	0.060 (0.942)
D–E – Utilities	−0.813 (1.457)	1.628 (1.660)	0.236 (1.356)	0.631 (1.220)
F – Construction	−0.238 (1.155)	−3.529** (1.611)	−3.840*** (1.058)	1.937* (1.128)
G – Wholesale and retail	−0.827 (0.877)	−0.546 (1.140)	−1.380 (0.923)	0.346 (0.980)
H – Transport and storage	−0.578 (1.009)	−1.501 (1.332)	−3.640*** (0.974)	1.700** (0.826)
I – Accommodation and food services	−1.044 (0.932)	−4.880*** (1.294)	−4.829*** (1.041)	2.182* (1.226)
J – Information and communications	−0.675 (1.154)	0.899 (1.283)	0.863 (0.946)	0.412 (1.098)
M – Professional and scientific activities	−1.140 (1.241)	−0.170 (1.401)	−1.209 (1.154)	−0.178 (1.050)
N – Administrative	−1.964** (0.773)	−2.133* (1.136)	−1.998** (0.851)	−1.318 (0.854)
O – Public administration	−1.282 (1.137)	−1.108 (1.429)	−1.232 (1.034)	0.378 (1.016)

	Well-being	Exhaustion	Work–family conflict	Engagement
P – Education	–0.413 (1.064)	–4.486*** (1.119)	–3.295*** (0.878)	3.519*** (1.033)
Q – Health and social work	–0.780 (1.007)	–5.179*** (1.227)	–4.804*** (1.100)	3.318*** (1.038)
R–S – Other services	–0.410 (1.234)	–1.588 (1.382)	–2.387** (1.039)	1.942* (1.020)
Workplace size (Micro: 1–9 = baseline)				
Small: 10–49	–1.392*** (0.468)	–1.840*** (0.632)	–1.245*** (0.409)	–1.068*** (0.314)
Medium: 50–249	–1.537*** (0.488)	–1.946** (0.736)	–1.227** (0.509)	–2.211*** (0.409)
Large: 250+	–2.360*** (0.591)	–1.135 (0.945)	–0.991 (0.754)	–3.162*** (0.466)
Employee representation (No formal employee representation = baseline)				
With employee representative	1.709*** (0.335)	–0.654 (0.454)	0.652 (0.515)	1.346*** (0.371)
Telework status (Works at employer's premises = baseline)				
Telework	–3.015*** (0.482)	–0.866 (0.614)	–5.520*** (0.649)	–1.090*** (0.324)
Member State (Denmark = baseline)				
Austria	3.608*** (0.268)	–6.019*** (0.369)	–2.048*** (0.274)	–2.144*** (0.182)
Belgium	–6.191*** (0.228)	–3.558*** (0.264)	–7.300*** (0.223)	–3.671*** (0.190)
Bulgaria	–0.233 (0.308)	–5.050*** (0.414)	–2.094*** (0.363)	–3.886*** (0.271)
Croatia	–2.967*** (0.322)	–9.116*** (0.493)	–7.158*** (0.372)	–9.773*** (0.281)
Cyprus	–3.693*** (0.363)	–12.890*** (0.537)	–12.813*** (0.406)	0.392 (0.330)
Czechia	–8.178*** (0.293)	–10.296*** (0.394)	–6.052*** (0.334)	–13.020*** (0.273)
Estonia	–0.532** (0.230)	–4.744*** (0.289)	–4.320*** (0.330)	–3.705*** (0.209)
Finland	–4.140*** (0.185)	–1.781*** (0.257)	–4.771*** (0.196)	–8.398*** (0.178)
France	0.586** (0.248)	–7.244*** (0.338)	–2.926*** (0.250)	–2.473*** (0.212)
Germany	–9.477*** (0.262)	–2.548*** (0.356)	–3.328*** (0.306)	–7.888*** (0.242)
Greece	–2.468*** (0.343)	–6.120*** (0.493)	–9.644*** (0.395)	–6.760*** (0.359)
Hungary	–1.398*** (0.369)	–7.070*** (0.561)	1.808*** (0.410)	–12.143*** (0.339)
Ireland	3.048*** (0.241)	–6.154*** (0.230)	–2.652*** (0.258)	–1.315*** (0.177)
Italy	–1.728*** (0.304)	–0.572 (0.505)	–4.890*** (0.307)	–8.337*** (0.291)
Latvia	–4.144*** (0.253)	–4.428*** (0.356)	–8.683*** (0.337)	–6.594*** (0.233)
Lithuania	–2.725*** (0.254)	–6.582*** (0.350)	1.231*** (0.338)	–0.840*** (0.235)
Luxembourg	–3.985*** (0.253)	–11.256*** (0.300)	–11.280*** (0.255)	–5.043*** (0.178)
Malta	–8.298*** (0.258)	–1.183*** (0.330)	–10.227*** (0.325)	–7.126*** (0.204)
Netherlands	1.351*** (0.137)	6.064*** (0.135)	0.534*** (0.154)	–0.130 (0.134)
Poland	–2.947*** (0.332)	–3.056*** (0.433)	3.009*** (0.371)	–6.668*** (0.274)
Portugal	–2.267*** (0.394)	–6.373*** (0.551)	–6.444*** (0.380)	–8.775*** (0.385)
Romania	0.483 (0.306)	–8.921*** (0.494)	–8.740*** (0.361)	–4.068*** (0.270)
Slovakia	–2.215*** (0.279)	–11.708*** (0.444)	–2.611*** (0.360)	–8.116*** (0.250)
Slovenia	–1.598*** (0.228)	–3.708*** (0.351)	–1.484*** (0.290)	–5.184*** (0.180)
Spain	0.119 (0.252)	–0.030 (0.463)	–7.356*** (0.296)	–8.778*** (0.257)
Sweden	–6.979*** (0.185)	2.453*** (0.246)	–4.249*** (0.194)	–6.595*** (0.141)
Constant	78.624*** (0.955)	73.690*** (1.654)	78.689*** (1.172)	81.399*** (1.024)
Observations (*n*)	20 233	20 197	19 490	20 232

Notes: Table shows the average marginal effects from linear models, with standard errors clustered at the Member State level. All models control for gender–age group, education, permanent contract, occupation (ISCO 1-digit level), sector (NACE), workplace size, trade union presence, telework and Member State. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations based on EWCS 2024.

Annex 4: Construction and operationalisation of job demands, resources and strain indicators

Table A8: Full coding scheme for job demands and resources

Construct	Label	Item in dataset	Item description	Scale	Threshold	Validity	Self-employment routing
D1	D1: Physical risks (≥ 1 hazard ≥ 1/4 of the time)	noise	Loud noise	7-point frequency scale (1 = all the time ... 7 = never)	≤ 4 (≥ 1/4 of the time)	Missing only if all 7 inputs missing	Asked of all workers
D1	D1: Physical risks (≥ 1 hazard ≥ 1/4 of the time)	hightemp	High temperatures	7-point frequency scale	≤ 4 (≥ 1/4 of the time)	Missing only if all 7 inputs missing	Asked of all workers
D1	D1: Physical risks (≥ 1 hazard ≥ 1/4 of the time)	lowtemp	Low temperatures	7-point frequency scale	≤ 4 (≥ 1/4 of the time)	Missing only if all 7 inputs missing	Asked of all workers
D1	D1: Physical risks (≥ 1 hazard ≥ 1/4 of the time)	smoke	Smoke, fumes powder and dust	7-point frequency scale	≤ 4 (≥ 1/4 of the time)	Missing only if all 7 inputs missing	Asked of all workers
D1	D1: Physical risks (≥ 1 hazard ≥ 1/4 of the time)	vapour	Vapours (for example solvents, thinners)	7-point frequency scale	≤ 4 (≥ 1/4 of the time)	Missing only if all 7 inputs missing	Asked of all workers
D1	D1: Physical risks (≥ 1 hazard ≥ 1/4 of the time)	chemicals	Chemical products	7-point frequency scale	≤ 4 (≥ 1/4 of the time)	Missing only if all 7 inputs missing	Asked of all workers
D1	D1: Physical risks (≥ 1 hazard ≥ 1/4 of the time)	infect	Infectious materials	7-point frequency scale	≤ 4 (≥ 1/4 of the time)	Missing only if all 7 inputs missing	Asked of all workers
D2	D2: Physical demands (≥ 2 of 6 items at threshold)	tiring_positions	Tiring or painful positions	7-point frequency scale	≤ 4	rownonmiss ≥ 2	Asked of all workers
D2	D2: Physical demands (≥ 2 of 6 items at threshold)	lifting	Lifting or moving people	7-point frequency scale	≤ 4	rownonmiss ≥ 2	Asked of all workers
D2	D2: Physical demands (≥ 2 of 6 items at threshold)	heavy_loads	Carrying heavy loads	7-point frequency scale	≤ 4	rownonmiss ≥ 2	Asked of all workers
D2	D2: Physical demands (≥ 2 of 6 items at threshold)	rep_movements	Repetitive hand/arm movements	7-point frequency scale	≤ 4	rownonmiss ≥ 2	Asked of all workers
D2	D2: Physical demands (≥ 2 of 6 items at threshold)	vibration	Vibrations from tools/machinery	7-point frequency scale	≤ 4	rownonmiss ≥ 2	Asked of all workers
D2	D2: Physical demands (≥ 2 of 6 items at threshold)	sitting	Sitting	7-point frequency scale	≤ 3 (≥ 3/4 of the time)	rownonmiss ≥ 2	Asked of all workers
D3	D3: Quantitative demands (≥ 2 of 5 items)	highspeed	Working at high speed	7-point frequency scale	≤ 3 (≥ 3/4 of the time)	rownonmiss ≥ 2	Asked of all workers
D3	D3: Quantitative demands (≥ 2 of 5 items)	tightdead	Tight deadlines	7-point frequency scale	≤ 3	rownonmiss ≥ 2	Asked of all workers
D3	D3: Quantitative demands (≥ 2 of 5 items)	enough_time	Enough time to get the job done	5-point frequency scale (1 = always ... 5 = never)	≥ 4 (rarely/never)	rownonmiss ≥ 2	Asked of all workers

Construct	Label	Item in dataset	Item description	Scale	Threshold	Validity	Self-employment routing
D3	D3: Quantitative demands (≥ 2 of 5 items)	interrupt_disrupt	Interruptions are disruptive	3-category (1 = disruptive, 2 = no consequences, 3 = beneficial)	== 1 (disruptive)	rownonmiss ≥ 2	Asked of all workers; workers who answer 'Never' to the interruption frequency item are coded 0, because for them the condition cannot arise.
D3	D3: Quantitative demands (≥ 2 of 5 items)	pace_determinants	Number of pace determinants	Count (0 ... n)	≥ 3	rownonmiss ≥ 2	Asked of all workers
D4	D4: Emotional demands (≥ 1 of 4 items at threshold)	hide_feelings	Hiding own feelings at work	5-point frequency scale (1 = always ... 5 = never)	≤ 2 (most of the time / always)	Missing only if all 4 inputs missing	Asked of all workers
D4	D4: Emotional demands (≥ 1 of 4 items at threshold)	angry_clients	Handle angry clients	7-point frequency scale	≥ 3	Missing only if all 4 inputs missing	Asked of all workers
D4	D4: Emotional demands (≥ 1 of 4 items at threshold)	emot_disturb	Emotionally disturbing situations	7-point frequency scale	≥ 3	Missing only if all 4 inputs missing	Asked of all workers
D4	D4: Emotional demands (≥ 1 of 4 items at threshold)	lonely	Feeling lonely at work	5-point frequency scale	≤ 2 (always / most of the time; round 1: tightened from ≤ 3)	Missing only if all 4 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	asb_violence	Physical violence	Yes/no (1/2)	== 1 (yes)	Missing only if all 9 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	asb_sexharass	Sexual harassment	Yes/no	== 1	Missing only if all 9 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	cyber_bull	Cyberbullying or harassment	Yes/no	== 1	Missing only if all 9 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	asb_bully	Bullying or harassment	Yes/no	== 1	Missing only if all 9 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	asb_verbal	Verbal abuse	Yes/no	== 1	Missing only if all 9 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	asb_unwanted_sexatt	Unwanted sexual attention	Yes/no	== 1	Missing only if all 9 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	asb_threats	Threats	Yes/no	== 1	Missing only if all 9 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	asb_humil	Humiliating behaviours	Yes/no	== 1	Missing only if all 9 inputs missing	Asked of all workers
D5	D5: Social demands (any ASB or discrimination)	discrimination	Discrimination at work	Yes/no	== 1	Missing only if all 9 inputs missing	Asked of all workers
D6	D6: Time-related demands (≥ 1 of 9 conditions)	usual_hours_2cat	Usual weekly hours category	Binary (1 < 48, 2 ≥ 48)	== 2 (≥ 48 hours a week)	Missing only if all 9 inputs missing	Asked of all workers
D6	D6: Time-related demands (≥ 1 of 9 conditions)	longday	Days of > 10 hours per month	Count	> 0	Missing only if all 9 inputs missing	Asked of all workers

Construct	Label	Item in dataset	Item description	Scale	Threshold	Validity	Self-employment routing
D6	D6: Time-related demands (≥ 1 of 9 conditions)	norest	< 11 hours between 2 working days (past month)	Yes/no (1/2)	== 1	Missing only if all 9 inputs missing	Asked of all workers
D6	D6: Time-related demands (≥ 1 of 9 conditions)	weekend	Weekend working days per month	Count	> 0	Missing only if all 9 inputs missing	Asked of all workers
D6	D6: Time-related demands (≥ 1 of 9 conditions)	freetime_work	Worked in free time to meet demands	5-point frequency scale	≤ 3 (several times per month or more)	Missing only if all 9 inputs missing	Asked of all workers
D6	D6: Time-related demands (≥ 1 of 9 conditions)	night	Nights worked per month	Count	> 0	Missing only if all 9 inputs missing	Asked of all workers
D6	D6: Time-related demands (≥ 1 of 9 conditions)	emp_wt_predict	Working hours not predictable	3-point scale (1 = quite accurately ... 3 = no)	== 3 (no, not predictable)	Missing only if all 9 inputs missing	Asked of all workers
D6	D6: Time-related demands (≥ 1 of 9 conditions)	wt_arrangements_change	Short-notice schedule change	5-point scale (2 = same day ... 5 = weeks ahead)	in {2, 3} (same day or day before)	Missing only if all 9 inputs missing	Asked of all workers
D6	D6: Time-related demands (≥ 1 of 9 conditions)	shift	Shift work	Yes/no (1/2)	== 1 (any shift work)	Missing only if all 9 inputs missing	Asked of all workers
D7	D7: Financial and job insecurity (≥ 2 of 5 conditions)	losejob	Strongly / tend to agree that might lose job (in next 6 months)	5-point agreement scale (1 = strongly agree ... 5 = strongly disagree)	≤ 2	rownonmiss ≥ 2 (propclient counted in count but not in validity)	prop_rev_client only asked of self-employed; imputed to 0 for employees in count; kept missing in validity
D7	D7: Financial and job insecurity (≥ 2 of 5 conditions)	easy_similarjob	Easy to find similar job (reversed)	5-point agreement scale	≥ 4 (hard to find)	rownonmiss ≥ 2 (propclient counted in count but not in validity)	prop_rev_client only asked of self-employed; imputed to 0 for employees in count; kept missing in validity
D7	D7: Financial and job insecurity (≥ 2 of 5 conditions)	qual_ins	Expects undesirable change in work	5-point agreement scale	≤ 2	rownonmiss ≥ 2 (propclient counted in count but not in validity)	prop_rev_client only asked of self-employed; imputed to 0 for employees in count; kept missing in validity
D7	D7: Financial and job insecurity (≥ 2 of 5 conditions)	prop_rev_client	>75 % revenue from one client (self-employed)	Categorical (1 < 25 %, 2 = 25–75 %, 3 > 75 %)	== 3	rownonmiss ≥ 2 (propclient counted in count but not in validity)	prop_rev_client only asked of self-employed; imputed to 0 for employees in count; kept missing in validity
D7	D7: Financial and job insecurity (≥ 2 of 5 conditions)	predict_earnings	Earnings not predictable over next 3 months	3-point scale (1 = quite accurately ... 3 = no)	== 3 (no, not predictable)	rownonmiss ≥ 2 (propclient counted in count but not in validity)	prop_rev_client only asked of self-employed; imputed to 0 for employees in count; kept missing in validity

Construct	Label	Item in dataset	Item description	Scale	Threshold	Validity	Self-employment routing
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	support_colleagues	Support from colleagues (5-point agreement scale, employees)	5-point agreement scale	≤ 2	peer and manager support: at least 2 of the 3 support items answered; leadership quality: at least 4 of the 6 manager items answered	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	support_colleagues_or_peers	Support from colleagues/peers (alternate route, self-employed)	5-point agreement scale	≤ 2	rownonmiss ≥ 2 of 3; lead_sub: rownonmiss ≥ 4 of 6	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	support_manager	Support from manager	5-point agreement scale	≤ 2	rownonmiss ≥ 2 of 3; lead_sub: rownonmiss ≥ 4 of 6	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	boss_respect	Boss respects me as a person	5-point agreement scale	≤ 2	rownonmiss ≥ 2 of 3; lead_sub: rownonmiss ≥ 4 of 6	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	boss_cooperation	Boss encourages cooperation	5-point agreement scale	≤ 2	rownonmiss ≥ 2 of 3; lead_sub: rownonmiss ≥ 4 of 6	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	boss_conf	Boss has confidence in me	5-point agreement scale	≤ 2	rownonmiss ≥ 2 of 3; lead_sub: rownonmiss ≥ 4 of 6	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	boss_feedback	Boss provides useful feedback	5-point agreement scale	≤ 2	rownonmiss ≥ 2 of 3; lead_sub: rownonmiss ≥ 4 of 6	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	boss_development	Boss helps with personal development	5-point agreement scale	≤ 2	rownonmiss ≥ 2 of 3; lead_sub: rownonmiss ≥ 4 of 6	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R1	R1: Social support (peers ≥ 2/3 **OR** leadership ≥ 4/6)	boss_explains	Boss provides clear goals/explanations	5-point agreement scale	≤ 2	rownonmiss ≥ 2 of 3; lead_sub: rownonmiss ≥ 4 of 6	Both subscales not asked of self-employed, so R1 forced to 0 (structural absence)
R2	R2: Autonomy (≥ 2 of 3 dimensions, always/often)	autonomy_order	Choose order of tasks	5-point frequency scale (1 = always ... 5 = never)	≤ 2 (always/often)	rownonmiss ≥ 2	Asked of all workers
R2	R2: Autonomy (≥ 2 of 3 dimensions, always/often)	autonomy_methods	Choose methods of work	5-point frequency scale	≤ 2	rownonmiss ≥ 2	Asked of all workers

Construct	Label	Item in dataset	Item description	Scale	Threshold	Validity	Self-employment routing
R2	R2: Autonomy (≥ 2 of 3 dimensions, always/often)	autonomy_speed	Choose speed/rate of work	5-point frequency scale	≤ 2	rownonmiss ≥ 2	Asked of all workers
R3	R3: Working time flexibility (≥ 1 of 3 forms)	take_break	Can take break when wishes	5-point frequency scale	≤ 2 (always / most of the time)	Missing only if all 3 inputs missing	Asked of all workers (terms differ for employees vs self-employed)
R3	R3: Working time flexibility (≥ 1 of 3 forms)	wt_arrangements	Working time arrangements	Categorical (1 = set by organisation ... 4 = fully decided by self)	≥ 2 (not entirely set by organisation)	Missing only if all 3 inputs missing	Asked of all workers (terms differ for employees v self-employed)
R3	R3: Working time flexibility (≥ 1 of 3 forms)	able_hour_off	Ease of taking 1 hour off	4-point scale (1 = very easy ... 4 = very difficult)	== 1 (very easy)	Missing only if all 3 inputs missing	Asked of all workers (terms differ for employees v self-employed)
R4	R4: Training and learning (≥ 2 of 4 channels)	training_employer	Training paid by employer (last 12 months)	Yes/no (1/2)	== 1 (yes)	rownonmiss ≥ 2	Not asked of self-employed
R4	R4: Training and learning (≥ 2 of 4 channels)	training_onthejob	On-the-job training (last 12 months)	Yes/no	== 1	rownonmiss ≥ 2	Asked of all workers
R4	R4: Training and learning (≥ 2 of 4 channels)	opp_impr_skills	Enough opportunities to use knowledge/ skills (version 4: moved from R5)	5-point agreement scale	== 1 (strongly agree only)	rownonmiss ≥ 2	Asked of all workers
R4	R4: Training and learning (≥ 2 of 4 channels)	learning_new_things	Job involves learning new things	Yes/no	== 1	rownonmiss ≥ 2	Asked of all workers
R5	R5: Career advancement (single item, strongly agree)	prospects	Job offers good prospects for advancement	5-point agreement scale	== 1 (strongly agree only)	Missing only if input missing	Asked of the self-employed, but a quarter of them are routed to 'does not apply' (code –991), reflecting the absence of an internal career ladder; those cases are coded 0. Refusals and 'don't know' answers remain missing.
R6	R6: Rewards (≥ 3 of 6 elements)	recognition	Recognition for work done	5-point agreement scale	== 1 (strongly agree only)	rownonmiss ≥ 3	Asked of all workers
R6	R6: Rewards (≥ 3 of 6 elements)	er_balance	Effort/reward in balance	5-point agreement scale	== 1	rownonmiss ≥ 3	Asked of all workers
R6	R6: Rewards (≥ 3 of 6 elements)	apply_ideas	Able to apply own ideas at work	5-point agreement scale	≤ 2 (always / most of the time)	rownonmiss ≥ 3	Asked of all workers
R6	R6: Rewards (≥ 3 of 6 elements)	useful_work	Doing useful work	5-point agreement scale	≤ 2	rownonmiss ≥ 3	Asked of all workers
R6	R6: Rewards (≥ 3 of 6 elements)	fair_treatment	Treated fairly at workplace	5-point agreement scale	≤ 2	rownonmiss ≥ 3	Not asked of self-employed
R6	R6: Rewards (≥ 3 of 6 elements)	work_welldone	Feeling of work well done	5-point agreement scale	≤ 2	rownonmiss ≥ 3	Asked of all workers

Construct	Label	Item in dataset	Item description	Scale	Threshold	Validity	Self-employment routing
R7	R7: Participation and voice (≥ 2 of 3 forms, always / most of the time)	consulted	Consulted before objectives set	5-point frequency scale	≤ 2	rownonmiss ≥ 2 (round 7: tightened from ≥ 1)	All 3 items not applicable to self-employed, so R7 forced to 0 (structural absence)
R7	R7: Participation and voice (≥ 2 of 3 forms, always / most of the time)	improv_workorg	Involved in improving work organisation	5-point frequency scale	≤ 2	rownonmiss ≥ 2 (round 7: tightened from ≥ 1)	All 3 items not applicable to self-employed, so R7 forced to 0 (structural absence)
R7	R7: Participation and voice (≥ 2 of 3 forms, always / most of the time)	decision_influence	Influence on decisions important for work	5-point frequency scale	≤ 2	rownonmiss ≥ 2 (round 7: tightened from ≥ 1)	All 3 items not applicable to self-employed, so R7 forced to 0 (structural absence)

Notes: ASB, antisocial behaviour. Social support is built from two subscales, one covering support from colleagues, peers and the immediate manager and one covering the quality of managerial leadership. It is scored as present where either subscale is met: at least two of the three support items or at least four of the six leadership items are answered 'strongly agree' or 'tend to agree'.
Source: Authors.

Table A9: Summary statistics

	n (%)
Automated task allocation	
No	19 510 (82.2 %)
Yes	4 232 (17.8 %)
Automated scheduling	
No	21 331 (89.7 %)
Yes	2 444 (10.3 %)
Performance monitoring	
No	19 155 (81.2 %)
Yes	4 439 (18.8 %)
Algorithmic management intensity (0–100)	18.5 (26.4)
Recourse against automated decisions	
No	2 871 (42.7 %)
Yes	3 848 (57.3 %)
Gender and age (three bands)	
Female: < 35	3 222 (13.4 %)
Female: 35–54	6 049 (25.2 %)
Female: 55+	2 311 (9.6 %)
Male: < 35	3 780 (15.7 %)
Male: 35–54	6 086 (25.3 %)
Male: 55+	2 602 (10.8 %)
Education (three levels)	
Low	3 956 (16.5 %)
Medium	9 500 (39.6 %)
High	10 552 (43.9 %)
Has permanent contract	
No	3 204 (13.8 %)
Yes	20 008 (86.2 %)

	n (%)
Occupation (ISCO-08 major group)	
1. Managers	1 104 (4.6 %)
2. Professionals	5 511 (23.0 %)
3. Technicians	3 941 (16.5 %)
4. Clerical workers	2 653 (11.1 %)
5. Services and sales workers	3 976 (16.6 %)
6. Skilled agricultural workers	242 (1.0 %)
7. Craft workers	2 528 (10.6 %)
8. Plant and machine operators	1 907 (8.0 %)
9. Elementary occupations	2 074 (8.7 %)
Sector (NACE)	
A–B – Agriculture and mining	398 (1.7 %)
C – Manufacturing	3 984 (16.5 %)
D–E – Utilities	461 (1.9 %)
F – Construction	1 459 (6.1 %)
G – Wholesale and retail	3 221 (13.4 %)
H – Transport and storage	1 365 (5.7 %)
I – Accommodation and food services	1 184 (4.9 %)
J – Information and communications	939 (3.9 %)
K–L – Finance and real estate	846 (3.5 %)
M – Professional and scientific activities	1 103 (4.6 %)
N – Administrative	1 155 (4.8 %)
O – Public administration	1 949 (8.1 %)
P – Education	2 008 (8.3 %)
Q – Health and social work	2 870 (11.9 %)
R–S – Other services	1 138 (4.7 %)
Workplace size	
Micro: 1–9	6 201 (26.6 %)
Small: 10–49	7 490 (32.1 %)
Medium: 50–249	5 371 (23.0 %)
Large: 250+	4 275 (18.3 %)
With formal employee representation	
No	9 970 (43.7 %)
Yes	12 831 (56.3 %)
Whether employee works from home (at least occasionally)	
No	17 406 (72.3 %)
Yes	6 673 (27.7 %)
Member State	
Austria	533 (2.2 %)
Belgium	602 (2.5 %)
Bulgaria	350 (1.5 %)
Croatia	198 (0.8 %)
Cyprus	58 (0.2 %)
Czechia	608 (2.5 %)
Denmark	389 (1.6 %)

	n (%)
Member State	
Estonia	83 (0.3 %)
Finland	317 (1.3 %)
France	3 440 (14.3 %)
Germany	5 391 (22.4 %)
Greece	384 (1.6 %)
Hungary	553 (2.3 %)
Ireland	331 (1.4 %)
Italy	2 356 (9.8 %)
Latvia	104 (0.4 %)
Lithuania	172 (0.7 %)
Luxembourg	39 (0.2 %)
Malta	37 (0.2 %)
Netherlands	1 180 (4.9 %)
Poland	1 881 (7.8 %)
Portugal	534 (2.2 %)
Romania	856 (3.6 %)
Slovakia	300 (1.2 %)
Slovenia	120 (0.5 %)
Spain	2 612 (10.8 %)
Sweden	650 (2.7 %)
Health and well-being outcomes (mean scores)	
Well-being	69.19
Exhaustion	59.57
Work–family conflict	65.18
Engagement	70.61

Source: Authors' calculations based on EWCS 2024.

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Algorithmic management – measured in this report as whether employees are subject to the use of computer programs to monitor performance, allocate tasks and schedule work – is an important feature of workplace digitalisation. Drawing on Eurofound's European Working Conditions Survey 2024, this report provides a snapshot of the prevalence of algorithmic management in European workplaces and investigates how it is reshaping work and affecting working conditions and employees' well-being. The analysis shows that the use of algorithmic management varies significantly by sector and occupation. Employees subject to algorithmic management report higher job demands, especially quantitative demands (which indicate work intensity), and are more likely to experience job strain than employees who are not subject to algorithmic management. Among the three functions examined, performance monitoring is most strongly associated with poorer health and well-being outcomes and exacerbates the adverse effects of job strain in already strained jobs.

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