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# Changing Job Tasks as Risk or Chance for Employees' Perceived Job Quality? A Longitudinal Analysis

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**Abstract** In recent decades, job tasks have changed significantly, driven primarily by technological change, with some tasks being automated and others gaining in importance. This may affect employees in two ways: On the one hand, changing tasks might decrease perceived job quality through, e.g., cognitive overload. On the other hand, task changes could be a chance, e.g., by automating undesirable tasks such as hard physical work. This study analyses how individual-level task changes influence job satisfaction as a measure of perceived job quality, using data from the German National Educational Panel Study. Fixed-effects models revealed that performing fewer manual and more analytic and autonomy tasks significantly improved job satisfaction, suggesting generally positive effects of recent task changes. However, we also observed age-related differences, with older employees reporting lower satisfaction when performing fewer routine tasks. These results provide valuable insights into the impact of evolving job tasks and highlight areas where further research and policy interventions are needed.

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## **Tätigkeitswandel als Risiko oder Chance für die wahrgenommene Arbeitsqualität Beschäftigter? Eine Längsschnittanalyse**

**Zusammenfassung** In den letzten Jahrzehnten haben sich Arbeitsaufgaben erheblich verändert, was in erster Linie auf den technologischen Wandel zurückzuführen ist. Einige Tätigkeiten können von Maschinen übernommen werden, während andere an Bedeutung gewinnen. Dies kann sich auf zweierlei Weise auf die Beschäftigten auswirken: Einerseits können veränderte Tätigkeiten die wahrgenommene Arbeitsqualität verringern, beispielsweise durch kognitive Überlastung. Andererseits können Tätigkeitsveränderungen eine Chance sein, beispielsweise durch die Automatisierung unerwünschter Tätigkeiten wie schwerer körperlicher Arbeit. Diese Studie analysiert anhand von Daten des Nationalen Bildungspanels, wie sich Aufgabenänderungen auf individueller Ebene auf die Arbeitszufriedenheit als Maß für die wahrgenommene Arbeitsqualität auswirken. Fixed-Effects-Modelle zeigen, dass weniger manuelle sowie mehr analytische und autonome Tätigkeiten die Arbeitszufriedenheit signifikant verbessern, was auf positive Auswirkungen vergangener Aufgabenänderungen hindeutet. Allerdings beobachten wir auch altersbedingte Unterschiede, wobei ältere Beschäftigte eine geringere Zufriedenheit angeben, wenn sie weniger Routineaufgaben ausführen. Diese Ergebnisse liefern wertvolle Erkenntnisse über die Auswirkungen sich verändernder Arbeitsaufgaben und zeigen Bereiche auf, in denen weitere Forschung und politische Maßnahmen erforderlich sind.

**Schlüsselwörter** Jobqualität · Arbeitsbedingungen · Automatisierung · Digitalisierung · Arbeitszufriedenheit

### **1 Introduction**

Global trends, such as digitalisation, globalisation and changes in the workforce (e.g. education, age), are transforming the world of work. One area particularly affected is the nature of job tasks, especially due to the different ways in which they are impacted by technological change (Autor et al. 2003; Acemoglu et al. 2024; Acemoglu and Autor 2011): Rule-based cognitive or manual routine tasks, such as record keeping or sorting, can be executed by computers and computer-controlled machines and are less often performed by humans, whereas analytic and interactive nonroutine tasks, such as researching or managing, are complementary to such digital technologies and therefore are increasing in demand. Furthermore, digitalisation is associated with greater employees' autonomy (Kirchner 2015; Meyer et al. 2019).

These task changes can affect employees in different ways, including both economic (e.g. employment or wages) and noneconomic outcomes such as job quality (Grimm 2024). Job quality is a concept about what constitutes a 'good' job (Kalleberg 2016, p. 112), including multiple dimensions, such as job (in)security, work

intensity, autonomy and flexibility (Cazes et al. 2015; Stefana et al. 2021; Warhurst et al. 2017). Given the numerous and diverse factors that contribute to a good job, some authors use job satisfaction as an overarching measure that reflects an individual's overall evaluation of their job across its various dimensions (Clark 2015; Liu 2023; Kortmann et al. 2021). Job satisfaction thus serves as an indicator of perceived job quality in this study.

Task changes can pose both risks and chances for perceived job quality. On the one hand, increasing demand for complex analytic tasks may lead to cognitive overload, stress and thus dissatisfaction. On the other hand, decreasing demand for undesirable tasks characterised by monotony or hard physical work can reduce creative constraints and health burdens. Although the relationship between changing job tasks and macro-level employment and wage trends is well researched (Matthes et al. 2014; Zeyer-Gliozzo 2023), albeit with partly mixed results (Haupt and Ebner 2020), less is known about their effect on perceived job quality. Furthermore, most research focuses on task information measured at the occupational level, such as the (task-based) automation potential or routine task intensity (e.g. Kortmann et al. 2021; Nazareno and Schiff 2021; Grimm 2024). However, this neglects important task differences within occupations (Arntz et al. 2016). Few studies have examined the impact of individual-level job tasks (Minardi et al. 2023). Additionally, most studies in this context relied on cross-sectional data, failing to link changes in job tasks to changes in job satisfaction over time. In contrast, the use of longitudinal data allows for the analysis of within-individual variation, controlling for time-invariant, unobserved characteristics—factors that influence both the tasks performed and job satisfaction—thereby reducing potential bias.

In this article, we address these research gaps by investigating how changes in job tasks affect job satisfaction as a measure of perceived job quality. Specifically, we ask, do individual-level task changes influence changes in job satisfaction? This question is highly relevant, as job quality directly impacts employee well-being (Munoz De Bustillo et al. 2011), offering insights into the relationship between occupations and social inequality. Furthermore, job quality is crucial for firms, given its strong link to job and business performance (Harter et al. 2002; Judge et al. 2020). Beyond this, it has relevant policy implications, as higher job satisfaction can influence retirement decisions (Wang and Shultz 2010), encouraging longer labour force participation, which is highly important in times of labour shortages.

We first discuss the expected and observed task changes in recent decades, particularly in the context of digitalisation, drawing on the task-based approach (TBA) by Autor et al. (2003). Subsequently, we derive hypotheses on how changing job tasks affect job satisfaction, integrating mechanisms linking automation to well-being (Nazareno and Schiff 2021) with insights from job quality research. Afterwards, drawing on longitudinal data of the German National Educational Panel Study (NEPS), we apply machine-learning imputation methods for missing data and estimate fixed-effects models, controlling for individual unobserved heterogeneity to approximate causal effects. Finally, we present and discuss the findings.

## 2 Background, State of Research, Theory, and Hypotheses

### 2.1 Changing Job Tasks

Research on changes in job tasks originated from observed U-shaped trends in employment and wages in many industrialised countries, e.g. growth in high-skilled and low-skilled jobs and decline in middle-skilled jobs, with technological progress and its impact on job tasks assumed to be the driving force (Matthes et al. 2014; Acemoglu and Autor 2011). Against this background, the TBA was formalised by Autor et al. (2003) and further developed by others (e.g. Acemoglu and Autor 2011; for a recent summary, see Acemoglu et al. 2024). It examines occupations as collection of job tasks, ‘unit[s] of work activity that produce output’ (Acemoglu and Autor 2011, p. 1075).

The TBA highlights how technology affects labour markets by increasing the productivity for certain tasks, automating others or creating entirely new tasks (Acemoglu et al. 2024). A key distinction is between routine tasks—standardised and rule-based tasks such as sorting (manual), bookkeeping or repetitive customer service (cognitive)—and nonroutine tasks, including analytic tasks that require problem-solving skills and abstract thinking (e.g. legal writing), interactive tasks that require management and communication skills (e.g. persuading others) and manual tasks (e.g. janitorial services). Routine tasks are susceptible to automation, whereas analytic and interactive nonroutine tasks tend to be complemented by technology. Autonomy tasks, although influenced by other factors such as work organisation, can also be considered nonroutine and therefore rather resistant to automation (Matthes et al. 2014).

The assignment of task to routine (automatable) and nonroutine (nonautomatable) evolves with technological progress (Matthes et al. 2014). The description above reflects machine and computer-based automation and excludes modern technologies such as artificial intelligence (AI; Frey and Osborne 2017). However, AI adoption remains limited, with 8% of Organisation for Economic Co-operation and Development (OECD) companies and 13% of German firms using it in 2023 and significant variation across sectors and company sizes (Licht and Wohlrabe 2024; Calvino et al. 2024; Arntz et al. 2020).

Empirical studies have confirmed shifts in job tasks since the 1970s: Employment in jobs with routine tasks or routine task intensity has declined, while employment in analytic and interactive nonroutine jobs or intensity in those tasks has risen across the United States (Autor et al. 2003; Cortes et al. 2017), Europe (Hardy et al. 2018) and Germany (Bachmann et al. 2018; Spitz-Oener 2006). Yet some studies noted a slow-down or slight reversal of some of these trends after 2006 (Bachmann et al. 2018). Other classifications indicated rising social and analytic tasks (1999–2012) alongside declining manual tasks (1999–2006) in Germany (Nedelkoska and Quintini 2018). Some studies analysed task changes in finer detail and showed, for example, that in Germany (1973–2011), extraction/manufacturing tasks declined sharply, while education/training/etc. and nursing/treating medically or cosmetically increased (Maier 2022). In the United Kingdom (1997–2006), influencing, literacy tasks and self-planning tasks especially increased (Green 2012). Although most research linked

changes in job tasks to technological progress and automation, other factors such as education upgrading, demographic shifts, structural changes and offshoring have also been shown to play a role (Hardy et al. 2018; Reijnders and De Vries 2018; Cortes et al. 2017).

Task classifications vary between studies. Often, cognitive, physical and interactive task domains, along with their corresponding skill domains, are distinguished and further broken down into subcategories (Green 2012), for instance into routine/nonroutine, as done by Autor et al. (2003). However, these distinctions are not always clear-cut. For instance, calculating tasks may be classified as either cognitive routine or analytic nonroutine (Green 2012). Other approaches considered these dimensions individually and separated task content (physical, intellectual and social tasks) from how it is performed (autonomy, teamwork, routine; Fernández-Macías and Bisello 2022).

## 2.2 Empirical Findings on the Effects of Job Tasks on Employees' Job Satisfaction

Changing job tasks are assumed to impact job quality (Grimm 2024). Job quality is defined differently in the literature: According to one strand of research, job quality is a multidimensional concept with objective and subjective dimensions (Cazes et al. 2015; Stefana et al. 2021; Warhurst et al. 2017). Objective dimensions include economic factors such as wages and working conditions, which, following the job demands and resources model (Bakker and Demerouti 2007), consist of both negative aspects such as job insecurity, physical health risk factors and work intensity, and positive aspects such as learning opportunities, autonomy and conditions that support work–life balance (Eurofound 2021; Leschke and Watt 2014; Cazes et al. 2015). Subjective dimensions include, for example, meaningfulness and fulfilment (Warhurst et al. 2017). Several studies have created job quality indices using various mixes of these dimensions (Crespo et al. 2017; Leschke and Watt 2014; Munoz De Bustillo et al. 2011). Alternatively, other studies considered job satisfaction as an overall measure for job quality (Clark 2015; Liu 2023), supported by empirical evidence linking it to job quality dimensions (Clark 2005; Leontaridi and Sloane 2004; Sousa-Poza and Sousa-Poza 2000). Job satisfaction reflects an individual assessment of working conditions (Clark 2005; Clark and Kozák 2023; Munoz De Bustillo et al. 2011) and thus serves as an overall indicator of perceived job quality.

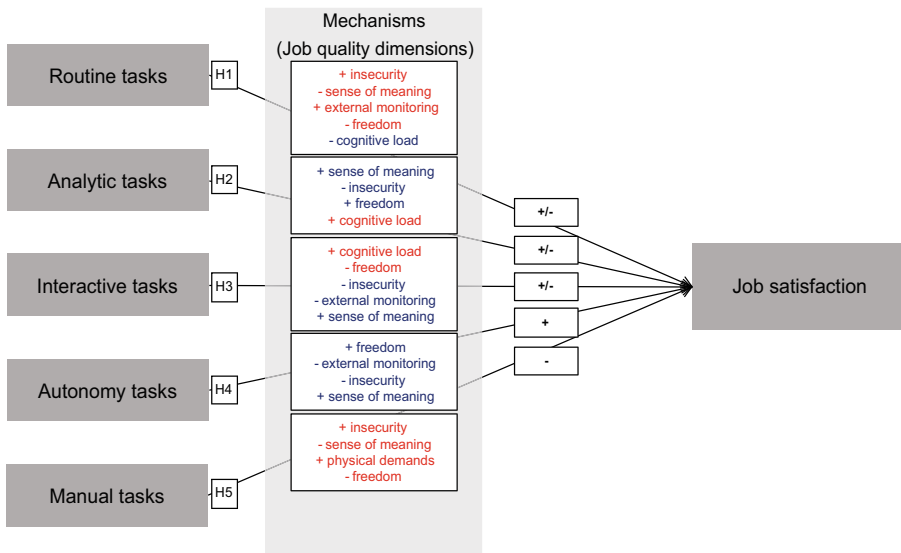
Several studies have analysed how job tasks affect job quality indicators or job satisfaction, typically using occupation-level data, such as occupational-level routine task intensity (Grimm 2024) or automation or substitution potentials (e.g. Dengler and Tisch 2020; Kortmann et al. 2021; Nazareno and Schiff 2021; Grimm 2024). The latter measurement refers, for example, to the proportion of tasks within an occupation that can be automated. Findings on job satisfaction are mixed. Some cross-sectional studies found a negative correlation between automation potential and job satisfaction (Nazareno and Schiff 2021; Liu 2023), while Grimm (2024) showed no significant link between routine task intensity or substitution potential and job satisfaction. In contrast, Kortmann et al. (2021) observed higher job satisfaction with higher levels of substitution potentials in Germany.

Only a few studies have focused on individual-level job tasks. Minardi et al. (2023) found that routine tasks negatively affected job satisfaction, while cognitive tasks and autonomy had a positive impact, which mediated the relationship between computer use and job satisfaction.

### 2.3 Task Changes as a Risk and Chance: A Theoretical Framework

The interplay between job tasks and perceived job quality is complex, requiring a theoretical framework to illustrate the underlying mechanisms (Fig. 1). We conceptualised job quality dimension as interrelated mechanisms that collectively influence job satisfaction.

Our approach builds on the framework of Nazareno and Schiff (2021) linking automation to well-being indicators. We adapted this to explore how job tasks influence job satisfaction, as its proposed mechanisms align with various objective job quality indicators such as job security, work intensity and autonomy, as well as with a key subjective indicator, sense of meaning (Cazes et al. 2015; Eurofound 2021; Leschke and Watt 2014; Warhurst et al. 2017; Holler 2013). Furthermore, we incorporated physical risks as an objective job quality dimension to assess how shifts in manual tasks affect job satisfaction (Munoz De Bustillo et al. 2011; Warhurst et al. 2017). The outlined mechanisms, highlighted in the light grey area in Fig. 1 (red mechanisms stand for positive effects on job satisfaction and blue mechanisms for negative effects), are discussed in detail below.<sup>1</sup>



**Fig. 1** Theoretical framework for the relationship between job tasks and job satisfaction. Red mechanisms have a negative impact on job satisfaction, while blue mechanisms have a positive impact

<sup>1</sup> In the printed version, red corresponds to light gray and blue to dark gray.

*Insecurity* is a central issue in the debate about technological development (Nazareno and Schiff 2021). The risk for job loss from automation has often been discussed, such as Frey and Osborne (2017) finding that 47% of U.S. employment is at high risk for automation. The anticipation of technological substitution may lead to concerns regarding job security. A study found that 30% of respondents across 16 countries feared automation-induced unemployment (Innocenti and Golin 2022). Job insecurity is a subdimension of job quality (Eurofound 2021; Leschke and Watt 2014) and has been shown to negatively impact job satisfaction (Kortmann et al. 2021; Schwabe and Castellacci 2020).

Task changes can also affect employees' job satisfaction through a *loss of meaning*. Laaser and Karlsson (2022) suggest that meaningful work is characterised by objective and subjective dimensions of autonomy, dignity and recognition. Individuals who lose core parts of their job such as direct participation, their work's value and thus self-worth or the ability to secure livelihood from work due to digitalisation-related changes in tasks are particularly vulnerable to perceive their work as less meaningful. Meaningfulness is a subdimension of job quality (Holler 2013; Warhurst et al. 2017) and has been empirically linked to higher job satisfaction (Bailey and Madden 2020; Allan et al. 2019). Automation-induced loss of meaning may decrease job satisfaction, as assumed by Nazareno and Schiff (2021).

Job satisfaction can also be impaired when employees face new roles or tasks without proper training. They often need to adapt and upskill to keep up with technological change (Zeyer-Gliozzo 2023; Nazareno and Schiff 2021; Arnold et al. 2016), with automation being associated with higher job complexity (De Witte and Steijn 2000). Furthermore, increasing demands due to digitalisation and information and communications technologies (ICT) usage, such as interruptions or time pressure (Meyer and Hünefeld 2021), can increase work intensity, which can lead to a higher *cognitive load* (Nazareno and Schiff 2021). Work intensity, time pressure or workload itself are also aspects of job quality (Eurofound 2021; Warhurst et al. 2017; Cazes et al. 2015; Munoz De Bustillo et al. 2011). Studies have shown that task complexity and time pressure, when perceived as hindrances, negatively correlated with job satisfaction (e.g. Gerich and Weber 2020).

*External monitoring* is another mechanism, as ICT use increases the possibility that employees' work will be monitored (Gerten et al. 2019). With easier tracking of work processes and results, employees could feel controlled, for example by video surveillance or time- or attention-tracking software. This can impair perceived job quality by affecting employees' privacy and autonomy (Eurofound 2020). Performance monitoring has been shown to negatively impact job satisfaction (Jeske and Santuzzi 2015), and Nazareno and Schiff (2021) assumed that surveillance could decrease job satisfaction.

Technological changes that replace physically demanding tasks can improve occupational safety and health (Dengler and Tisch 2020; Gihleb et al. 2022) and reduce physical job intensity (Gihleb et al. 2022). *Physical risks* are a dimension of job quality (Cazes et al. 2015; Munoz De Bustillo et al. 2011; Warhurst et al. 2017), and physical demands are negatively related to job satisfaction (Humphrey et al. 2007).

Finally, employees can be supported by automation of monotonous tasks, allowing them to focus on more creative tasks or abstract thinking (Nazareno and Schiff

2021). The decline of manual tasks and growing use of cognitive tasks can also enable greater access to remote work (Mergener 2020). These shifts can increase (spatial) autonomy and *freedom*, leading to more control over employees' execution of work and flexible working organisation, which may facilitate work–life balance (Entgelmeier et al. 2022) and contribute to higher job satisfaction (Boxall and Macky 2014). Control and autonomy are subdimensions of job quality and are positively associated with job satisfaction (de Lange et al. 2003; Nazareno and Schiff 2021).

## 2.4 Hypotheses

We examined the following task dimensions: routine, analytic, interactive, manual and autonomy tasks. These five dimensions are considered separately because job quality factors such as job insecurity, physical relief and cognitive load are generally related to individual task dimensions rather than their combinations (e.g. routine manual vs. nonroutine manual tasks). This classification therefore provides a clearer understanding of how each task type influences job satisfaction. In addition, it helps to address challenges of classification such as determining whether specific analytic tasks fall under routine cognitive or nonroutine analytic tasks.

In our framework, autonomy plays a dual role. First, it is a task dimension that is changing, partly due to digitalisation, and that affects job satisfaction through mechanisms related to job quality dimensions, such as job insecurity and sense of meaning. Second, autonomy is also a dimension of job quality itself. In our theoretical model, this second role is represented by the mechanism we refer to as 'freedom'. The following section focuses on autonomy as a task dimension; its role as a mechanism is addressed in further analyses and in the discussion.

### 2.4.1 Routine Tasks

Routine tasks may negatively impact job satisfaction, as their automatable nature can lead to greater fear of job insecurity (Nazareno and Schiff 2021; Schwabe and Castellacci 2020). This aligns with research linking occupational substitution potential to perceived risk of job loss (Müller et al. 2021) and cognitive job insecurity (Dengler and Gundert 2021), as well as findings that routine tasks are associated with negative assessments of future labour market chances in the context of digitalisation (Friedrich et al. 2021). Due to automation, routine tasks may also be associated with employees losing parts of their work, leading to a perceived loss of meaning (Nazareno and Schiff 2021). Moreover, routine tasks, due to their fixed rules and procedures, are often easier to monitor digitally and can be negatively associated with autonomy and freedom (Nazareno and Schiff 2021; Minardi et al. 2023). On the positive side, routines cause 'feelings of safety and confidence', a basic human need (Avni-Babad 2011, p. 223), and more routine tasks could reduce cognitive load and performance pressure, thereby reducing stress and potentially improving job satisfaction (Nazareno and Schiff 2021). Thus, we have opposing mechanisms at work, illustrated by the negative (red) and positive (blue) influences of routine tasks on job satisfaction (Fig. 1, arrow H1). There tend to be more negative than

positive effects, but the weighting is unclear, so we are putting forward the following competing hypotheses:

*H 1a* Fewer routine tasks lead to lower job satisfaction.

*H 1b* Fewer routine tasks lead to higher job satisfaction.

#### 2.4.2 Analytic Tasks

On the one hand, challenging cognitive tasks can promote personal development (Karasek 1979). Development opportunities and successfully overcoming workplace challenges enhance the sense of meaning (Rosso et al. 2010; Lysova et al. 2019), contributing to higher job satisfaction. As specific analytic tasks have become more prevalent in recent years, especially within jobs (Green 2012; Maier 2022; Nedelkoska and Quintini 2018), they are probably negatively related to job insecurity. Research supports a positive link between analytic tasks and assessed future labour market chances (Friedrich et al. 2021). Additionally, a positive relationship between cognitive tasks and access to remote work (Mergener 2020) implies that more analytic tasks increase freedom. On the other hand, more (complex) analytic tasks could also lead to cognitive overload, negatively affecting employees' job satisfaction (Nazareno and Schiff 2021). These opposing mechanisms are shown in Fig. 1 (arrow H2, red for negative and blue for positive effects); with slightly more positive than negative mechanisms. However, since we do not know the weighting, this leads to the following competing hypotheses:

*H 2a* More analytic tasks lead to lower job satisfaction.

*H 2b* More analytic tasks lead to higher job satisfaction.

#### 2.4.3 Interactive Tasks

High cognitive load or stress can result from demanding interactive tasks (Nazareno and Schiff 2021), which are often complex because of low predictability (Wehrmann 2023). Interactions with customers, colleagues and supervisors could also cause emotional dissonance when positive emotions must be expressed in demanding interactions (Wehrmann 2023), which may indicate low levels of freedom. Conversely, interactive tasks have been increasing within and between occupations in Germany (Nedelkoska and Quintini 2018), potentially reducing job insecurity and enhancing job satisfaction. However, research has found no clear link between interactive tasks and perceived job loss risk due to digitalisation or future labour market chances (Friedrich et al. 2021), suggesting only a weak correlation, if any. Furthermore, interactive tasks are difficult to monitor. Finally, interactive work is often seen as beneficial for society and as highly meaningful, which can boost job satisfaction (Wehrmann 2023; DGB-Index Gute Arbeit 2018). Overall, positive and negative mechanisms appear to be somewhat balanced (Fig. 1, arrow H3), but the weighting is unclear, suggesting the following conflicting hypotheses:

*H 3a* More interactive tasks lead to lower job satisfaction.

*H 3b* More interactive tasks lead to higher job satisfaction.

#### 2.4.4 *Autonomy Tasks*

Since autonomy is closely linked to freedom, it should lead to higher job satisfaction (Bakker and Demerouti 2017; de Lange et al. 2003; Luchman and González-Morales 2013). In addition, autonomy is inherently negatively related to monitoring. Because autonomy tasks are hard to automate (Matthes et al. 2014) and have been increasing over time (Green 2012), more autonomy tasks can increase job security, as supported by positive links to assessed labour market chances and negative links to perceived risk of job loss (Friedrich et al. 2021). This may lead to higher job satisfaction. In this context, autonomy tasks should also promote a greater sense of meaning, consistent with findings from other studies (Lysova et al. 2019; Rosso et al. 2010). Therefore, we hypothesise the following (Fig. 1, arrow H4):

*H 4* More autonomous tasks lead to higher job satisfaction.

#### 2.4.5 *Manual Tasks*

The performance of manual tasks has tended to decline (Nedelkoska and Quintini 2018; Maier 2022), with nearly 30% of German employees reporting relief from physically demanding tasks due to technological changes (Arnold et al. 2016). This may lead to loss of sense of meaning and concerns about job security. Research findings are mixed: While some findings demonstrated a negative correlation between manual tasks and perceived job loss risks, others linked manual tasks to poorer labour market prospects or showed that workers with manual tasks more likely feared automation-induced unemployment than those with knowledge-based tasks (Innocenti and Golin 2022; Friedrich et al. 2021). These tasks are also linked to physical demands, which were negatively correlated with job satisfaction (Humphrey et al. 2007) and negatively associated with access to remote work (Mergener 2020), limiting freedom. These assumptions lead to our final hypothesis (Fig. 1, arrow H5):

*H 5* Fewer manual tasks lead to higher job satisfaction.

## 3 Data and Methods

### 3.1 Data

Our analyses were based on the adult cohort of the German National Education Panel Study (NEPS, SC6: 12.1.0), which provides data on education, professional careers and competence development over the adult life course (Allmendinger et al. 2019; Blossfeld et al. 2011). A key advantage of the NEPS data is its detailed information on job tasks over time at the individual level.

The target population consists of individuals born between 1944 and 1986 residing in private households in Germany. Four representative subsamples were drawn between 2007 and 2011 (Forschungsdatenzentrum Leibniz Institute for Educational Trajectories [FDZ-LIfBi] 2021).<sup>2</sup> We used NEPS waves 3 (2011/2012), 7 (2015/2016) and 11 (2019/2020), which are the survey waves of job tasks.<sup>3</sup> Our sample included full-time employees working at least 30h per week (Federal Statistical Office of Germany 2022), excluding temporary workers, seasonal workers, secondary labour market workers, apprentices and the self-employed ( $N=6867$  in wave 3,  $N=4334$  in wave 7 and  $N=3333$  in wave 11).

The dataset contains missing values due to item and wave nonresponse, leaving gaps in the time-varying data. Detailed summary statistics are presented in the Online Appendix, Sect. A. Missing values were imputed in R using the package *missRanger* (Mayer 2019; R Core Team 2022; Schwerter et al. 2024), which performs a fast missing value imputation by chained random forests with predictive mean matching.<sup>4,5</sup> Imputation was done in wide format, where one row corresponds to one person and information from different waves is stored in separate variables. Only values for individuals with more than 50% valid information in our main variables were imputed (McNeish 2017; Mishra and Khare 2014; Strauss et al. 2003), leaving us with 3637 individuals per wave. Most of the excluded individuals were removed because they took part in only one wave (Fig. A.1 in the Online Appendix). After creating 50 imputed datasets per person, we excluded all person-waves which did not belong to the sample of interest, resulting in a final sample size of  $N=3285$  in wave 3,  $N=3482$  in wave 7 and  $N=3318$  in wave 11. Analysis results were combined according to Rubin's rules using the *mi* estimate commands in Stata (Rubin 1987; StataCorp 2021).<sup>6</sup>

## 3.2 Measurement

### 3.2.1 Outcome

Job satisfaction serves as a measure of perceived job quality. It reflects an individual's overall evaluation of their job (Clark 2015; Liu 2023; Kortmann et al. 2021) and

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<sup>2</sup> For more information on, e.g., response rates, see the method reports (e.g. for the first five NEPS waves, Hammon et al. 2016).

<sup>3</sup> For the sake of simplicity, we will refer to 2011, 2015 and 2019 in the following.

<sup>4</sup> Specific missing values, i.e. in the federal state if persons reported 'changing places of residence' and in occupational prestige if working in occupations for which no values are available in the MPS scale (occupations without specific job specification, officers, noncommissioned officers or members of the regular armed forces in other ranks) were not imputed (126 individuals).

<sup>5</sup> We used the predictive mean matching option to obtain only existing realisations of the respective variables to preserve the distribution of values (van Buuren 2018) while also raising the variance in the resulting conditional distributions to a realistic level (Mayer 2019). Parameters of *missRanger* were set as follows: a maximum tree depth equal to 6, *splritrue* *extratrees* (Geurts et al. 2006), 100 trees (Stekhoven and Buhlmann 2012) and a sample fraction of 0.1 (Stekhoven and Buhlmann 2012).

<sup>6</sup> To calculate the within  $R^2$  in our models, we applied Fisher z transformation first (Harel 2009; van Buuren 2018).

correlates with several dimensions of job quality (e.g. Clark 2005; Sousa-Poza and Sousa-Poza 2000). In addition, overall job satisfaction is related to multiple-item measures of job satisfaction (Dolbier et al. 2005). Job satisfaction was assessed by ‘How satisfied are you with your work?’, using a scale from 0 to 10, with 0 being ‘completely unsatisfied’ and 10 being ‘completely satisfied’.

### 3.2.2 Job Tasks

Although job tasks have been widely examined in the past, their measurement is rather inconsistent (Matthes et al. 2014). Matthes et al. (2014) developed a new instrument implemented in NEPS whose conceptual design is closely based on the TBA (Autor et al. 2003). Data were collected on five different task types: interactive, analytic, routine, autonomy and manual tasks.

Interactive and analytic tasks cover the cognitive dimension. Tasks for which (personnel) communication is required were defined as *interactive*. Items were included in the questionnaire about how often a person had customer contact or must teach in the job (1 = ‘always or very often’ to 5 = ‘very rarely or never’). *Analytic* tasks contain thinking and reasoning. Respondents were asked in multiple steps whether reading, writing or calculating was part of their job and to what extent, whereby the information was aggregated, e.g. to a reading scale ranging from 1 = ‘no reading’ to 5 = ‘25 pages or more’. *Manual* tasks were assessed by physical requirements of respondents’ jobs, such as the frequency of lifting heavy weight or standing for a long period. To measure the routine dimension, inverse items with difficult-to-automate tasks were included, first with tasks concerning job complexity (*(non)routine*), e.g. frequency of solving difficult problems or reacting to unanticipated situations. Second, *autonomy* was measured, for instance by questions regarding how often employees could influence the order or pace of their work or how often they could make their own decisions.

All items were recoded so that high values corresponded to a high frequency in the job. Indices for the task types were built based on averages of the corresponding items and of the subscales in the case of analytic tasks. Afterwards, they were normalised and ranged from 0 to 1. Overall, the reliability was satisfying (most  $\alpha > 0.7$ ; Matthes et al. 2014).<sup>7</sup> For our analyses, all variables on job tasks were standardised within the waves. Summary statistics on job satisfaction and job tasks are presented in Table 1.

The majority of the sample experienced changes in the composition of their tasks (see the distribution of within-person changes in task intensity in the Online Appendix, Fig. B.1 and Fig. B.2). The within-person task change was calculated by the difference between two waves, e.g. routine task intensity in wave 7 minus routine task intensity in wave 3. For example, it can be seen that a high proportion of workers recorded a slight increase in routine tasks within 4 years (visible in the ‘peak’ a little above zero in Fig. B.2). Changes in the intensity of interactive

<sup>7</sup> When replicating the indices with data of NEPS waves 3, 7 and 11, we obtained the following Cronbach’s alpha values: analytic tasks 0.71, interactive tasks 0.74, manual tasks 0.84, routine tasks 0.83 and autonomy tasks 0.67.

**Table 1** Sample characteristics. Source: German National Education Panel Study SC6: 12.1.0, waves 3, 7 and 11, unweighted, without imputations

Variable	Mean	Standard deviation	Values/Range	<i>N</i>
<i>Job satisfaction</i>	7.23	1.69	0–10	9451
<i>Job tasks</i>				
Routine tasks	0.42	0.18	0–1	8782
Analytic tasks	0.60	0.21	0–1	8792
Interactive tasks	0.48	0.21	0–1	8783
Manual tasks	0.28	0.27	0–1	8786
Autonomy tasks	0.56	0.21	0–1	8777

Job tasks in wave 3 were not measured for the refreshment sample from 2011

tasks were the most common (87%), with a reduction being slightly more prevalent. Analytic tasks were the most often not changed (by 31% of the sample), although there was still a high proportion of respondents with variation.

### 3.3 Methods

To examine the effect of job tasks on job satisfaction, we estimated the following linear model<sup>8</sup>:

$$y_{it} = \mathbf{j}'_{it}\boldsymbol{\alpha} + \mathbf{x}'_{it}\boldsymbol{\beta} + a_i + u_{it}$$

where  $y_{it}$  represents measures of individual  $i$ 's job satisfaction at time  $t$  (2011, 2015, 2019),  $\mathbf{j}_{it}$  is a vector of task variables (routine, analytic, interactive, manual and autonomy),  $\mathbf{x}_{it}$  are time-varying control variables,  $\boldsymbol{\alpha}$  and  $\boldsymbol{\beta}$  are the parameters to be estimated and  $a_i$  and  $u_{it}$  represent the error terms (time-constant and idiosyncratic error).

It is likely that changes in the intensity of one task type are accompanied by changes in the intensity of another, e.g. less routine and more analytic tasks. We therefore included all task variables simultaneously. In additional analysis, models were estimated separately for all tasks.

Because there might be unobserved factors related to the tasks performed and employees' job satisfaction, we exploited the panel structure of the data and examined time variation in our variables. This was done by estimating our models as fixed-effects models (Wooldridge 2013) to eliminate the time-constant (individual) error term  $a_i$  and control for unobserved time-constant heterogeneity. With this, all other time-constant factors drop out of the equation.

However, time-varying factors that affect job tasks as well as workers' job satisfaction still need to be controlled for (Kohler et al. 2024). One main factor is a change of job, which could be associated with a change of occupation or sector with implications for job tasks and job satisfaction (e.g. due to a different working environment, wages and employment security associated with occupations and sectors). In addition, changes in job characteristics could influence both changes

<sup>8</sup> The statistical software Stata MP (version 17) was used for the analyses.

in job tasks and job satisfaction, such as having a management or permanent position. A manager has different tasks from someone involved in operational execution, for example, and a permanent position can be associated with higher responsibility and other tasks than a temporary position. Both factors can also influence job satisfaction, among other things, through the mechanisms of pay and job security. Furthermore, we controlled for computer use, which, based on the TBA, is linked to job tasks and has been shown to impact job satisfaction (Minardi et al. 2023; Sarti and Torre 2019). Working hours were also taken into account because they can affect job satisfaction by influencing work–life balance and because different tasks require different, sometimes unconventional, working hours. The employer’s distribution of tasks may also vary in the context of changing working hours, as a reduction, for example, could be perceived as a sign of lack of dedication (Schulz and Zoch 2024; Cech and Blair-Loy 2014). In addition, factors from the private sphere included the number of children younger than 6 years in the household, as there seems to be a motherhood penalty for both job tasks (Schulz and Zoch 2024) and job quality (Jones et al. 2023), and age, which impacts the tasks workers perform—for example, fewer manual tasks are done in older age—as well as job satisfaction (Dobrow et al. 2018). Finally, we controlled for period effects, as the period can impact tasks performed as well as job satisfaction through economic circumstances.

Concerning weighting, we used a model-based approach for our multivariate analyses (Hammon et al. 2016, p. 14; Würbach et al. 2021, p. 47). That means we included in our model all (time-varying) variables for which a significant effect on participation probabilities was found and which were used for constructing the weights in NEPS concerning nonresponse.<sup>9</sup> Thus, marital status, household size, federal state and contact attempts were included as additional controls. Tables C.1 and C.2 in the Online Appendix provide summary statistics on the control variables.

## 4 Results

The average job satisfaction in our sample (without imputations) was 7.2. Job satisfaction differed by task intensity, with the strongest relationship seen for autonomy tasks (Fig. D.1 in the Online Appendix). Employees in the lowest quartile of autonomy tasks reported an average job satisfaction of 6.8, while those in the highest quartile reported 7.7.<sup>10</sup>

### 4.1 The Effect of Changing Job Tasks on Job Satisfaction

Table 2 contains the results of the fixed-effects models analysing the effect of changing job tasks on changes in job satisfaction. An increase in the intensity of analytic and autonomy tasks and a decrease in manual tasks led to an increase in job satisfaction (model 1, controlling only for model-based weighting). Changes in the intensity

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<sup>9</sup> Time-constant sampling variables were not included because they drop out of fixed-effects models.

<sup>10</sup> The Online Appendix also contains a correlation matrix of all dependent, independent and control variables in Table D.1.

**Table 2** Effect of changes in job tasks on job satisfaction. Source: German National Educational Panel Study SC6:12.1.0, waves 3, 7, and 11

	(1)	(2)
Routine tasks	-0.044 (0.034)	-0.034 (0.034)
Analytic tasks	0.108** (0.039)	0.125** (0.039)
Interactive tasks	-0.014 (0.038)	-0.007 (0.037)
Manual tasks	-0.180*** (0.049)	-0.171*** (0.048)
Autonomy tasks	0.253*** (0.033)	0.250*** (0.033)
Further controls	-	x
<i>N</i>	10085	10085
Within R2	0.028	0.042

Fixed-effects regression models. Cluster-robust standard errors in parentheses. All models include variables for model-based weighting, i.e. marital status, household size, federal state and contact attempts. Further controls in model (2) comprise computer use, job change, management position, temporary contract, working hours, age, number of children younger than 6 years living in the household and wave. Significance levels: †0.1, \*0.05, \*\*0.01, \*\*\*0.001

of routine and interactive tasks were not significantly associated with changing job satisfaction. All coefficients were in a favourable direction against the background of recent task changes: More analytic tasks, more autonomy and less manual work were associated with better perceived job quality. The effect of changes in autonomy tasks was the largest, followed by the effect of manual tasks. For instance, an increase of one standard deviation in the frequency of performing autonomy tasks led to a 0.25-point increase in job satisfaction.

Including control variables in the model had little effect on the relationship between job tasks and job satisfaction (model 2). The coefficients of the control variables revealed that computer use was not significantly associated with employees' job satisfaction when job tasks were controlled for (Table E.1 in the Online Appendix). Furthermore, job satisfaction was influenced by job change, temporal contract, age and time period.

#### 4.2 Nonlinear Relationships

The relationship between task changes and job satisfaction may be nonlinear. For example, while some routine tasks can provide cognitive relief, a job that consists of such tasks which can be automated to a very large extent may lower satisfaction due to high job insecurity. This aligns with the autonomy paradox, where too much autonomy can be detrimental (Mazmanian et al. 2013; Zhao and Wu 2023).

To test for nonlinearity, we used quartile-based task categories. Results revealed that the very frequent performance of routine tasks (fourth quartile) was linked to lower job satisfaction ( $p < 0.1$ ), whereas moderate levels showed no significant

differences to infrequent performance of routine tasks (first quartile). A nonlinear pattern also appeared for analytic tasks, where positive effects weakened at higher levels. Other tasks followed mostly linear trends. See the results and a discussion in the Online Appendix, Sect. E.2.

### 4.3 Heterogeneities by Group

It needs to be emphasised that job satisfaction is a subjective measure, meaning that personal factors—such as age—may impact how task changes influence perceived job quality: Older workers may be more affected by cognitive pressure and job insecurity. Considering age-related effects is also practically relevant, as job satisfaction is important for older employees to remain in the workforce.

We found that reducing routine tasks increased satisfaction for employees younger than 40 years, whereas for those 60 and older, fewer routine tasks tend to result in lower job satisfaction (see Sect. E.3 in the Online Appendix for results and a discussion). Additionally, more interactive tasks lowered job satisfaction for younger employees ( $p < 0.1$ ), but enhanced it for those aged 50 and older. For other task types, age did not lead to meaningful differences.

### 4.4 Single Task Items

Finally, we estimated the effect of the individual task items instead of the task indices to analyse which specific tasks were driving the former results (Sect. E.4 in the Online Appendix). The effects varied within task categories. For instance, among routine-related tasks, only learning new things, a negative indicator of routine task intensity, had a significant positive impact on job satisfaction. Within autonomy tasks, scheduling own tasks had the weakest and a nonsignificant impact, while other autonomy tasks showed a stronger influence. Differences also emerged within other task types. These findings indicate that individual task dimensions did not uniformly affect job satisfaction.

## 5 Sensitivity Checks and Supplementary Analyses

### 5.1 Sensitivity Checks

We performed various additional analyses to check the robustness of our main results. In doing so, we tested the sensitivity of the results with respect to the imputation method, the sample selection and the use of control variables. Comparable results were shown throughout, and the conclusion remains basically the same. The respective results are presented and discussed in the Online Appendix (Sect. F.1–F.3).

A comparison of models analysing only the effect of one task type with models analysing the effects of all task types simultaneously showed in many cases that the task coefficients were smaller when the other tasks were controlled for (Sect. F.4 in the Online Appendix). The (negative) effect of changes in routine tasks, for example,

was significant. Thus, some of the bivariate relationships were due to the effects of simultaneous changes in other tasks, confirming the importance of including all tasks simultaneously.

Since autonomy is both a task dimension and a job quality dimension and can act as a mechanism linking task changes to job satisfaction, additional analyses were run, excluding autonomy tasks (Sect. F.5 in the Online Appendix). The results suggest that autonomy may partly mediate the effect of other task changes on job satisfaction. However, as this was not a full mediation analysis and as autonomy could also be a confounding factor, these findings should be interpreted with caution.

## 5.2 The Role of Task Changes in the Effect of Digitalisation on Job Satisfaction

Several studies have found positive correlations between ICT use and job satisfaction (e.g. Sarti and Torre 2019). Given that digitalisation affects task changes, computer use—as a proxy for digitalisation—may impact job satisfaction through changing job tasks. Minardi et al. (2023) supported this assumption using a structural equation model with pooled cross-sectional data. We investigated this with fixed-effects models in a longitudinal design (Sect. G.1 in the Online Appendix). For comparison, we also estimated an ordinary least squares (OLS) regression with pooled data (pooled OLS).

First, we examined whether changes in computer use were related to task changes. Fixed-effects models showed that increased computer complexity was linked to fewer routine and manual tasks and more analytic, interactive and autonomy tasks. The pooled OLS showed a positive effect of computer use on job satisfaction, which, when job tasks were controlled for, was negative, closer to zero and/or nonsignificant in most cases. However, when we conducted the analyses with a fixed-effects model, the main effect of computer use was no longer significant. Although adding job tasks reduced the coefficients, the absence of a significant main effect suggested no mediation when considering changes over time and accounting for potential unobserved, time-invariant individual differences.

Since computer complexity may not fully capture digitalisation, we also analysed computer use frequency using the BIBB/BAuA Employment Survey 2012 and 2018 (Hall et al. 2020a, b). Additional robustness analyses were also carried out using the measurement of computer complexity of this dataset. The results were consistent throughout.

## 5.3 Interactions Between Tasks

Finally, we incorporated interactions between routine/autonomy and analytic, interactive and manual tasks to measure the task categories of Autor et al. (2003) more closely (routine cognitive and routine manual as well as manual, interactive and analytic nonroutine tasks). The coefficients of the interaction effects were close to zero and all were not significant. Therefore, the individual task categories as they were integrated here, and not their interaction, played a role for perceived job quality (Sect. G.2 in the Online Appendix).

## 6 Discussion and Conclusion

### 6.1 Summary and Discussion

Our analyses investigated the effects of individual-level changes in job tasks on perceived job quality, measured with job satisfaction, by using longitudinal data. Based on NEPS data from 2011, 2015 and 2019, our fixed-effects analyses showed that an increase in analytic and autonomy tasks and a decrease in manual tasks led to higher job satisfaction.

Thus, the competing hypotheses on the effects of routine tasks on job satisfaction (*H 1a* and *H 1b*) must be rejected, likely due to opposing mechanisms: job insecurity, reduced sense of meaning, greater monitoring and less freedom versus lower cognitive load. However, additional analyses suggested that beyond a certain threshold, routine tasks led to lower job satisfaction. This may indicate that in highly routine jobs, negative effects such as job insecurity and loss of meaning are more pronounced, while moderate task performance still offers cognitive relief. The role of cognitive load may also vary with age. Although routine tasks reduced job satisfaction for younger workers, they tended to increase it for older workers, possibly because certain cognitive demands, particularly those requiring fluid abilities, become more strenuous with age (Abbasi and Bordia 2019). For analytic tasks (*H 2a* and *H 2b*), we found support for *H 2b*, indicating a positive effect on job satisfaction. This suggests that increased sense of meaning, security and freedom presumably outweighed the potential negative effects of higher cognitive load. However, the weakening of the positive effect at higher levels of analytic tasks suggests that cognitive load may still play a role at some point. Both hypotheses on the effects of interactive tasks must be rejected (*H 3a* and *H 3b*), probably because the opposing mechanisms did not show a clear pattern. However, interactive tasks increased job satisfaction for older employees. This suggests that for this group, the benefits of reduced insecurity, less monitoring and greater sense of meaning outweighed the potential drawbacks of cognitive load and reduced freedom connected with interactive tasks. Finally, we found support for hypotheses *H 4* and *H 5*: More autonomy and fewer manual tasks improved the perceived job quality. In contrast to the other task dimensions, no opposing mechanisms were identified, likely explaining their strong impact on job satisfaction. Autonomy tasks enhance freedom, reduce monitoring and insecurity and increase sense of meaning, while manual tasks are linked to higher insecurity, physical demands and lower sense of meaning and freedom.

Our results align with previous studies that found no effect of routine task intensity or substitution potential on job satisfaction (Grimm 2024), but they contrast with studies showing negative effects of routine tasks (Minardi et al. 2023) or automation potential (Nazareno and Schiff 2021; Liu 2023). A key difference is that our study used panel data to assess changes over time and examined tasks at the individual level, rather than relying on occupational task data, which may explain the contrasting results.

## 6.2 Limitations and Further Research

Our analyses are not without limitations. For example, we could not directly test the presumed mechanisms because key variables, such as those relating to cognitive load, were not available across all waves. We focused solely on autonomy, which functions both as a task dimension and as an aspect of job quality itself. In the latter role, it is part of the mechanism in our model referred to as 'freedom', which links task changes to job satisfaction. Although the results suggest a potential mediating role of autonomy, it may also act as a confounding factor. New NEPS waves (2019 and 2020) include measures such as fear of losing one's job due to digitisation. This will allow for more detailed future analysis, for example via longitudinal structural equation models.

Although we used longitudinal data and controlled for time-invariant unobserved heterogeneity, which is an extension to much of the existing research in this field, some time-varying unobserved factors may still have biased results. For example, the relationship between autonomy and job satisfaction might be influenced by job promotion, which we could not fully control for. However, we did our best to rule out most confounding effects by controlling for job changes and management position.

Additionally, we did not find support for a mediation of digitalisation on job satisfaction via task changes in the fixed-effects models. However, our measurement of digitalisation (computer use) was limited. Future studies should develop more precise measures, as 'different technologies affect different tasks in production, which leads to distinct effects on occupations and workers' (Grimm 2024, Sect. 5). The level of digitalisation, i.e. not computerised, computerised (e.g. ICT or computer-controlled machines and systems) or additionally intelligently networked, can play a crucial role for its consequences on job quality (Tisch et al. 2021).

The shift towards fewer routine and more nonroutine tasks appears to have weakened in recent years (e.g. Bachmann et al. 2018), possibly because ICT-driven changes have already taken place on a large scale. However, advances in AI and mobile robotics are creating further automation possibilities for 'former' nonroutine tasks (Frey and Osborne 2017). For example, AI can perform cognitive tasks such as medical diagnostics, while automation remains limited in areas requiring social or creative intelligence and manual dexterity (Frey and Osborne 2017). However, there is also evidence that AI even increases specific routine tasks such as monitoring or operating machines and technical processes (Gathmann et al. 2024). Future research should account for evolving automation, e.g. by reconsidering task classifications. However, those changes cannot be observed extensively yet, as AI adoption remains in its early stage (Licht and Wohlrabe 2024; Calvino et al. 2024; Arntz et al. 2020).

Finally, the role of organisational characteristics in shaping the influence of task changes on job satisfaction could also be taken into account in the future. Studies have shown large differences in the adoption of digital technologies depending on establishment characteristics (Ohlert et al. 2022). There may also be differences in the further handling of associated changes, for example in the provision or nonprovision of adaptation training.

## 7 Conclusion

Despite these limitations, our study advances prior research by providing the first longitudinal analysis of the influence of changing job tasks at the individual level on changes in job satisfaction, which serves as a measurement of perceived job quality. Thus, we provide valuable insights into the impact of evolving job tasks.

We conclude that the effects of recent task changes, driven in particular by digitalisation, generally enhanced perceived job quality. A shift towards more analytic and autonomy tasks and fewer manual tasks had a positive effect on job satisfaction. However, not all employees experience these changes equally. Older employees, in particular, tended to be less satisfied when performing fewer routine tasks, possibly due to cognitive demands. Addressing this issue is crucial for mitigating labour shortages, as low job satisfaction can influence retirement decisions (Wang and Shultz 2010).

Finally, although task changes in these directions generally improve perceived job quality, not all employees may be equally able to take part in these changes, and there are still employees whose occupations consist of many routine or manual tasks. Further training could facilitate task changes, yet employees in highly routine-intensive jobs are less likely to participate in training (Zeyer-Gliozzo 2023, 2024). Notably, this group also reports lower job satisfaction than those with fewer routine tasks. Ensuring that all employees benefit equally from digitalisation and task changes should therefore be a key social and policy concern.

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**Conflict of interest** B. Zeyer-Gliozzo, C. Kunz, J. Schwerter, and M. Brandt declare that they have no competing interests.

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