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**RESEARCH ARTICLE**

# Employee acceptance of digital monitoring systems while working from home

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**Abstract**

Digitalisation and COVID-19 led to an expansion of remote work arrangements, raising the question of whether and how employers should monitor remote workplaces. However, before the implementation of monitoring methods, it is important to consider employees' acceptance of this approach. Therefore, we contribute to current research on electronic performance monitoring by empirically investigating employees' evaluations of performance monitoring at home. This paper presents an analysis of how certain monitoring technologies for work-from-home arrangements are perceived as undesirable and whether other job aspects can compensate for these unattractive monitoring components. Using an experimental factorial survey design, German employees evaluated remote work arrangements with randomly varying characteristics. We show that respondents accept a certain degree of monitoring at home but increasingly reject monitoring systems as they become more invasive. However, in some cases, the negative impact of monitoring at home can be mitigated by certain incentives, such as money or the purpose of monitoring.

**KEYWORDS**

electronic performance monitoring, employee attitudes, employee monitoring, experimental survey design, privacy concerns, remote work, social exchange theory

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## INTRODUCTION

In recent decades, technological developments have increased the possibilities for engaging in location-independent work. During the COVID-19 pandemic, the concept of working from home became even more widespread (Bick et al., 2020; Brynjolfsson et al., 2020; Frodermann et al., 2020) and will most likely take root beyond this crisis (Beiersmann, 2020). However, the implementation of remote work in the future implies new challenges for the relationship between employees and employers (Jeske, 2022), such as the issue of supervising home-based subordinates (Badawy & Schieman, 2021; Felstead & Henseke, 2017; Felstead et al., 2003; Rainey & Melzer, 2021; Wu, 2020). Employers are well advised to consider the effects that employee acceptance of monitoring systems can have on their behaviour in terms of legal ramifications, norms and values and work relationships (Jeske & Santuzzi, 2015; Kidwell & Sprague, 2009; Nelson et al., 2019; Panina & Aiello, 2005; Quade et al., 2020; Stanton & Julian, 2002; Yost et al., 2019).

New technologies offer various possibilities for implementing monitoring systems—even for remote work (Jeske & Santuzzi, 2015; Panina & Aiello, 2005; Stanton, 2000a, 2000b; Wu, 2020). These monitoring systems—most commonly, electronic performance monitoring (EPM)—can be defined as ‘the practice of using computers and/or telecommunication technology to collect, analyse and report information about employee performance’ (Panina & Aiello, 2005, p. 270). The acceptance of EPM systems has been investigated mainly in the context of regular workplaces by experimental designs (Aiello & Svec, 1993; Davidson & Henderson, 2000; McNall & Roch, 2009; Princi & Krämer, 2019; Stanton & Barnes-Farrell, 1996) or survey-based analyses (Grant & Higgins, 1991; Jeske & Santuzzi, 2015; Stanton & Weiss, 2000; Stanton, 2000b; Yost et al., 2019).

Accounting for the expansion of remote work arrangements, we aim to investigate the acceptance of digital monitoring systems by remote (at-home) working employees. Hence, we use a survey-based experimental research design to answer the following questions: 1. How do employees evaluate electronic monitoring while working from home? 2. Can favourable working conditions—such as higher wages—compensate for EPM at home?

We build on social exchange theory (SET) by suggesting that electronic employee monitoring is characterised by an inherent assessment of resource exchange—more specifically, an information exchange, for example, employee behaviour and performance—and social power asymmetries (Stanton & Stam, 2003). Referring to Blau's (1964) presumption that the behaviour of goodwill implies trust by managers and reciprocates in corresponding employee behaviour (Chernyak-Hai & Rabenu, 2018), we aim to analyse whether and how electronic employee monitoring influences the exchange relation (e.g., by diminishing trust, gaining valuable information, etc.). Thus, gains of information regarding employee work behaviour through electronic workplace monitoring ‘must come attached to reciprocal exchanges [...] in the form of promised rewards or potential sanctions’ (Stanton & Stam, 2003). Second, we focus on the reciprocal component of the exchange relation by exploring the extent to which favourable working conditions—especially wages—work as an exchange mechanism to compensate for EPM. To date, little is known about compensation possibilities and employee reactions to (non-)monetary incentives to justify workplace surveillance—especially for home-located work settings (Allgulgin & Ellingsen, 2002; Arai, 1994). Consequently, this work examines the impact of varying the conditions for remote work on employee acceptance of certain monitoring systems to determine which elements have a positive effect on acceptance. Therefore, we supplement our SET framework with arguments from the Theory of

Compensating Wage Differentials, which proposes a tradeoff between wages and unfavourable working conditions. First, we introduce the theoretical framework from which the hypotheses are derived. Subsequently, our experimental vignette study is described and analysed. Finally, the paper concludes by presenting the results and discussing further implications.

## **DIGITAL EMPLOYEE MONITORING THROUGH THE LENS OF SET**

To explore employees' acceptance of EPM when working from home, we draw on SET (Blau, 1964; Cropanzano et al., 2017). This theory postulates that human interactions can be perceived as a series of transactions or exchanges between two or more parties (Blau, 1964; Cross & Dundon, 2019; Stanton & Stam, 2003). The relationship between employer and employee can be understood as an exchange, where both parties aim to balance inputs and outputs. For instance, an employee provides their labour and expertise in exchange for a salary, benefits and job security, while an employer offers resources and support to aid the employee in performing their job duties (Masterson et al., 2000). Thus, following this reasoning, employees are less likely to accept electronic monitoring if the benefits of the exchange—specifically, the benefits of the gained information on employee behaviour—are skewed towards the employer. Hence, if the balance of inputs and outputs in asymmetric workplace relationships—such as hierarchical supervisor–subordinate relationships—does not appear fair, employees are more likely to reject the monitoring technology (Stanton & Stam, 2003; Wayne et al., 2002). Conversely, employees are more likely to accept monitoring technologies if they see benefits on their end—such as improved feedback on job performance, career growth, professional development, and so forth (McNall & Roch, 2009; Stanton & Stam, 2003).

Within this framework, electronic monitoring has an impact on the supervisor–employee relationship by providing control and/or feedback (McNall & Roch, 2009; Stanton & Stam, 2003). On the one hand, control enhances the employer's output and the employee's input by reducing the information uncertainty of the employer regarding the behaviour of the employee (McNall & Roch, 2009; Stanton & Stam, 2003). For example, EPM helps employers ensure that employees are working effectively and efficiently, even when working remotely (McNall & Roch, 2009). On the other hand, feedback provides employees with valuable information about evaluation standards, enabling them to identify their strengths and weaknesses and improve their job performance (Stanton & Stam, 2003).

### **Effects of the monitoring system's characteristics**

Based on these two mechanisms that influence the assessment of the social exchange relationship, we can derive hypotheses on the characteristics of the monitoring system. As the literature postulates, one of the main drawbacks of EPM is its invasiveness (Grant & Higgins, 1991; Ravid et al., 2020; Stanton, 2000a, 2000b). If employees feel that the monitoring system is too intrusive—for example, by tracking every move and activity—they will conclude that the employer gains more from such a system than they do. Conversely, if the monitoring system is perceived to be less invasive—for example, by restricting monitoring to activities relevant to job/task performance—employees may be more likely to accept it (Grant & Higgins, 1991; Ravid et al., 2020). Based on these premises, our first hypothesis (H1) states that

*employees are more likely to accept electronic monitoring while working from home if the monitoring system is perceived to be less intrusive.*

In EPM literature, it is often argued that the way monitoring is implemented in the work process influences workers' acceptance (Alder, 2001; Alge, 2001; McParcland & Connolly, 2019). Specifically, monitoring can occur continuously or randomly. From the viewpoint of SET, this mode can influence acceptance by two mechanisms. First, a random assignment produces uncertainty for the worker, which is perceived as unfavourable per se and thus leads to stress at the workplace (Schmidt et al., 2014; Vitak & Zimmer, 2023). Second, punishment in the case of worker misconduct is more difficult to justify since the frequency of misconduct is not known. This may lead to uncertainty about whether punishment is truly fair, which has been shown to have negative effects on the worker (Matta et al., 2017). Consequently, workers can interpret random EPM as a violation of justice principles in the exchange relationship. Both arguments lead to our second hypothesis (H2), which posits that *employees are more likely to accept monitoring while working from home if surveillance is conducted continuously as opposed to randomly.*

Concerning the purpose of EPM, our assumptions about the role of feedback and control in the exchange relationship lead to a straightforward argument. Feedback offers employees valuable information about their performance, allowing them to improve their skills and increase overall job satisfaction (Sommer & Kulkarni, 2012). In contrast, we assume that evaluating employee productivity through monitoring is perceived as intrusive and negatively impacts job satisfaction (Chen & Park, 2005; Gerten et al., 2019; Urbaczewski & Jessup, 2002). Hence, feedback-aimed monitoring indicates benefits for employees as well and, therefore, adds to the exchange relationship on both ends. Conversely, monitoring to track productivity signals only benefits the employer and thus implies a rather sanction-oriented exchange relationship. Consequently, hypothesis H3 proposes that *employees are more likely to accept monitoring while working from home if the monitoring system provides feedback on job performance rather than evaluating employee productivity.*

## **Tradeoffs between determinants**

While our first three hypotheses are based on the *ceteris paribus* variation of a specific determinant (monitoring system [H1], monitoring frequency [H2], and monitoring purpose [H3]), the same input/output relation from the exchange relationships can be achieved through different combinations of determinants. This leads to three hypotheses that focus on possible tradeoffs: Are workers willing to accept EPM more readily if some other conditions mitigate or compensate for the disadvantages of EPM? For our first tradeoff hypothesis, we introduce the assumption that people are comparing their results from an exchange relationship with those from others and that they value a just allocation of returns of the labour relationship (Blau, 1964; Buunk & Gibbons, 2007). Consequently, workers who think that others are less monitored than themselves are less likely to accept this situation. Hence, employees view monitoring as less intrusive if it is a common practice in their workplace, and therefore, their colleagues are also subject to the same conditions (Stanton, 2000b). Moreover, employees may feel more at ease if they can discuss the monitoring system and its implications with their colleagues and thus increase their perception of the transparency and fairness of the monitoring technology (Grant & Higgins, 1991; Panina & Aiello, 2005; Ravid et al., 2020; Stanton, 2000a, 2000b). Consequently, we perpetuate our previous assumption about monitoring invasiveness (H1) and suggest that (H4)

*the adverse effects of invasive monitoring while working from home can be mitigated if more colleagues are subjected to the same conditions.*

Thus far, we argue that in a SET framework, electronic monitoring acceptability is evaluated by an analysis of resource exchange in a social context (Stanton & Stam, 2003). As stated in H1, invasiveness reduces the gain from the employment relationship for the worker. However, to increase acceptance, the employer can try to compensate for this negative determinant by offering other gains, thus equalising the disequilibrium of the exchange relationship (Stanton & Stam, 2003). This is also the idea of the theory of compensating wage differentials (CWDs). This approach posits that unattractive or unpleasant working conditions (e.g., poor work environment, monotonous tasks, close monitoring) must be compensated by higher wages (Kray & Robertson, 1991). This wage premium represents "the marginal disutility experienced from working in a particular job" (Kray & Robertson, 1991, p. 156). We borrow this idea and supplement our SET framework by assuming that employees are willing to accept unfavourable monitoring conditions if the exchange with the employer is balanced by other, more favourable conditions. Thus, CWD provides a theoretical underpinning in the SET framework that actors are willing to make tradeoffs between different outcomes of an exchange relationship and which compensations are important in the employment relationship. Hence, it should be possible to compensate employees who work under such monitoring systems for their aversion to monitoring (Kray & Robertson, 1991; Rosen, 1986). This compensation could be in the form of money or other job characteristics that increase the employee's overall utility.

Therefore, we will investigate the evaluation process of monitoring acceptability by combining pleasant and unpleasant job characteristics. First, we will focus on monetary changes to determine if employees can be incentivised, or compensated, for being monitored while working from home. We assume that in *ceteris paribus*, employees will try to avoid invasive monitoring and evaluations of their individual productivity. Drawing on these arguments of CWD and SET, we hypothesise that *the negative effects of more invasive monitoring while working from home can be reduced by offering higher wages* (H5). Second, we posit that *the negative effects of monitoring to track employee productivity can be reduced by offering higher wages* (H6).

## **METHODS AND DATA**

### **A factorial survey to measure the acceptability of monitoring systems in home offices**

We employ a factorial survey experiment to examine the acceptability of monitoring systems in a remote work setting. This methodological approach is based on descriptions of situations with dimensions that vary systematically (independent variables) and a rating scale used to measure the attractiveness of the presented job situation (the dependent variable). Factorial survey experiments aim to capture respondents' reactions to hypothetical situations (i.e., vignettes). The effect of each dimension on the respondent's decision or judgement can be estimated by independently varying the dimensions of the vignettes (for an overview, see Auspurg and Hinz, 2015). Thus, individual factors that are often confounded in reality can be isolated. The varying dimensions reflect the variables of interest (treatments) that are hypothesised to influence the dependent variable. The latter is measured by asking the respondents to evaluate these descriptions (vignettes). Each respondent is randomly assigned to several hypothetical situations/vignettes. Thus, interpersonal as well as intrapersonal variation can be used to analyse the effects and the relative importance of



description). At the end of each vignette, the respondents were asked to rate how attractive the partly home-located job appeared to them by using the given scale (1, ‘not attractive’ to 7, ‘very attractive’). Our vignette design resulted in a vignette universe with all possible level combinations ( $2 \times 2 \times 2 \times 4 \times 2 \times 4 \times 2 = 256$  vignettes) of our six dimensions (Table 1).

We used the full universe by creating 43 decks consisting of six randomly assigned vignettes to each respondent. In our study, each deck was rated by approximately 7 participants on average. The vignettes were integrated into an online survey that included additional questions about the respondents’ work situation and workplace (employment status and job description, tasks, company size, working hours, experience working from home, and income), work-related and monitoring-related attitudes (appropriateness of monitoring and job satisfaction), and sociodemographic information (gender, age, and education). The choice of vignette dimensions (independent variables) and the concluding levels were chosen in reference to previous literature findings and practicability in terms of the research design. Thus, we kept our design concise and focused on dichotomous variables. However, regarding our research question, we pay particular interest to the monitoring system and the capability of monetary compensation. Hence, we categorised these two dimensions in a more detailed manner—concluding in four categories each. By doing so, we tried to compromise the tradeoff between accessible information and the feasibility of the factorial survey design.

## **A note on the legal framework for workplace surveillance in Germany**

Crucial for vignettes is their empirical realism: although they describe hypothetical situations, respondents should perceive these situations as realistic to make meaningful assessments. In our case, illegal surveillance activities would be problematic. Hence, we designed our vignettes to describe plausible surveillance options. In Germany, workplace surveillance is regulated by employee data protection rules by several legal sources. On a national level, regulation relies mainly on the case law of the Federal Labour Court (Bronowicka et al., 2020; Middel, 2019) and the Federal Data Protection Acts of 2009 and 2017. Nevertheless, these reforms provide a rather general legal framework (Bronowicka et al., 2020). Most of the groundwork for employee data protection is rooted in European Union regulations, especially the General Data Protection Regulation of 2018 (Bronowicka et al., 2020; Hugl, 2013; Middel, 2019). The Council of Europe defined fundamental privacy and data protection principles (necessity, finality, proportionality, transparency, and security) as guidelines for lawful workplace monitoring (Mitrou & Karyda, 2006). Overall, these legislative rules are vague and do not generally prohibit specific surveillance methods. Consequently, our monitoring options are likely considered plausible, as respondents neither rejected certain vignettes nor criticised them at the end of the questionnaire.

## **Measures—Dependent variable**

### **Acceptance**

Following comparable studies (van Acker et al., 2020; Grant & Higgins, 1991; Jacobs et al., 2019; Nam, 2019; Princi & Krämer, 2019), we used an attractiveness response scale (from 1 ‘not



attractive at all' to 7 'very attractive') at the end of each vignette to evaluate the described (home-located) job.

## Measures—Independent variables

### Monitoring system

The first hypothesis (H1) states that employees are less likely to accept monitoring while working from home if they are monitored intensely. Therefore, we altered four monitoring systems across our vignettes to reflect different levels of invasiveness. In each situation that is described, employees face monitoring assuming that 'documenting work hours' is the least invasive form. We included 'screen tracking' as a more invasive form of monitoring that captures the extent and kind of all computer activities (website and programme usage). The third level of invasiveness is the recording of video conferences, for example, using video software tools such as Zoom, Microsoft Teams, Skype or similar programmes. Finally, 'face tracking' represents the most invasive form of direct employee monitoring, as such systems involve directly recording and analysing videos of employees. All these monitoring systems are supposed to represent exemplary surveillance options that could realistically be used. An additional analysis of the perceived invasiveness of the monitoring systems supports the hypothesised ranking (see Table A1).

### Frequency of monitoring

For hypothesis H2, the dimension 'frequency of monitoring' captures whether the employee would be either continuously (during working hours) or randomly (several times during working hours, but only for a short period) monitored. In terms of monitoring systems, we argue that both random and continuous monitoring are possible for each system.

### Purpose of monitoring

Furthermore, we consider the purpose of monitoring to be a considerable factor for employees (H3). In reference to previous studies (e.g., Abraham et al., 2019), the purpose of monitoring was described as either giving the employee feedback on his or her work performance ('feedback') or analysing his or her productivity to measure work efficiency ('productivity').

### Peer effects

To test H4, we examined whether a greater share of colleagues working from home might reduce feelings of loneliness or isolation and/or increase feelings of equality. To this end, we distinguish between situations in which the respondent feels like a part of a minority (10%–15% of colleagues work from home as well) versus being part of a majority (70%–75% of colleagues also work from home). Thus, we want to capture whether having a significant number of peers facing the same monitoring conditions is relevant to the acceptability of monitoring systems.

## Income

A special interest of our study is to investigate the extent to which individuals may accept (intense) monitoring in exchange for monetary compensation. In our survey, we focused on two possible tradeoffs. First, we examined whether higher wages can compensate for more invasive monitoring (H5). Second, we tested whether a more threatening monitoring purpose ('measuring productivity') can be 'sold' to employees (H6). Therefore, wages altered randomly across vignettes: no income change, a 5% higher salary, a 10% higher salary, or a 5% lower salary than the respondent's current wage. One might argue that individuals are strongly averse to pay cuts (Ahrens et al., 2014; Kube et al., 2013), which leads to reductions of approximately 20% in productivity (Kube et al., 2013). Nevertheless, previous studies have shown that employees are highly responsive to nonmonetary job characteristics and would consider up to a 20% wage decrease to avoid fixed (work) schedules (Mas & Pallais, 2016). Specifically, the possibility of working from home was found to justify 8% lower wages (Choudhury et al., 2021; Mas & Pallais, 2016). Therefore, the wage reduction category of 5% tests which effect dominates in a monitoring context. Our special focus on wage compensation implies an exchange logic—trading one negative/positive aspect in terms of receiving more/less money in return. Thus, this tradeoff analysis asks for interaction effects, which gain complexity with increasing combination possibilities (depending on the number of categories of the variables in question). However, we aim to investigate how sensitive individuals are to monetary compensation regarding digital monitoring at home. Therefore, we compare situations of decreased or unchanged wages with situations of comparatively higher wages but tied to more invasive monitoring systems. These combinations, then, can indicate not only employees' willingness to accept more invasive monitoring in exchange for more money. They will also mirror their aversion to digital monitoring at home by asking about their willingness to 'sacrifice' a portion (5%) of their current wage to avoid intense monitoring at home.

## Frequency of working from home

Regarding the evaluation of preferences, our theoretical framework suggests that flexibility is often mentioned as a main advantage of working from home (Hilbrecht et al., 2013). Therefore, we altered the number of expected weekdays to work from home to analyse whether those can compensate employees for being monitored more invasively. Thus, we vary in our vignettes if working from home is a rather special and rare (1 day/week) or a more common and frequent (3 days/week) situation.

## Control variables

To account for possible confounding variables at the individual level, we further considered sociodemographic variables in our analysis. Thus, relying on previous EPM literature (Grant & Higgins, 1991; Jacobs et al., 2019; McNall & Roch, 2009; Nam, 2019), we control for age (metric), gender ('male' vs. 'female'), education ('no vocational training/school' vs. 'vocational training/school' vs. 'college/university/PhD degree'), income (nine income categories), weekly working hours (metric) and personnel responsibility ('yes' vs. 'no').

## Data collection and sample

### Participants and procedure

Our online survey was conducted in October 2020. To test our hypotheses, we used an online sample of German respondents provided by the Norstat Convenience Panel ([www.norstat.de](http://www.norstat.de))—a commercial provider that maintains very large and demographically balanced panels. Individuals are actively recruited by Norstat with accessible and regularly updated background information about panellists. The German Norstat panel holds 160,000 panellists, with an approximately equal representation of key demographics (e.g., sex, age) (Norstat, 2020). Conscientious completion of the survey is incentivised by Norstat (bonus points that can be exchanged for money or items). Consequently, it should be carefully taken into account that the sample is not a random draw of the population and, therefore, the generalisability of the results is unclear. Thus, our results are explorative and preliminary.

### Sample

Our sample was restricted to currently employed people (18–64 years of age) who worked on a computer for at least 20% of their working hours. This preselection was intended to increase the plausibility of remote working in our vignette situations. Of 651 invited panellists (via email), 354 started and 313 participants finished the survey. On average, our respondents were 42.9 years old ( $SD = 12.6$ , median = 44); 53% of the respondents were women and 74% lived in households without children under 15 years of age. Furthermore, 12% of respondents experienced a reduction in working hours due to the COVID-19 crisis. Approximately 50% of respondents were currently working partly from home, compared to 35% before the pandemic. A total of 85% of the respondents were full-time employees. On average, the participants worked 37 h a week and spent approximately 74% of their work time on a computer (Table 2).

### Data analysis

Our data structure imposes two challenges for data analysis: First, the estimation of error terms is influenced by hierarchically nested data (six vignettes for each respondent), and second, our dependent categorical variable requires decisions on the functional form of the model. Regarding the first question, we opt for a multilevel model (Auspurg & Hinz, 2015) which takes the effect of the nested data structure for the estimation of standard errors into account. Sometimes, this can also be dealt with by cluster-robust standard errors. Yet, both approaches yield comparable effects in terms of magnitude and significance (see Table A2). However, the multilevel model results in a significantly positive effect on attractiveness from having more days working from home, while an ordinary least squares (OLS) with cluster-robust standard estimation yields a nonsignificant effect (see Table A2). This might be because multilevel estimations allow for more flexibility and "explicitly focus on the multilevel structure of error terms" (Auspurg & Hinz, 2015, p. 90). As for the second problem, a 7-point Likert scale like that of our acceptance ratings (dependent variable) is often treated as continuous (Auspurg & Hinz, 2015). Following this assumption, our dependent variable meets the methodological requirement of a linear regression estimation. However, being aware of the controversial

TABLE 2 Sample description.

	<b>N</b>	<b>Mean</b>	<b>Percent</b>	<b>Standard deviation</b>	<b>Minimum</b>	<b>Maximum</b>
Variables on respondent level						
Age	313	42.88		159.23	19	64
Sex (1 = male)	312		47.12	0.25	0	1
Children under 15 years	313					
No children under 15	233		74.44		0	1
One child under 15	47		15.02		0	1
Two and more children under 15	33		10.54		0	1
Corona: Less working hours (1 = yes)	313		12.14	0.11	0	1
Currently working from home (1 = yes)	313		50.80	0.25	0	1
Pre-corona working from home (1 = yes)	313		34.50	0.23	0	1
Employment situation	313					
Full-time	267		85.30		0	1
Part-time	41		13.10		0	1
Marginally employed	1		0.32		0	1
In training	1		0.32		0	1
Short-time	3		0.96		0	1
Working hours (weekly)	300	37.10		33.22	8	48
Computer-based work (in %)	313	74.35		584.56	20	100
Education	308					
No vocational training	7		2.27		0	1
Vocational school/ vocational training	178		57.79		0	1
College/university/PhD	123		39.94		0	1
Income (in €)	293					
500 to <1000	4		1.37		0	1
1000 to <1500	29		9.90		0	1
1500 to <2000	48		16.38		0	1
2000 to <2500	59		20.14		0	1
2500 to <3000	55		18.77		0	1
3000 to <3500	22		7.51		0	1
3500 to <4000	25		8.53		0	1

(Continues)

TABLE 2 (Continued)

	<b>N</b>	<b>Mean</b>	<b>Percent</b>	<b>Standard deviation</b>	<b>Minimum</b>	<b>Maximum</b>
4000 to <4500	16		5.46		0	1
4500 to <5000	16		5.46		0	1
5000 or more	19		6.48		0	1
Personnel responsibility (1 = yes)	313		34.82	0.23	0	1
Variables on vignette level						
DV: Attractiveness of home working conditions	1862	3.38		4.54	1	7

assumption of continuity regarding our dependent variable, we tested our model specification by calculating models that are suited for categorical dependent variables and allow for more flexible functional forms. Thus, we conducted multilevel ordered logit and multilevel ordered probit models. Our results show similar estimation effects for all models (see Table A2). Regarding the assumption of parallel lines for ordered logit models, we further tested this assumption by conducting a Brant test to identify variables that may violate this assumption (see Table A3). Williams (2006, 2016) suggests using generalised ordered logit models to overcome the parallel lines assumption. However, the Brant Test was not significant for either the global test of our model or for the test of each variable of our vignette study (see Table A3). Thus, the parallel lines assumption of the ordered logit model is not violated for our data. Furthermore, comparing the ordered logit specification to the generalised ordered logit model, the criteria of model fit (Akaike information criterion [AIC] and Bayesian information criterion [BIC]) indicate a better fit of the ordered logit model to our data (see Table A2). We proceed with our linear multilevel model for reasons of empirical evidence for robustness across all model estimations (see Tables A2 and A4) and purposes of interpretation straightforwardness. Even though the empirical criteria of model fit (AIC and BIC) suggest the multilevel ordered logit model, we believe the interpretation of probabilities for logistic regression models is less suitable for reasonable interpretations of the coefficients referring to the response scale (for an overview, see Fullerton, 2009). Since our model comparison estimations show that on the vignette level, our multilevel linear model is identical in significance and, at most, more modest in effect sizes compared to the multilevel ordered logit model (see Table A2), we expect our interpretations to be sound. Thus, especially in terms of a reasonable interpretation of our coefficients, we hold on to our multilevel model in the following.

Additionally, we integrated further variables on the individual level to control for possible confounding factors (see Table A4). Thus, we estimated OLS with robust standard errors, multilevel linear models, and multilevel ordered logit estimations including respondents' age, gender, education, income (nine categories), weekly working hours and responsibility for other personnel (supervisor: yes/no). Regarding individual characteristics, we want to emphasise that our research aim focuses on the acceptance of electronic monitoring systems while working from home. Thus, we aim to disclose (remotely working) employees' attitudes towards such monitoring practices more generally rather than analysing individual differences in terms of monitoring acceptability. However, we account for possible individual effects by including

individual characteristics (similar approaches, see Grant & Higgins, 1991; McNall & Roch, 2009). As we see only small and nonsignificant effects for any of the individual characteristics (see Table A4), our interpretation builds on the models without those variables.

## RESULTS

A look at the ratings (Figure 2) shows that the total range of the scale from 1, 'very unattractive' to 7, 'very attractive', is covered. With 31% of all vignettes being rated as very unattractive, the distribution of our dependent variable is skewed. This may have various causes. On the one hand, a general rejection of working from home could drive 'unattractive' ratings. However, mean ratings of attractiveness by the number of days worked from home (1 day vs. 3 days) show no significant differences. On the other hand, the large number of 'unattractive' ratings could indicate a general aversion to being monitored at home. A cross-table analysis shows that approximately 36% of all 'very unattractive' ratings (equalling 212 vignettes) were allotted to the 'face tracking' technology. Additionally, approximately 40% of all 'very unattractive' ratings (232 ratings) stem from wage reduction vignettes compared to 22% (130 ratings) facing vignettes without wage changes. Thus, monetary changes (esp. loss aversion) might contribute to the augmented 'least attractive' ratings.

The remaining rating options were chosen approximately equally (10%–12% for each category). In total, we obtained 1862 observations with a mean evaluation of 3.38 on the rating scale.

### Regression analysis

We estimated a multilevel regression model to analyse the effects of the vignette dimensions on the attractiveness ratings (Table 3). Regarding our first hypothesis, the results support the expected negative effect of increasingly invasive monitoring systems on the attractiveness of a working-from-home scenario. The results show that attractiveness ratings are reduced by 0.839

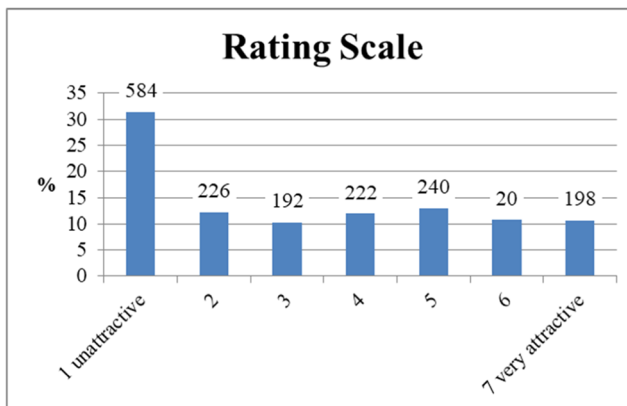


FIGURE 2 Distribution of the attractiveness of home office work surveillance, vignette level. [Color figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

**TABLE 3** Summary of linear regression analysis for variables predicting the main effects of the hypotheses.

	H	Coefficient	Standard error
Control system (reference working hours documentation)	H1		
Screen tracking		−0.839***	(0.103)
Video conference		−1.266***	(0.101)
Face tracking		−1.856***	(0.103)
Frequency (reference random)	H2		
Permanent		−0.509***	(0.073)
Purpose (reference productivity)	H3		
Feedback		0.235**	(0.073)
Days working from home (reference 1 day/week)			
3 days/week		0.169*	(0.072)
Income (reference current wage)			
5% more wage		0.371***	(0.100)
10% more wage		0.662***	(0.102)
5% less wage		−1.211***	(0.101)
Coworkers (reference 10%–15%)			
70%–75%		0.095	(0.073)
Constant		4.409***	(0.139)
Observations		1862	
Log-likelihood		−3578.732	
Wald $\chi^2$ (10)		766.01	
Prob > $\chi^2$		0.000	
<b>Random-effects parameters</b>	<b>Estimate</b>	<b>Standard error</b>	<b>[95% confidence interval]</b>
ID:identity			
var(_cons)	1.529	(0.151)	1.2600    1.8548
var(Residual)	2.059	(0.074)	1.9191    2.2094
LR test versus linear model	chibar <sup>2</sup> (01) = 499.77		Prob ≥ chibar <sup>2</sup> = 0.0000

Note: Coefficients from multilevel regression, standard errors in brackets. Dependent variable: Attractiveness (1 ‘not attractive at all’ to 7 ‘very attractive’).

Abbreviation: LR, likelihood ratio.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

points if the respondent had to face screen tracking surveillance (see Table 3). Participants were even more displeased if they were confronted with monitoring by video conferences (−1.266). The most invasive form of surveillance—face tracking—reduced the attractiveness of working from home by a highly significant 1.856 points on the rating scale. Significant differences among monitoring technologies were further confirmed by changing the reference category

(not shown in Table 3). Therefore, the hypothesis that employees reject invasive monitoring (H1) is supported by our data.

Furthermore, the effect of the frequency of monitoring on the attractiveness of the remote working situation was highly significant. However, contrary to our hypothesis (H2) and the findings of previous EPM studies (Grant & Higgins, 1991; Stanton, 2000b), being monitored continuously—compared to randomly—reduced the attractiveness ratings by 0.509 points (Table 3). Thus, we reject H2, as our results suggest a preference for random monitoring when working from home. Continuous monitoring might, therefore, give an impression of intense control rather than assuring the employee that performance is being captured reliably. Furthermore, employees might be accustomed to social controls in an office environment (e.g., presence of colleagues, office concepts/architecture, surroundings) and, therefore, perceive continuous monitoring as excessively invasive. Previous literature has suggested that employees value having a feeling of control over monitoring (Stanton, 2000b; Stanton & Barnes-Farrell, 1996), which might be (subconsciously) threatened by continuous surveillance. In particular, working in one's private space carries the risk of uncontrollable (interrupting) factors, for example, pets, family/household members or delivery services.

Addressing the purpose of the monitoring system, our results support the hypothesis that employees prefer feedback-related monitoring to productivity-related monitoring (H3). We found that feedback monitoring increases the attractiveness of the remote working situation by 0.235 points on the rating scale (Table 3). Finally, the results show that the number of days working from home (1 day/week vs. 3 days/week) increases the attractiveness of the home-working job situation by 0.169 points, whereas the portion of colleagues who share the same remote working situation (10%–15% vs. 70%–75%) has no significant effect on the attractiveness ratings.

## Interaction effects and Tradeoffs

For further analysis, we estimated additional regression models that include interaction effects.

### Interaction between invasiveness and peer surveillance

In the first step, we aim to investigate social influences—specifically peer effects—on the acceptability of (invasive) monitoring (H4). We assume that equal work and monitoring conditions across peers influence feelings of equality and, therefore, the acceptability of invasive monitoring. To this end, we distinguish between situations in which the respondent feels like a part of a minority (10%–15% of colleagues work from home as well) versus being part of a majority (70%–75% of colleagues also work from home) for each monitoring system. Thus, we want to capture whether having a significant number of others facing the same monitoring conditions is relevant to the acceptability of monitoring systems (H4). Even though none of our coefficients (Table 4) were significant and thus H4 is not supported, the direction of the effects mainly follows the hypothesised relation. The attractiveness ratings were more positive for each monitoring system if most colleagues were working from home as well—except for screen tracking, which was rated less attractive. Contrary to our proposed hypothesis, the effect of screen tracking indicates a lower acceptability of monitoring if more colleagues work from home. A possible explanation might be a peer effect that enhances the



**TABLE 4** Tradeoff between monitoring system invasiveness and the number of coworkers working remotely, predictive marginal effects (H4).

Interaction effects		Predicted attractiveness	Change relative to 10%–15% coworkers at home	$p >  z $
Working hours	10%–15% coworkers at home	4.294 (0.122)		
	70%–75% coworkers at home	4.437 (0.124)	0.143 (0.144)	0.320
Screen tracking	10%–15% coworkers at home	3.625 (0.123)		
	70%–75% coworkers at home	3.429 (0.122)	–0.196 (0.144)	0.175
Video conference	10%–15% coworkers at home	2.983 (0.121)		
	70%–75% coworkers at home	3.213 (0.121)	0.230 (0.103)	0.103
Face tracking	10%–15% coworkers at home	2.405 (0.123)		
	70%–75% coworkers at home	2.605 (0.123)	0.200 (0.145)	0.168

Note: Predictive margins obtained from a multilevel regression model with a two-way interaction control system × coworkers working from home; SE, in parentheses; DV, attractiveness (1 ‘not attractive at all’ to 7 ‘very attractive’); controls, all other vignette dimensions.

\*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ ; † $p < 0.1$ .

former aversion to screen tracking rather than buffers it. Notably, the results show no significant distinction in the peer effect (share of remote coworkers) for either monitoring system. Hence, even though the coefficients point towards our hypothesised relation between monitoring acceptability and peer involvement, the effects remain without significant power. Consequently, the monitoring system’s attractiveness evaluation is not significantly affected by the share of coworkers working from home. At this point, it should be noted that the main effect of the share of coworkers working from home in our main model (Table 3) as well as the interaction effects presented in Table 4 are not significant. Thus, our interaction effects regarding the compensability of invasive monitoring by social mechanisms—such as peer effects—may be too noisy or weak within our sample to this end. Furthermore, if a minority of employees work from home while being monitored by working hour documentation, they feel significantly better off compared to more invasive monitoring systems—even if they would share this condition with 70%–75% of their coworkers (see Table A5). Thus, peer effects might either not provide the hypothesised (moral) support or being part of a minority reflects an—unexpected—feeling of ‘uniqueness’ that is valued by employees. In conclusion, our data do not support the hypothesis that acceptance of more intensive monitoring increases if more coworkers work from home (H4).

## Analysis of monetary tradeoffs

Expanding our interaction model, we proceed with our monetary tradeoff hypotheses by comparing specific combinations of job conditions in terms of monetary compensation. Following the logic of tradeoff analysis, we try to identify attractive and unattractive job attributes to determine which attractive attribute determines which unattractive attribute (interactions). Hence, these tradeoffs force our respondents to decide between—or compromise on—(more/less valuable) attributes in a specific pair of job components (vignette dimensions). We build on our main analysis (Table 3) to determine the (un)desirable option for each dimension of our tradeoff combinations. Consequently, to test our income tradeoff hypotheses (H5 and H6), the desirable attributes are reflected by the least invasive form of monitoring (working hours documentation) (H5) and being monitored to provide feedback (H6). These attributes come with either one's current wage (current wage) or even a wage reduction (5% less wage). However, higher wages (5% or 10% more wage) are offered for the more unattractive options of the monitoring system (H5) and the monitoring purpose (productivity monitoring) (H6). To focus on relevant results, we display marginal effects and the corresponding differentials between combinations. A significant positive effect indicates a preference for the suggested combination of characteristics compared to the reference combination, whereas a negative effect posits a preference for the reference combination. Furthermore, a nonsignificant effect indicates that we cannot find a difference in the acceptance rating between these two situations. Thus, respondents are more likely to trade the reference and the comparison combinations for each other in terms of attractiveness.

## Tradeoffs between invasiveness and wages

Thus far, our analysis has focused on the effects of invasive monitoring systems. Proceeding, we aim to determine how likely employees are to trade (intense) work surveillance for money (higher wages). Thus, H5 suggests the possibility of reducing the negative effect of invasive monitoring on the attractiveness of working from home by offering a higher wage. We created a tradeoff by creating a reference combination with the default options of light monitoring (working hours documentation) and no wage change (current wage) (Table 5). Furthermore, we test the acceptability of (intense) monitoring by analysing employees' preferences if avoiding intense monitoring (facing only working hours documentation) results in a wage reduction (see Table A6 and Figure A1).

The marginal effects (Table 5) show that higher wages cannot significantly compensate for any monitoring compared to a situation with no wage changes and light monitoring (working hours documentation). However, screen tracking seems to be more sensitive to monetary incentives since a difference in attractiveness ratings for a wage increase if monitoring was conducted by screen tracking— compared to light monitoring (working hours documentation) and receiving one's current wage—is hardly visible in terms of effect size ( $\Delta = 0.248$ ) and not significant anymore ( $p = 0.221$ ). Thus, by offering 10% higher wages, employers may be able to compensate employees for screen tracking—even if this is still perceived to be less attractive compared to working hour documentation to one's current wage. Furthermore, we see in our extended analysis (see Table A6) that employees are willing to accept more invasive monitoring systems to avoid wage cuts. Thus, a light monitoring situation (working hours documentation) leading to a wage reduction (5% less wage) was compared to situations with more invasive

**TABLE 5** Tradeoff between the monitoring system and wages, predictive marginal effects (H5).

Combinations of characteristics		Predicted attractiveness	Change relative to working hours and current wage	$p >  z $
Working hours	Current wage	4.616		
		(0.161)		
Screen tracking	5% more wage	3.944	-0.671**	0.001
		(0.161)	(0.208)	
	10% more wage	4.368	-0.248	0.221
		(0.157)	(0.202)	
Video conference	5% more wage	3.417	-1.199***	0.000
		(0.155)	(0.201)	
	10% more wage	3.868	-0.748***	0.000
		(0.160)	(0.203)	
Face tracking	5% more wage	2.820	-1.795***	0.000
		(0.157)	(0.198)	
	10% more wage	2.994	-1.622***	0.000
		(0.157)	(0.205)	

*Note:* Predictive margins obtained from a multilevel regression model with two-way interaction control system  $\times$  wages; SE in parentheses; DV, attractiveness (1 'not attractive at all' to 7 'very attractive'); controls, all other vignette dimensions.

\*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ ; + $p < 0.1$ .

monitoring but at least one's current wage. The results show that invasive monitoring is either not significantly more/less attractive (video conferences if current wage, face tracking if current or more wage) or even more attractive (screen tracking if current or more wage, video conferences if more wage) than accepting a wage reduction to avoid intense monitoring (only working hours documentation). Thus, employees are likely to accept intense monitoring to avoid wage loss. However, monetary incentives can hardly compensate for attractiveness penalties caused by intense digital workplace monitoring at home. Hence, there are limits to employees' willingness to trade money for surveillance. Instead, our results suggest that surveillance is somewhat tradeable for avoiding wage losses.

Next, we investigate whether monitoring to examine employee productivity can be monetarily compensated for (H6). Therefore, we compare situations with feedback monitoring if wages remained unchanged (current wage) to productivity monitoring if wages either stayed the same (current wage) or wages increased (5% or 10% more wage). As expected, productivity monitoring was significantly less attractive—compared to feedback monitoring—if wages remained the same (see Table 6). If individuals faced productivity monitoring but received 5% higher wages, the attractiveness ratings were only slightly more positive but no longer significant. Thus, the judgement of employees was not significantly different and, therefore, can be monetarily compensated for being monitored to evaluate their productivity (as compared to being monitored to receive feedback). Offering 10% more wages, however, increased the attractiveness ratings by 0.247 points on the rating scale and showed some

**TABLE 6** Tradeoff between the purpose of monitoring and wages, predictive marginal effects (H6).

Combinations of characteristics		Predicted attractiveness	Change relative to feedback monitoring and current wage	$p >  z $
Feedback monitoring	Current wage	3.691 (0.123)		
Productivity monitoring	5% more wage	3.705 (0.123)	0.015 (0.146)	0.920
	10% more wage	3.938 (0.123)	0.247 <sup>+</sup> (0.146)	0.091

Note: Predictive margins obtained from a multilevel regression model with two-way interaction monitoring purpose  $\times$  wages working from home; SE in parentheses; DV, attractiveness (1 'not attractive at all' to 7 'very attractive'); controls, all other vignette dimensions.

\*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ ; + $p < 0.1$ .

indication of significance ( $p = 0.091$ ). Hence, employees even prefer productivity monitoring over feedback monitoring if wages increase by at least 10%. Even stronger reactions can be shown for the wage loss scenario. In line with the previous findings of wage loss aversion (see H5), employees evaluate productivity monitoring as significantly more attractive even without wage changes (current wage) compared to feedback monitoring with less compensation (see Table A7).

## DISCUSSION

This study addresses the acceptability of electronic monitoring while working from home in a computer-based work environment that mirrors recent labour market developments (Gonzalez et al., 2019). We build on two theoretical approaches, SET and CWD, thereby incorporating core arguments from CWD into a social exchange framework. This leads to two sets of hypotheses. First, SET provides arguments on the main effects of EPM determinants on workers' acceptance. Second, we can introduce tradeoff considerations regarding the unfavourable monitoring conditions on the one hand and wages on the other. Our results confirm a general rejection of invasive monitoring during work time at home. This is following arguments from SET that monitoring within employment relationships generally reduces the gain. Additionally, following previous findings (McNall & Roch, 2009; Ravid et al., 2020; Yost et al., 2019), we found a preference for feedback-based monitoring over monitoring to detect lacking productivity. However, in contrast to previous studies on regular workplaces (Grant & Higgins, 1991; Stanton, 2000b), our results suggest that continuous monitoring—compared to random monitoring—contributes to a feeling that surveillance is invasive rather than reliable, transparent and representative. We suggest that this discrepancy is because continuous monitoring at home is clashing with the worker's increased interest in privacy compared to the regular workplace. Moreover, permanent monitoring might reduce the sense of control, which (Carlson et al., 2023) found important for remote workers. These findings contribute to the literature by demonstrating that EPM at home is seen as a violation of the exchange relationship that can be analysed by SET.

Given this general aversion to being monitored, it is an interesting question whether employees are willing to trade this unfavourable characteristic for higher wages. Intuitively, the first attempt to conciliate employees for being monitored at home lies in monetary encouragement. Several studies show that employees are sensitive to wage changes (Ahrens et al., 2014; Choudhury et al., 2021; Kube et al., 2013; Mas & Pallais, 2016). While some studies show a strong aversion, especially to pay cuts (Ahrens et al., 2014; Kube et al., 2013), others disclose employees' willingness to compromise on lower wages for certain nonmonetary job characteristics, such as flexible schedules or working from home (Choudhury et al., 2021; Kube et al., 2013). We find that monitoring at home can be compensated for by combining strongly invasive monitoring systems with different incentives, specifically higher wages. However, there are clear limits to this effect: While productivity monitoring can be traded for monetary incentives (e.g., higher salaries), most surveillance technologies (especially video conference monitoring and face tracking) cannot. The possibility of tradeoffs is another contribution to the EPM literature and shows that the core arguments of CWD should be integrated into the theoretical framework for analysing EPM. In combination with assumptions on more or less preferred job characteristics and workplace conditions, CWD provides a rationale for analysing workers' acceptance of EPM. Here, future research can enhance our understanding regarding which types of EPM are hard for employers to compensate their employees for.

In conclusion, our results suggest that employees are averse to monitoring but can—somewhat—be compensated for monitoring by offering incentivising job conditions. This entails implications for human resource management since it shows that, first, maintaining control by digitally monitoring employees working from home yields a basic resentment from the workers' side. However, a second result is that employee rejection of digital monitoring is not absolute and depends on situational and contractual conditions. Consequently, we showed that employee acceptance of monitoring devices can be enhanced in certain situations by offering more favourable conditions (e.g., higher wages or feedback on job performance). Thus, managers should critically question their need to monitor remotely working employees excessively, and if so, they should consider the consequences of monitoring employees on job attractiveness. Judging by our results, compensation for digital employee monitoring might be costly and may not necessarily outweigh the benefits of the monitoring data.

However, this study was conducted in Germany, and hence, attitudes and reactions about employee monitoring technologies may be perceived differently in other countries. The literature on EPM suggests that American employees are less likely to reject workplace monitoring and are less concerned about privacy issues than German employees. Rather, they value reward systems based on objective assessments of individual attainment/performance (Panina & Aiello, 2005). This might stem from cultural differences concerning workplace relations, such as power relations and work norms. Thus, cultural differences concerning monitoring acceptability should be further investigated and accounted for by globally operating firms.

The use of experimental vignettes allowed us to manipulate and control the independent variables to assess hypothetical evaluations of real-life situations. Therefore, our design provides a certain external and internal validity (Auspurg & Hinz, 2015). Nevertheless, our study measures evaluations of hypothetical situations, which may differ from real-life decisions. Auspurg and Hinz (2015) suggest, however, that vignette study results and real-life behaviour are usually highly correlated. Furthermore, we selected participants based on the compatibility of their jobs with a remote working setting to enhance external validity. One drawback of our study is the use of a nonrandom convenience sample. Consequently, it is an

open question whether the causal effects of our factorial design are stable in a random sample of the working force. Finally, our results reflect—, respectively, to our vignettes—attitudes about home-located working environments only. Further research might investigate differences in attitudes towards surveillance related to the work environment (in an office vs. working from home). Additionally, the role of personal attributes on employee attitudes and reactions to electronic monitoring systems is based on personal characteristics such as personality (Zweig & Webster, 2003) or one's locus of control (Aiello & Svec, 1993; Kolb & Aiello, 1996), which both offer further research potential.

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## APPENDIX

See Figure A1 and Tables A1–A8.



FIGURE A1 Plotted interactions of the control system and wage changes (from multilevel regression). [Color figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

TABLE A1 Regression model of invasiveness of privacy.

	Coefficient	SE
Control system (reference working hours documentation)		
Screen tracking	1.116***	(0.108)
Video conference	1.353***	(0.106)
Face tracking	2.068***	(0.108)
Frequency (reference random)		
Permanent	0.454***	(0.076)
Purpose (reference productivity)		
Feedback	-0.171*	(0.077)
Days working from home (reference 1 day/week)		
3 days/week	-0.103	(0.076)
Income (reference same wage)		
5% more wage	-0.173	(0.105)

(Continues)

TABLE A1 (Continued)

	Coefficient	SE		
10% more wage	-0.092	(0.107)		
5% less wage	1.148	(0.107)		
Coworkers (reference 10%–15%)				
70%–75%	-0.019	(0.077)		
Constant	3.283***	(0.144)		
Observations	1862			
Log likelihood	-3661.658			
Wald $\chi^2(10)$	432.71			
Prob > $\chi^2$	0.000			
Random-effects parameters	Estimate	SE	[95% confidence interval]	
ID:Identity				
var(_cons)	1.498	(0.152)	1.2287	1.8266
var(Residual)	2.290	(0.082)	2.1340	2.4569
LR test versus linear model	chibar <sup>2</sup> (01) = 436.53		Prob $\geq$ chibar <sup>2</sup> = 0.0000	

Note: Coefficients from multilevel regression, standard errors in brackets. Dependent variable: Invasiveness of privacy (1 'not at all invasive' to 7 'very invasive').

Abbreviation: LR, likelihood ratio.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Source: Vignette study.

TABLE A2 Regression estimations: OLS, multilevel, multilevel-ordered logit/probit, and generalised-ordered logit.

	OLS	Multilevel	Multilevel-ordered logit	Multilevel-ordered probit	Generalised-ordered logit
Control system (reference working hours documentation)					
Screen tracking	-0.780*** (0.146)	-0.860*** (0.109)	-1.135*** (0.152)	-0.647*** (0.080)	-0.665*** (0.126)
Video conference recordings	-1.24*** (0.141)	-1.267*** (0.105)	-1.692*** (0.153)	-0.971*** (0.081)	-1.119*** (0.128)
Face tracking	-1.734*** (0.159)	-1.843*** (0.108)	-2.554*** (0.166)	-1.477*** (0.087)	-1.596*** (0.152)
Frequency (reference random)					
Permanent	-0.570*** (0.103)	-0.567*** (0.076)	-0.808*** (0.107)	-0.408*** (0.058)	-0.517*** (0.096)

TABLE A2 (Continued)

	OLS	Multilevel	Multilevel- ordered logit	Multilevel- ordered porbit	Generalised- ordered logit
Purpose (reference productivity)					
Feedback	0.303** (0.096)	0.228** (0.077)	0.282** (0.107)	0.161** (0.058)	0.255** (0.085)
Days working from home (reference 1 day/week)					
3 days/week	0.088 (0.098)	0.173* (0.076)	0.223* (0.105)	0.128* (0.057)	0.195 (0.116)
Income (reference current wage)					
5% more wage	0.330* (0.134)	0.404*** (0.104)	0.532*** (0.141)	0.262*** (0.077)	0.246* (0.112)
10% more wage	0.530*** (0.145)	0.650*** (0.108)	0.861*** (0.146)	0.492*** (0.079)	0.508*** (0.122)
5% less wage	-1.225*** (0.138)	-1.205*** (0.105)	-1.795*** (0.158)	-0.997*** (0.084)	-0.994*** (0.146)
Coworkers (reference 10%–15%)					
70%–75%	0.055 (0.095)	0.057 (0.077)	0.043 (0.107)	0.071 (0.058)	0.081 (0.087)
Constant	4.467*** (0.182)	4.453*** (0.145)			1.820*** (0.190)
lns1_1_1					
Constant		0.210*** (0.052)			
lnsig_e					
Constant		0.347*** (0.019)			
cut1			-2.971*** (0.229)	-1.628*** (0.120)	
cut2			-1.971*** (0.221)	-1.080*** (0.117)	
cut3			-1.155*** (0.217)	-0.638*** (0.116)	

(Continues)

TABLE A2 (Continued)

	OLS	Multilevel	Multilevel-ordered logit	Multilevel-ordered probit	Generalised-ordered logit
cut4			-0.255 (0.215)	-0.120 (0.115)	
cut5			0.885*** (0.217)	0.505*** (0.115)	
cut6			2.144*** (0.226)	1.183*** (0.119)	
var(_cons[ID])			3.941*** (0.494)	1.166*** (0.133)	
<i>N</i>	1642	1642	1642	1862	1862
<i>R</i> <sup>2</sup>	0.217				
Adjusted <i>R</i> <sup>2</sup>	0.213				
AIC	6746.584	6297.469	5184.085	5944.693	6482.1
BIC	6806.024	6367.717	5275.947	6038.693	6614.865

Note: Coefficients from regression models, standard errors in brackets. Dependent variable: Attractiveness (1 'not attractive at all' to 7 'very attractive').

Abbreviation: OLS, ordinary least square.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Source: Vignette study.

TABLE A3 Brant test of parallel regression assumption.

Brant test of parallel regression assumption	$\chi^2$	$p > \chi^2$	<i>df</i>
All	66.76	0.057	50
Control system (reference working hours documentation)			
Screen tracking	3.22	0.666	5
Video conference recordings	8.70	0.121	5
Face tracking	6.08	0.299	5
Frequency (reference random)			
Permanent	2.59	0.764	5
Purpose (reference productivity)			
Feedback	6.22	0.285	5
Days working from home (reference 1 day/week)			
3 days/week	9.47	0.092	5
Income (reference current wage)			
5% more wage	2.99	0.701	5

TABLE A3 (Continued)

<b>Brant test of parallel regression assumption</b>	$\chi^2$	$p > \chi^2$	<i>df</i>
10% more wage	9.12	0.104	5
5% less wage	9.38	0.095	5
Coworkers (reference 10%–15%)			
70%–75%	4.43	0.489	5

Note: A significant test statistic provides evidence that the parallel regression assumption has been violated.

TABLE A4 Regression models including controls: OLS, multilevel, and multilevel-ordered logit regression.

	<b>OLS</b>	<b>Multilevel</b>	<b>Multilevel-ordered logit</b>
Control system (reference working hours documentation)			
Screen tracking	−0.717*** (0.144)	−0.852*** (0.106)	−1.117*** (0.148)
Video conference recordings	−1.238*** (0.137)	−1.298*** (0.103)	−1.722*** (0.149)
Face tracking	−1.664*** (0.152)	−1.841*** (0.105)	−2.540*** (0.161)
Frequency (reference random)			
Permanent	−0.573*** (0.100)	−0.571*** (0.074)	−0.812*** (0.104)
Purpose (reference productivity)			
Feedback	0.337*** (0.097)	0.259*** (0.075)	0.308** (0.103)
Days working from home (reference 1 day/week)			
3 days/week	0.086 (0.095)	0.154* (0.074)	0.202* (0.102)
Income (reference current wage)			
5% more wage	0.317* (0.131)	0.382*** (0.102)	0.499*** (0.137)
10% more wage	0.619*** (0.137)	0.674*** (0.104)	0.893*** (0.142)
5% less wage	−1.197*** (0.136)	−1.211*** (0.103)	−1.778*** (0.154)

(Continues)

TABLE A4 (Continued)

	OLS	Multilevel	Multilevel-ordered logit
Coworkers (reference 10%–15%)			
70%–75%	0.071 (0.094)	0.083 (0.075)	0.067 (0.104)
Age	–0.012 (0.007)	–0.012 (0.007)	–0.022* (0.010)
Sex (reference female)			
Male	–0.081 (0.174)	–0.086 (0.173)	–0.132 (0.275)
Education (reference no vocational school/training)			
Vocational school/training	0.495 (0.385)	0.502 (0.580)	0.878 (0.925)
College/universiy/PhD	0.318 (0.387)	0.320 (0.579)	0.583 (0.923)
Working hours (weekly)			
	–0.025 (0.016)	–0.025 (0.015)	–0.047 (0.024)
Personnel responsibility (reference no)			
Yes	0.253 (0.176)	0.263 (0.173)	0.347 (0.274)
Constant			
	5.394*** (0.778)	5.439*** (0.854)	
lns1_1_1			
Constant		0.204*** (0.051)	
lnsig_e			
Constant		0.352*** (0.019)	
cut1			–4.805 (1.360)
cut2			–3.794 (1.357)
cut3			–3.011 (1.356)
cut4			–2.109 (1.355)

TABLE A4 (Continued)

	OLS	Multilevel	Multilevel-ordered logit
cut5			-0.986 (1.355)
cut6			0.273 (1.355)
var(_cons[ID])			3.896 (0.474)
<i>N</i>	1750	1750	1750
<i>R</i> <sup>2</sup>	0.229		
Adjusted <i>R</i> <sup>2</sup>	0.222		
AIC	7199.792	6731.97	5520.665
BIC	7292.737	6835.85	5646.415

Note: Coefficients from regression models, standard errors in brackets. Dependent variable: Attractiveness (1 'not attractive at all' to 7 'very attractive').

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; OLS, ordinary least square.

\**p* < 0.05; \*\**p* < 0.01; \*\*\**p* < 0.001.

Source: Vignette study.

TABLE A5 Interaction effects (marginal effects, H4).

Combinations of characteristics		Predicted attractiveness	Change relative to working hours & 10-15% coworkers at home	<i>p</i> >   <i>z</i>
Working hours	10%–15% coworkers at home	4.294 (0.122)		
Screen tracking	70%–75% coworkers at home	3.429 (0.122)	-0.865*** (0.145)	0.000
Video conference	70%–75% coworkers at home	3.213 (0.121)	-1.081*** (0.143)	0.000
Face tracking	70%–75% coworkers at home	2.605 (0.123)	-1.689*** (0.143)	0.000

Note: Predictive margins obtained from a multilevel regression model with a two-way interaction control system × coworkers working from home; SE in parentheses; DV, attractiveness (1 'not attractive at all' to 7 'very attractive'); controls, all other vignette dimensions.

\*\*\**p* < 0.001; \*\**p* < 0.01; \**p* < 0.05; †*p* < 0.1.



TABLE A6 Interaction effects (marginal effects, H5).

Combinations of characteristics		Predicted attractiveness	Change relative to working hours and wage reduction	$p >  z $
Working hours	5% less wage	2.759		
		(0.160)		
Screen tracking	Current wage	3.492	0.733***	0.000
		(0.156)	(0.197)	
	5% more wage	3.944	1.185***	0.000
		(0.161)	(0.206)	
	10% more wage	4.368	1.608***	0.000
		(0.157)	(0.201)	
Video conference	Current wage	3.031	0.272	0.172
		(0.156)	(0.199)	
	5% more wage	3.417	0.658**	0.001
		(0.155)	(0.199)	
	10% more wage	3.868	1.109***	0.000
		(0.160)	(0.203)	
Face tracking	Current wage	2.491	-0.268	0.186
		(0.157)	(0.203)	
	5% more wage	2.820	0.061	0.761
		(0.157)	(0.202)	
	10% more wage	2.994	0.235	0.247
		(0.157)	(0.203)	

Note: Predictive margins obtained from a multilevel regression model with two-way interaction control system  $\times$  wages; SE in parentheses; DV, attractiveness (1 'not attractive at all' to 7 'very attractive'); controls, all other vignette dimensions.

\*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ ; + $p < 0.1$ .

**TABLE A7** Interaction effects (marginal effects, H6).

Combinations of characteristics		Predicted attractiveness	Change relative to feedback monitoring and wage reduction	$p >  z $
Feedback monitoring	5% less wage	2.201 (0.124)		
Productivity monitoring	Current wage	3.139 (0.122)	0.938*** (0.147)	0.000
	5% more wage	3.705 (0.123)	1.504*** (0.147)	0.000
	10% more wage	3.938 (0.123)	1.737*** (0.147)	0.000

Note: Predictive margins obtained from a multilevel regression model with two-way interaction monitoring purpose  $\times$  wages; SE in parentheses; DV, attractiveness (1 'not attractive at all' to 7 'very attractive'); controls, all other vignette dimensions.

\*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ ; + $p < 0.1$ .

**TABLE A8** Model comparison (alternative model estimations: OLS, multilevel, ordered logit, and ordered probit).

	OLS model Coefficient	Multilevel model Coefficient	Multilevel ordered logit Coefficient	Multilevel ordered probit Coefficient
Monitoring system (reference working hours documentation)				
Screen tracking	-0.727*** (0.136)	-0.845*** (0.103)	-1.082*** (0.141)	-0.650*** (0.080)
Video conference recordings	-1.233*** (0.133)	-1.267*** (0.101)	-1.648*** (0.143)	-0.966*** (0.081)
Face tracking	-1.703*** (0.148)	-1.856*** (0.103)	-2.512*** (0.156)	-1.472*** (0.078)
Frequency (reference random)				
Permanent	-0.521*** (0.100)	-0.503*** (0.073)	-0.716*** (0.100)	-0.400*** (0.057)
Purpose (reference productivity)				
Feedback	0.303*** (0.093)	0.239** (0.073)	0.283** (0.099)	0.164** (0.058)
Days working from home (reference 1 day/week)				
3 days/week	0.104 (0.092)	0.174* (0.072)	0.214* (0.098)	0.133* (0.057)

(Continues)

TABLE A8 (Continued)

	OLS model Coefficient	Multilevel model Coefficient	Multilevel ordered logit Coefficient	Multilevel ordered probit Coefficient
Coworkers (reference 10%–15%)				
70%–75%	0.072 (0.090)	0.084 (0.074)	0.075 (0.100)	0.063 (0.058)
Income (reference same wage)				
Higher wages	0.447*** (0.113)	0.511*** (0.087)	0.662*** (0.117)	0.371*** (0.068)
Lower wages	-1.199*** (0.130)	-1.217*** (0.101)	-1.755*** (0.149)	-0.998*** (0.084)
Constant	4.374***	4.412***		
Observations	1642	1642	1642	1642
R <sup>2</sup>	0.21			
AIC	7682.24	7189.67	5918.58	5951.30
BIC	7737.53	7256.02	6007.05	6039.77

Note: Coefficients from regression models, standard errors in brackets. Dependent variable: Attractiveness (1 'not attractive at all' to 7 'very attractive').

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; OLS, ordinary least square.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

Source: Vignette study.

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