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Jansen, G.; Janssen, Suzanne; Levels, Mark; Fregin, Marie-Christine

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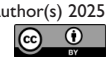
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Why are employees most susceptible to automation least likely to retrain? Automation risks and inequalities in learning intention, perceived opportunities, and learning participation among employee groups

Giedo Jansen
University of Amsterdam, AIAS-HSI, Faculty of Law, Netherlands

Suzanne Janssen
University of Twente, Faculty of Behavioural, Management and Social Sciences (BMS), Netherlands

Mark Levels
Marie-Christine Fregin
Maastricht University, Research Centre for Education and the Labour Market (ROA), Netherlands

Abstract

The rise of intelligent technologies is believed to change job requirements, urging individuals to engage in work-related learning to stay employable. Studies on workers' learning participation found that employees who are most at risk of automation are least likely to engage in work-related learning. To better understand this paradox, this study investigates to what extent differences in work-related learning for technological adaptation are explained by (a) workers' actual automation risk, (b) their subjective perception of automation risks, (c) differences in their learning intention, and (d) access to lifelong development opportunities and supportive learning environments. Novel survey data on Dutch employees ($N = 1{,}719$) are used. The results based on (generalized) structural equation modeling show that differences in learning between high- and low-risk workers can be explained by workers' differences in their learning intentions and their (perceived) access to education and supportive learning environments, but not by their subjective perceptions of automation.

Corresponding author:
Giedo Jansen, University of Amsterdam, AIAS-HSI, Faculty of Law, P.O. Box 15966, Amsterdam, 1001 NL, Netherlands.
Email: g.jansen@uva.nl

Keywords
Automation, informal learning, job insecurity, technological change, work-related learning

Introduction

The current technological transformation involving the rise of artificial intelligence and robotics is believed to profoundly change economic structures and jobs (Acemoglu and Restrepo, 2017; Arntz et al., 2016; Autor, 2015; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018). Tasks that previously could only be done by humans (such as reading, writing, recognizing patterns, and making decisions) can increasingly be taken over by autonomous technological systems. Estimations of the number of jobs at risk of automation vary widely, ranging from as high as 47% (Frey and Osborne, 2017) to as low as 9% (Arntz et al., 2016; Borland and Coelli, 2017). Regardless of the exact impact of intelligent technologies on job categories, scholars agree that the content of many jobs is likely to change (OECD, 2019). Empirical studies show how implementing new technologies reshapes work practices in profound ways (e.g., Beane and Orlikowski, 2015; Waardenburg et al., 2021). In particular, new skills will be required as people need to be able to work with, build, or complement such technological systems (Brynjolfsson and McAfee, 2014; Fleming, 2019). Thus, also in the case that machines might not immediately replace human jobs in total, new technologies require human adaptation to new skills and tasks.

When skills demands on the labor market change rapidly, workers may find that the skills they have acquired become obsolete; in which case they may have to reskill. As a consequence of changing skill requirements (Ra et al., 2019), individuals are urged to continuously update their skill sets to increase their employability (World Economic Forum, 2018). Sometimes portrayed as a 'Race between Education and Technology' (Goldin and Katz, 2009), people are only expected to keep up with rapid technological changes if they invest in learning activities both on and off the job (Kyndt and Baert, 2013). The responsibility for ensuring that their skill sets stay up to date is often placed on workers rather than on employers or governments (Dhondt et al., 2022; Mulas-Granados et al., 2019). Workers can engage in work-related learning in two complementary ways (Kyndt and Baert, 2013). First, they can engage in *formal learning activities*, which are structured and take place within educational settings specifically designed for learning (Bear et al., 2008; Tannenbaum et al., 2010). These activities can take place both on and off the job and include courses, training, seminars, and conferences. Second, they can engage in *informal learning*,[1] which is learner-initiated and takes place outside formal educational settings and encompasses learning from oneself (e.g., experimenting with new ways of performing work), learning from others (e.g., interacting with peers), and learning from non-interpersonal resources (e.g., reading professional publications; Noe et al., 2013). Informal learning is by far the most prevalent form of work-related learning (Cerasoli et al., 2018).

Although automation risks are potentially a driving force behind the need for retraining, there is little research on the relationship between the two at the individual level. Typically, attention has been paid to aggregate macro-level estimates of which jobs are

most susceptible to automation (e.g., Acemoglu and Restrepo, 2017; Arntz et al., 2016; Autor, 2015; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018), in that way prioritizing employees' need for reskilling and upskilling behaviors. Following a skill- or routine-biased technological change paradigm, these studies show how work-related technological changes would favor skill use at a college level or higher (skill-biased technological change; Acemoglu, 2002) or favor low- and high-skilled occupations (routine-biased technological change; Autor, 2015) (Acemoglu, 2002; Fregin et al., 2021). Especially for those who are in high-risk jobs, participation in work-related learning is utterly important. Recently, research has shifted attention to individual-level determinants of who engages in adult education in the context of job automation. A recurring finding in the few studies looking at this relationship is that employees who are most susceptible to job automation show the lowest propensity to engage in adult learning and lifelong development activities (Ioannidou and Parma, 2021; Koster and Brunori, 2021; Nedelkoska and Quintini, 2018). This paradox is not yet fully understood.

The purpose of our study is to consider how individual and organizational determinants serve as an explanation for the paradox that those most susceptible to automation are less likely to engage in reskilling activities. Our research question reads: *To what extent can differences in work-related learning for technological adaptation be explained by (a) workers' actual automation risk, (b) their subjective perception of automation risks, (c) differences in their learning intention, and (d) access to lifelong development opportunities and supportive learning environments?* We contribute to the literature in three ways. First, most studies focus on the general effect of 'objective' automation susceptibility, measured with some aggregate estimates based on the assumption that individuals in routine task-intensive occupations would be most at risk (Ioannidou and Parma, 2021; Koster and Brunori, 2021; Nedelkoska and Quintini, 2018). However, we know little about the relationship between *subjective perceptions* regarding the risk of job automation and the individual motivation to respond to automation-induced insecurity. Second, although considerable attention has been devoted to examining drivers of work-related learning, most research does not explicitly focus on automation risks as a specific energizer for work-related learning. Using novel survey data from the Netherlands, we study workplace learning and its determinants specifically in the context of technological change. This way, we also contribute to the scant literature on job insecurity and learning (e.g., Blau et al., 2008; Sanders et al., 2011; Van Hootegem et al., 2023b). Third, we investigate the *factors that mediate* the relationship between automation risks and employee learning. Building on the literature on work-related learning (cf. Cerasoli et al., 2018), we not only consider individual-level factors but also address the organizational context – employees' access to lifelong development opportunities and support for learning (Baert et al., 2006) – an aspect that received only limited attention so far in the debate on technological upskilling (Dhondt et al., 2022; Lukowski et al., 2021).

The remainder of this article is structured as follows. In the following section, we first discuss the theoretical relationship between job automation and participation in work-related learning, which we hypothesize to be negative. Subsequently, using the literature on work-related learning, we discuss two types of explanations for this negative relationship: individual-level factors related to learning intention and the organizational context

associated with the learning environment. In the next two sections, we discuss our data and methodology, based on (generalized) structural equation modeling (SEM) using a sample of Dutch employees ($N = 1{,}719$). Following on, our analysis section shows that differences in learning between high- and low-risk workers can be explained by workers' differences in their learning intentions and their (perceived) access to education and supportive learning environments, but not by their subjective perceptions of automation. In the final section, we present our conclusions and discuss the implications of our findings for both the literature on employees' work-related learning as well as the literature on the impact of technological innovation on socioeconomic inequalities in societies.

Theory and hypotheses

Job automation and participation in work-related learning

The theoretical relationship between automation susceptibility and training participation seems straightforward: job automation would lead to job insecurity, which may motivate individuals to enhance their skills. This expectation fits with prior research on job insecurity, arguing that employees in more insecure positions are more likely to seek out training opportunities to bolster their competence and effectively meet the demands of their current and future jobs (Van Hootegem et al., 2023b). Circumstantial evidence on automation concerns supports this expectation based on self-interest, suggesting that people most at risk of having their jobs replaced by technology are more concerned about the impact of automation, robotics, and artificial intelligence. For example, Dekker et al. (2017) found that people with more automatable jobs (i.e., lower-skilled and manual workers) are more negative about robotization in the workplace than people who are less at risk of automation, such as professionals and managers. Morikawa (2017) and Dodel and Mesch (2020) showed that groups in relatively disadvantaged positions were generally the most pessimistic about the impact of technology on their careers, while people in more privileged positions were less concerned. And Erebak and Turgut (2021) show the relevance of the speed of technological change in this matter: employees who are more anxious about the speed of technological development experience more job insecurity caused by robots.

However, when it comes to actual behaviors in work-related learning, the available empirical evidence repeatedly shows that those workers most at risk of automation are least likely to engage in education and training. For example, Nedelkoska and Quintini (2018) find that workers in fully automatable jobs are more than three times less likely to have participated in on-the-job training than workers in non-automatable jobs. This finding was broadly confirmed by Ioannidou and Parma (2021) and Koster and Brunori (2021), who also observe this relationship to be robust across welfare regimes. These findings show that the seemingly straightforward relationship between automation susceptibility and learning is more complicated.

Nedelkoska and Quintini (2018: 109) put forward three reasons for the negative effect of automation risks on retraining: First, automatable jobs are clustered among the lower educated who, they argue, might have a lower tendency to invest in human capital and learn new things. Second, due to lower earnings in such jobs, financial constraints might

inhibit workers from investing in training. And third, the demand for training might not be met by adequate supply. That is, even when employees do want to learn, limited access to training in their work environment might keep them from active participation. Prior studies, however, primarily rely on aggregate measures of automation risks, whereas the theoretical argument hinges on subjective perceptions of workers towards automation risks, their intention to learn, and their organizational access to training at the workplace. Before elaborating on these individual-level and organizational explanations, we reiterate the core expectation from previous research on the negative effect of 'objective' automation risk on work-related learning. Our hypothesis specifically deals with work-related learning to keep up with technological changes at the workplace:

H1. The more strongly workers are susceptible to automation, the less likely they are to participate in work-related learning activities that would help them adapt to automation.

Individual explanations

Building on the literature on work-related learning (cf. Cerasoli et al., 2018), we consider that both individual-level factors and the organizational context (Baert et al., 2006) may explain the negative relationship between automation susceptibility and learning behavior. Individuals who more strongly feel an educational need may have stronger intentions to participate in learning, leading to higher educational participation (Kyndt and Baert, 2013). From this perspective, individuals who find it more important to keep up with new technological developments at work would be inclined to engage in self-development activities. This assumes that the decision-making process of participating in work-related learning is essentially rational. In reality, this might not be the whole story: individual beliefs related to learning orientation or mindsets (Bozionelos et al., 2020) might impact this process (Baert et al., 2006). To understand the negative instead of the positive effect of automation susceptibility, we therefore need to reconsider the role of job insecurity on the willingness to learn. That is, the literature on job insecurity proposes an alternative, opposite effect on learning (Van Hootegem and De Witte, 2019; Van Hootegem et al., 2023a). Rather than motivating learning, uncertainty may also cause workers to participate less frequently in learning activities. In response to job insecurity, workers might become less inclined to invest in their learning because they view training as a potentially risky endeavor, which may not result in the desired level of skills, and they feel disengaged in their work situation.

Previous studies on workplace learning have indeed found that job insecurity can decrease workers' career adaptability resources and responses (Johnston, 2018; Klehe et al., 2011; Van Hootegem et al., 2023a). For example, Van Hootegem and De Witte (2019) find that job insecurity is related to lower levels of information-seeking and feedback-seeking from one's supervisor and colleagues. From this perspective, technology-induced insecurity may lead employees to believe that training does not matter or lead them to question their ability to complete such training successfully. We posit two hypotheses to test this reasoning. First, as previous research has shown, workers more strongly susceptible to automation

are more concerned about technological change in the workplace (Dekker et al., 2017; Dodel and Mesch, 2020; Morikawa, 2017). Second, if this is the case, the perceived insecurity resulting from automation should explain differences in training. In contrast to the self-interested reasoning that suggests a positive relationship between perceived automation risk and learning, we alternatively propose that workers who view automation as a threat may think it is harder to adapt to changing task demands and, consequently, are less likely to invest in learning. Hence, we formulate the following:

The negative relation between workers' objective automation susceptibility and their engagement in work-related learning activities that would help them adapt to automation is explained by (H2) high-risk employees' perceptions of being more strongly susceptible to automation, and a negative (H3a) instead of a positive (H3b) relation between perceived automation risk and the willingness to learn new technologies.

Organizational explanations

Access to a relevant supply of training and wider organizational resources and support are crucial for skill development (Cerasoli et al., 2018; Choi and Jacobs 2011; Dhondt et al., 2022; Nikolova et al., 2023; Tannenbaum et al., 2010). Cerasoli et al. (2018) summarize three potential sources of support, i.e., interpersonal support from other people (e.g., support from co-workers and supervisors), informal support (e.g., supportive learning environment, opportunities for feedback), and formal organizational support (e.g., HR policies tied to learning). Regarding all types of organizational resources, employees would be more likely to participate in work-related learning when they are supported to do so and provided with opportunities. Indeed, several studies show that organizational support (e.g., Hurtz and Williams, 2009; Kyndt et al., 2013; Leisink and Greenwood, 2007), social support (e.g., Garavan et al., 2010), or a supporting company policy (e.g., Bates, 2001) are positively related to participation in development activities (Kyndt and Baert, 2013). Conversely, the lack of organizational resources is a common barrier to learning participation of working adults (e.g., Brown and McCracken, 2009; OECD, 2020; Tabassi and Bakar, 2009). Hence, we expect that the negative relation between automation susceptibility and work-related learning can be explained by both differences in access to learning opportunities and differences in organizational support for learning activities.

It is often assumed that individuals are more likely to engage in work-related learning when sufficient opportunities exist (cf. Noe et al., 2013). Nedelkoska and Quintini (2018) propose that for employees at risk of automation, the demand for training might not be met by adequate supply. Both employers' and employees' perspectives might account for such differences in learning supply. From an employer's perspective, the willingness to provide training may diminish when financial resources are lacking, the need for lifelong development is not urgent, or the expected returns appear low or uncertain (Wotschack, 2020). Organizations pressured by technological change may offer limited training opportunities as financial resources are needed to manage organizational transitions

(Carbery and Garavan, 2005). And even when organizations are willing and able to invest in lifelong development, they have the option to either invest in the entire workforce or concentrate on strategic subgroups (Adolfsson et al., 2022). Previous research suggests that employers invest in lifelong development selectively, providing fewer opportunities to employees in insecure positions (e.g., temporary workers) for whom the expected returns on lifelong development are lowest or most uncertain (Adolfsson et al., 2022; Hoque and Kirkpatrick, 2003; Lukowski et al., 2021). From this perspective, the negative relation between automation susceptibility and learning can be attributed to employers anticipating greater returns on training investments for individuals at lower risk of automation.

Additionally, from the perspective of employees, research shows that their perceptions of their workplaces as learning environments can vary (Coetzer, 2007; Nikolova et al., 2023). In addition to having fewer opportunities available, individuals in uncertain job situations may also experience limited learning opportunities (Van Hootegem et al., 2023a). People with insecure jobs are less likely to recognize opportunities to learn (e.g., from colleagues and supervisors), partly because stressors such as job insecurity are resource-consuming and restrict information processing (Hart and Cooper, 2001). We expect that the negative effect of automation risks on work-related learning can be attributed to differences in perceiving such opportunities, as well as to actual differences in the availability of training opportunities. While we cannot differentiate between actual and perceived learning opportunities using self-reported data, both factors contribute to the same expectation:

H4. The negative relation between workers' objective automation susceptibility and their engagement in work-related learning activities that would help them adapt to automation is explained because high-risk employees experience less access to lifelong development opportunities.

Finally, we posit a similar hypothesis for the degree of formal organizational resources for learning. Often embedded in a broader concept of 'learning cultures' (Kyndt and Baert, 2013) or 'supportive learning environments' (Choi and Jacobs, 2011), such resources relate to organizational practices, policies, and rules that facilitate participation in learning and development activities (Cerasoli et al., 2018). Such practices include human resource development (HRD) policies and resources allocated for learning (e.g., formal recognition systems, compensation systems, and merit systems to stimulate learning) (Choi and Jacobs, 2011). Formal support has been noted as one of the main organizational characteristics to enhance positive outcomes regarding training and development (Cerasoli et al., 2018; Choi and Jacobs, 2011; Gil et al., 2023; Tannenbaum et al., 2010). Building upon the earlier hypothesis about access to learning, we anticipate that the availability of resources conducive to lifelong development is lower for individuals with a high risk of automation. This could be attributed to selective investments in high-risk employees compared to their low-risk counterparts or potential differences in the perception of support levels from the organization between high-risk and low-risk employees. Hence, we formulate:

H5. The negative relation between workers' objective automation susceptibility and their engagement in work-related learning activities that would help them adapt to automation is explained because high-risk employees work in less supportive learning environments.

In sum, Figure 1 depicts our theoretical model.

Method

Sample and procedure

We tested our hypotheses using individual-level survey data from the Netherlands. For this purpose, the LISS (Longitudinal Internet Studies for the Social Sciences) panel administered by Centerdata (Tilburg University, The Netherlands) was used. The LISS panel is a representative panel of the Dutch adult population consisting of approximately 7,000 individuals. The LISS panel consists of several core questionnaires that are repeated periodically. In addition, there is the opportunity for researchers to field one-time questionnaires on specific thematic topics. The latter was done for this study by designing a tailored-made survey on technological changes at work.

For this study, a new online questionnaire was developed about perceptions of technological change at the workplace in general, as well as attitudes and behavior related to formal and informal work-related learning. The data collection was funded by ODISSEI, the national research infrastructure for the Dutch social sciences, and the data are openly accessible via the LISS data archive (Jansen et al., 2020). Centerdata executed the fieldwork in June 2020. A sub-sample of 3,350 respondents was drawn from the LISS panel among employees, self-employed individuals, those who are unemployed or seeking employment, and prospective labor market entrants who were primarily engaged in education at the time of the survey. In total, 2,542 respondents completed the questionnaire (response rate 75.9%). For the analyses in this study, only employees ($N = 1{,}906$) were studied, and other groups were left out. Ultimately, after selecting only respondents with valid information on all relevant variables, 1,719 observations remained in the analyses presented below.

Measures

Dependent variable. To measure our dependent variable *participation in work-related learning*, we asked two questions on formal and informal learning. First, respondents were asked, 'In the last 12 months, have you followed any of the following types of training to keep up with technological changes in the content of your work?' Response categories were: (1) Training paid for or provided by your employer, (2) Self-funded training, (3) Direct explanation during work by colleagues or supervisor, and (4) Other training. For all options, respondents could answer 'not followed,' 'followed, but without attention to technological developments,' or 'followed, with attention to technological developments.' Subsequently, a question on self-study was asked: 'In the last 12 months, have you engaged in any of the following forms of self-study to keep up with technological changes in the content of your work?' (Yes/No): (1) Self-study using textbooks

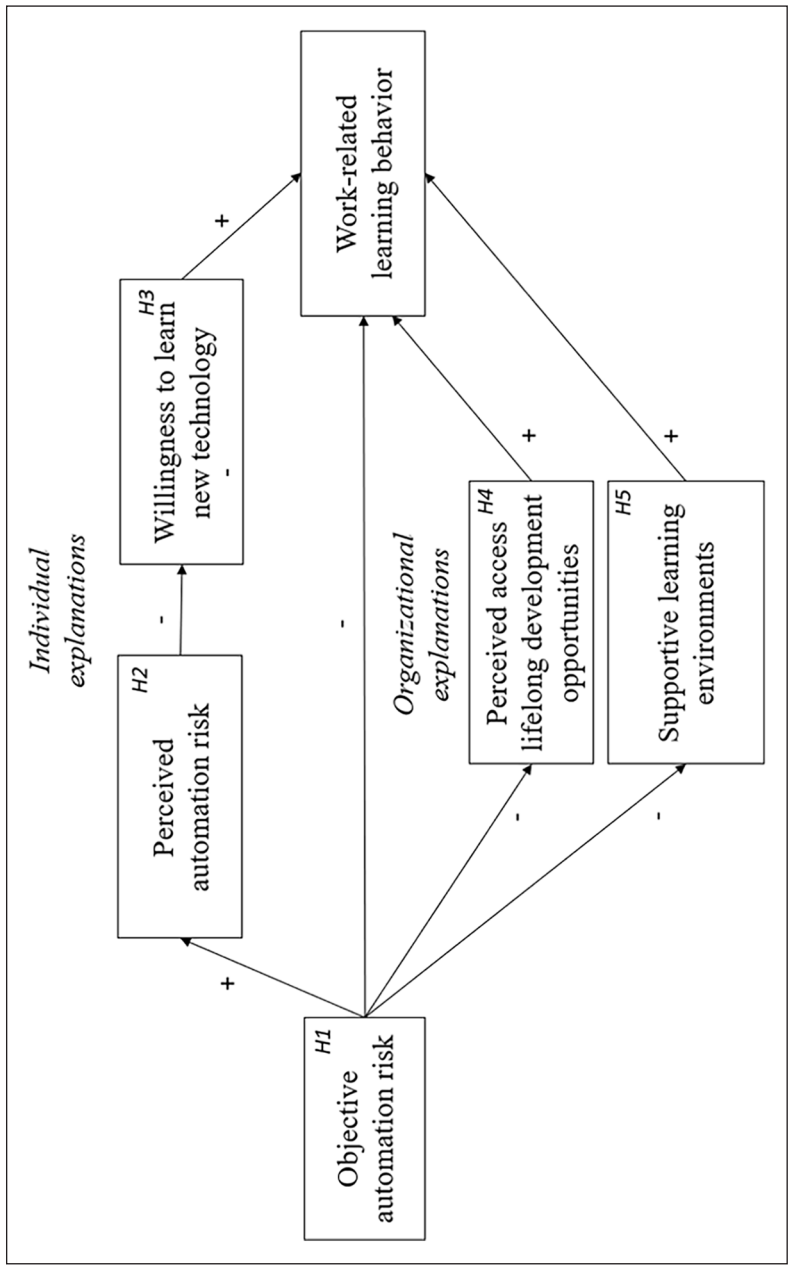

Figure 1. Theoretical model.

or (professional) literature, (2) Online self-study. Ultimately, a dichotomous variable indicated whether employees engaged in any work-related learning activity over the last 12 months to keep up with technological developments. Descriptive statistics show that 49.7% of employees have not engaged in any learning activity, while the other half have.

Independent variables and controls. To measure workers' *objective automation risk*, we used the aggregate automation susceptibility score per occupational group based on the OECD (Nedelkoska and Quintini, 2018), as to the best of our knowledge this is one of the few prior studies to investigate differences in training by automation susceptibility. In the questionnaire, respondents were asked to describe their job as precisely as possible. These open answers were then coded according to the ISCO-08 occupational classification. Finally, the share of workers at significant risk of automation per occupational group was linked to individual respondents based on the 2-digit ISCO-codes.

We measured the *willingness to learn new technologies* with a scale consisting of the following items: 'I find it important to keep up with new technological developments at work' and 'I am willing to spend extra time learning new technological skills at work.' Respondents could answer on a five-point Likert scale ranging from (1) 'totally disagree,' to 'totally agree' (5). A scale (1–5) is constructed by taking the mean value over the two items (Cronbach's alpha .77), where a higher score denotes a stronger willingness to keep up with work-related technological changes.

The subjective or *perceived risk of automation* was measured using three items: 'My job could be done by new technology (for example, artificial intelligence, robots, or algorithms),' 'I am personally worried that my job could be done by new technology,' and 'I am personally worried about my future in the labor market because new technology could replace humans.' The first item was intended to measure whether respondents think their job is automatable or not. The second and third items were intended to measure whether respondents worry about the consequences of such automation. The second item was adapted from measures of perceived job insecurity, and the third item was adapted from measures of perceived employment insecurity. Respondents could answer on a five-point Likert scale ranging from (1) 'totally disagree,' to 'totally agree' (5). A scale was constructed by taking the mean value over the three items (Cronbach's alpha .76), where a higher score denotes a higher perceived automation risk.

Regarding the organizational environment, perceptions regarding *access to lifelong development opportunities* were measured using four items on sources and opportunities for learning in their work environment. More specifically, in my organization, 'employees help each other to learn new technological skills,' 'employees get time to learn new technology skills,' 'employees get financial resources to learn new technological skills,' and 'employees are rewarded for learning new technological skills.' A factor analysis (Eigenvalue = 2.69, 53.7% of explained variance) confirmed the four items loaded on a single dimension. A scale was constructed by taking the mean value over the four items (Cronbach's alpha .79), allowing one missing value, where a higher score denotes more access to learning opportunities.

Relatedly, *supportive learning environments* was measured by the extent to which skill development is perceived to be embedded in HRM policy. Respondents were asked, 'In what way does your company or organization pay attention to keeping up with technological

changes that alter the content of work?' The possible HRM policies considered were 'performance pay or bonus,' 'regular intervision,' 'coaching,' 'job rotation,' 'internal secondment,' 'personal training or development plan,' 'regular supervision,' 'career plan,' 'performance and/or assessment interviews,' and 'job rotation.' For each policy, respondents could answer 'is not used,' 'is used, but without attention for technological developments,' or 'is used, with attention for technological developments.' A count variable was constructed that summarizes the number of HRM practices applied in the organization, focusing specifically on technological developments. The scale is truncated at 5 because only 6.3% of organizations apply 6 or more (out of 10) HRM practices simultaneously.

We standardized all independent variables for inclusion in the analyses. Finally, we controlled for age, age squared, gender, education, employment relationship, income, and whether a respondent works in the public or private sector. *Age* of the respondent was measured in years, and age squared was included to control for non-linear age effects. For *gender*, a dummy variable for 'female' (1) vs 'male' (0) was created. *Education* of the respondents was classified as 'low' (primary education, lower secondary, lower vocational), 'middle' (higher secondary and higher vocational training), or 'high' (university or higher), using 'low' as the reference category. For *employment relationships*, a dummy variable was created for temporary employment (fixed-term without a permanent contract prospect), using permanent or prospective permanent contracts as the reference category. *Income* was measured as personal net monthly income in euros (1000s). Finally, a dummy variable is included for employed in the *public sector* (1) vs the private sector (0). The descriptive statistics for all variables and Pearson's *r* correlations between the key variables are reported in Table 1.

Analyses

We used structural equations modeling (SEM) to test the relation between individual and organizational characteristics and work-related learning behavior. In our theoretical model, there are multiple causal paths and all factors are likely to simultaneously contribute to the explanation and, moreover, are interrelated. SEM models are multivariate models which assume various causal paths between observed and latent variables and estimate the relative contribution of direct and indirect relations between those variables. We used it to estimate direct and indirect explanations for work-related learning behavior. These models are accompanied by a graphic visualization of the relations and the identification of direct and indirect associations between variables (Ramlall, 2016). A key tool for explanatory analyses, SEM allows for depicting and simultaneous testing of relations between (assumed) exogenous and mediating endogenous explanatory variables and outcome variables. In our model, we assume the objective automation risk has an exogenous effect on workplace learning, and individual or organizational characteristics have an endogenous effect.

We estimated structural equation models using Stata 17, using maximum likelihood estimation with default standard errors.[2] We ran a series of nested models (see Table 2). The empty model (Model 1) measures the relation between the objective automation risks and work-related learning behavior. Model 2 includes the independent variables (individual and organizational explanations). Our full model (Model 3) includes both sets of explanatory variables and controls simultaneously. Table 2 shows the results of

Table 1. Descriptive statistics ($N = 1{,}719$) and correlation matrix (Pearson's r).

Panel A: Descriptive statistics	Min.	Max.	Mean	SD	Freq.
Learning participation	0.00	1.00	0.50	0.50	
Objective risk of automation	0.08	0.71	0.24	0.11	
Perceived risk of automation	1.00	5.00	1.77	0.82	
Willingness to learn	1.00	5.00	3.69	0.95	
Access to lifelong development	1.00	5.00	2.83	0.95	
Supportive learning environments	0.00	5.00	1.17	1.71	
0 – No HRM practices					59%
1					11%
2					9%
3					7%
4					5%
5 or more HRM practices					10%
Income (in euros 1000s)	0.00	7.90	2.16	0.93	
Age	16.00	79.00	44.09	12.43	
Gender (female)	0.00	1.00	0.53	0.50	
Education					
Low					42%
Medium					40%
High					18%
Temporary employment	0.00	1.00	0.06	0.24	
Public sector	0.00	1.00	0.40	0.49	

Panel B: Correlation matrix	1.	2.	3.	4.	5.	6.
1. Learning participation	-					
2. Objective risk of automation	–0.20***	-				
3. Perceived risk of automation	0.024	0.12***	-			
4. Willingness to learn	0.32***	–0.19***	0.05*	-		
5. Access to lifelong development	0.35***	–0.18***	0.04	0.40***	-	
6. Supportive learning environment	0.38***	–0.06**	0.08***	0.29***	0.41***	-

*$p < .05$; **$p < .01$; ***$p < .001$; (two-tailed for tests of coefficients),

the empty model, the model with independent variables, and the full model (including controls), reporting standardized coefficients. In Figure 2, we present the visualized results of the full structural equation model (Model 3) with objective automation risk and individual and organizational explanations directly or indirectly associated with workplace-related learning behavior.

Results

The direct relation between the objective automation risk and participation in workplace-related learning is negative and statistically significant in all models. In Models 2 and 3,

Table 2. Structural equation modelling (SEM) coefficients of associations between the objective automation risk, individual and organizational explanatory factors, and workplace-related learning behavior.

Variables	Model 1	Model 2					Model 3				
	Work-related learning behavior	Perceived automation risk (std.)	Willingness to learn new technology (std.)	Perceived access lifelong learning (std.)	Supportive learning environment (std.)	Work-related learning behavior	Perceived automation risk (std.)	Willingness to learn new technology (std.)	Perceived access lifelong learning (std.)	Supportive learning environment (std.)	Work-related learning behavior
Objective automation risk	–0.904***	1.029***		–0.567***	–1.617***	–0.569***	1.03***		–0.567***	–1.617***	–0.390***
	(0.105)	(0.211)		(0.215)	(0.211)	(0.098)	(0.211)		(0.215)	(0.211)	(0.108)
Willingness to learn new technology (std.)						0.082***					0.072***
						(0.012)					(0.012)
Perceived automation risk (std; H3)			1.030***					0.052***			
			(0.214)					(0.024)			
Perceived access lifelong development opportunities (std.)						0.127***					0.127***
						(0.012)					(0.012)
Supportive learning environments (std.)						0.078***					0.070***
						(0.012)					(0.012)
Income											0.016
											(0.015)
Female											–0.049**
											(0.023)
Age											0.002
											(0.006)
Age squared											–0.000
											(0.000)
Medium education											0.051**
											(0.025)
High education											0.129***
											(0.034)
Temporary contract											–0.024
											(0.047)
Public sector employment											0.027
											(0.023)
Observations	1,719	1,719					1,719				

Standard errors in parentheses; std = standardized variable. ***$p < .01$, **$p < .05$.

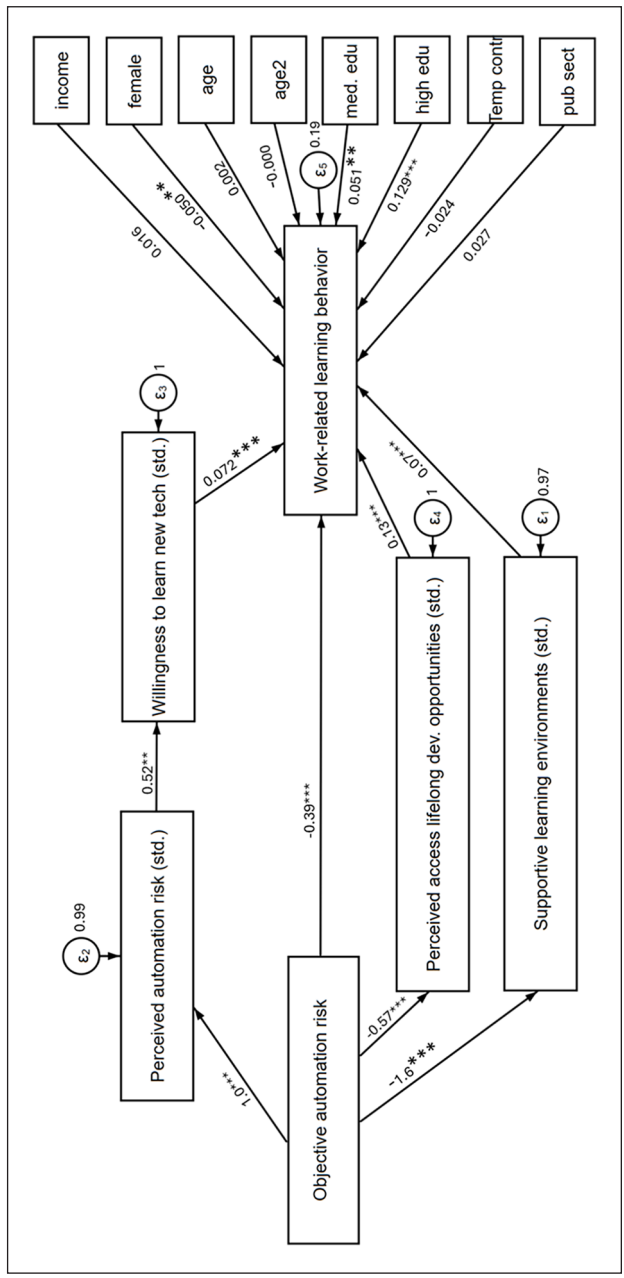

Figure 2. Structural equation model of associations between the objective automation risk, individual and organizational explanatory factors, and workplace-related learning behavior (full model).
Notes: standardized model coefficients are displayed; **$p < .01$; ***$p < .001$. Model fit: AIC 66282.41; BIC: 66424.41.63 RMSEA: .112 (pclose .000).

we measure the direct and indirect effects of objective automation risk on work-related learning behavior via three mechanisms (and controls). The total effect of objective automation risk on work-related learning is the sum of the direct and all significant indirect relations. Note that in the full model, the direct effect of the objective automation risk on learning is $b = -0.390$. However, there are indirect effects through the perceived automation risk and willingness to learn ($b = -1.029*0.52*0.072 = 0.038$), the perceived access to lifelong development opportunities ($b = -0.567*0.127 = -0.072$), and the perceived supportive learning environment ($b = -1.616*0.070 = -0.113$). As the indirect effect via perceived risk and the willingness to learn is positive instead of negative, it reduces the negative total effect. This means that the total effect is $b = -0.390+0.038-0.072-0.113 = -0.537$.

The model shows that, in line with the literature, the more workers are susceptible to automation, the less likely they are to participate in lifelong development opportunities to prepare for automation, confirming hypothesis H1. Note that these estimates are controlled for socioeconomic status indicators (income, education level), excluding that the main explanation revolves around socioeconomic differences.

Next to the direct relation between the objective automation risk and workplace-related learning behavior, we find relevant indirect relations, mediated through the individual-level and organizational-level variables outlined above. Our main conclusions are based on our full model (Model 3). Concerning the individual-level explanations, our full model shows that, in line with hypothesis H2 the objective automation risk is associated positively with perceived automation concerns ($b = 1.029$). If the aggregate automation risk is higher, the perceived automation risk is also higher. The relation is positive and statistically highly significant. In line with this hypothesis, we also find that the willingness to learn new technology is positively related to work-related behavior ($b = 0.072$). However, contrary to H3a, people are more willing to learn new technology if they perceive to be more at risk of automation ($b = 0.52$), rendering the overall net effect positive ($b = 0.038$). With the link between perceived automation risk and the willingness to learn being positive instead of negative, we find support for hypothesis H3b instead of H3a. This means that, the negative effect of objective automation susceptibility on work-related learning activities that would help them adapt to automation cannot be explained by lower willingness to learn among workers who perceive to be at high risk of automation.

Concerning the explanatory characteristics at the organizational level, both hypotheses are in line with empirical observations. First, the more access workers have to learning opportunities, the more they learn ($b = 0.127$); however, at least in their perception, access to learning opportunities is lower if the automation risk is higher ($b = -0.567$). This is in line with hypothesis H4. Similarly, workers are more likely to engage in work-related learning if the learning culture in an organization is supportive ($b = 0.070$), but, again, if the aggregate automation risk is higher, perceptions of a supportive learning environment are lower, which is in line with hypothesis H5.

Concluding, our analyses show that both individual and organizational factors are associated with workplace-related learning behavior and act as relevant pathways. Several control variables were included in the full model since previous research has found these to be associated with participation in workplace-related learning: income,

sex, age, age squared, education, type of employment contract, and public sector employment (for details, see above). Only the variables capturing female gender (reference: male) and higher as well as medium education (reference: low education) are statistically significant: female workers are less likely to participate in workplace-related learning, and high- and medium-educated workers are more likely to engage in learning than low-educated workers.

Discussion

Main findings

This study aimed to investigate the relationship between employees' automation risks and their participation in work-related learning, as acquiring new skills is considered a crucial strategy for enhancing employability, especially in response to the ongoing technological changes in the professional landscape. Our analyses of survey data from the Netherlands showed that differences in work-related learning for technological adaptation can be explained by employees' actual objective automation risk, differences in their learning intentions, and their (perceived) access to lifelong development opportunities and supportive learning environments. Interestingly, while our findings show that employees categorized as high-risk for automation tend to perceive automation risks as more pronounced than their low-risk counterparts, this heightened perception of risk is associated with increased rather than decreased willingness to keep up with new technological developments at work. This finding is in line with some of the few studies on job insecurity and work-related learning, arguing that insecure employees are more likely to engage in learning activities (Van Hootegem et al., 2023b). Job automation leads to perceived job insecurity, and this insecurity seems to serve as a motivation for individuals to enhance their skills. Contrary to our expectations, individual perceptions of automation risks therefore fail to explain why high-risk employees are less likely to engage in learning activities than low-risk employees. We find more support for our expectations related to the organizational environment. A key finding indicates that individuals with more automatable jobs encounter less supportive learning environments, lower access to lifelong development opportunities, and, consequently, are less likely to participate in learning activities to prepare for workplace automation.

The study results extend the current literature on employees' work-related learning behaviors in several ways. First, we contribute to the understanding of the automation-learning paradox (Ioannidou and Parma, 2021; Koster and Brunori, 2021; Nedelkoska and Quintini, 2018). Our results show that both the willingness to learn and learning participation positively correlate with supportive learning environments and access to lifelong development opportunities. These results highlight the importance of an organizational perspective toward workplace learning (Cerasoli et al., 2018; OECD, 2020), in which opportunities in the work environment and organizational policies and practices can serve as important enablers of learning participation. Future research may investigate the impact of the organization more closely. For both organizations and their employees, it is important to understand how to create a supporting environment for upskilling and reskilling, especially for those with a high automation risk. For example,

future studies may identify approaches, such as reward systems and compensation mechanisms, that trigger varied responses among distinct employee groups.

Second, our study sheds more light on the relationship between objective automation risks, employees' subjective evaluations of such risks, and their behaviors and opportunities to act upon such risks. Our findings showed that the effect of automation risk on learning behaviors cannot be explained by differences in the subjective risk perceptions between low- and high-risk employees. This does not mean that perceptions do not matter. On the contrary, our findings imply that automation-related insecurity can motivate individuals to improve their skills. We demonstrated that inequalities in automation risks are associated with inequalities in learning behavior. However, an important part of this effect can be explained by inequalities in learning intentions and inequalities in perceived organizational support for learning environments. Still, also after accounting for differences in learning intentions and supportive learning environments, a substantial net effect of automation susceptibility on learning participation remains (about 43%). Hence, this study's mediators are not exhaustive; future research should investigate further individual and organizational variables to interpret the link between automation susceptibility and learning. At the individual level, learning behavior is also related to a person's ability to learn, and their skill level in adapting to new technologies. Future research could therefore consider differences in digital skills as an additional explanatory factor. At the organizational level, specific incentives – such as performance bonuses or rewards – may encourage (high-risk) workers to engage in learning. Future studies could also explore how organizations differ not only in the extent of their training investments but also in whether these investments are designed to benefit the entire workforce or are primarily aimed at certain strategic subgroups.

Third, our study underscores the profound impact of technological innovation on socioeconomic inequalities in societies. This relationship is well-established in literature, showing that advanced economies are often associated with shifts in occupational structures and skill requirements (Hötte et al., 2021; Mokyr et al., 2015). With each major technological shift, a decrease in opportunities for some workers to use their skills and an increase for others becomes apparent. Our study contributes to the literature on inequalities as a result of automation by investigating not only macro-level (automation risk) but also meso-level (organizational-level), and micro-level (individual-level) determinants of who engages in reskilling and upskilling to mitigate the risks of automation. Unlike many studies focusing on macro-level determinants (Acemoglu and Restrepo, 2017; Arntz et al., 2016; Autor, 2015; Frey and Osborne, 2017), our study synthesizes insights from both macro-level technological upskilling determinants and literature on individual and organizational influences on work-related learning (Cerasoli et al., 2018; Hurtz and Williams, 2009; Kyndt and Baert, 2013). Our findings imply that emerging social inequalities may stem from disparities in opportunities to adapt to novel skill requirements. Skills are increasingly important for an employee's long-term success (Brynjolfsson and McAfee, 2014), potentially outweighing traditional predictors of social mobility and status, such as social class or educational attainment (Fregin et al., 2021). Therefore, access to workplace lifelong development opportunities and supportive learning environments may become pivotal drivers of inequalities in the future labor market.

Limitations and suggestions for future research

Some limitations should be taken into consideration when interpreting our findings. First, our study is cross-sectional, and thus the usual reservations regarding causality apply. Moreover, we collected data during a specific period (June 2020). At that time, the COVID-19 pandemic was in its early months. Consequently, this may have pushed long-term economic concerns, such as automation risks, from the public agenda. Further research is needed to explore the explanatory power of perceptions of automation risks – for which we did not find much support in this study.

Second, it is important to note that learning attitudes and behaviors are influenced by several other factors beyond automation risks. Other labor market risks can hinder workers' ability to engage in self-development activities. In the Netherlands, for instance, the trend towards labor flexibilization (e.g., the rise of temporary employment and increases in self-employment) is a well-known contributor to employment instability (Jansen, 2019). Employers are less likely to invest in education and lifelong development for employees in short-term employment. Future studies should investigate how the interaction between type-of-contract based segmentation and automation risks may exacerbate learning opportunities. Special attention may be given to those outside employment relationships, such as independent contractors and other self-employed workers who often have to invest in lifelong development themselves.

A final limitation involves our operationalization of automation. We provided a general description of automation to respondents, asking them to reflect on the increasing use of new technology, including robotics, artificial intelligence, and algorithms. Using general descriptions of technology is not uncommon in survey research (Dekker et al., 2017; Dodel and Mesch, 2020). But of course, there are many specific types of new technologies and automation that may be relevant, depending on the job, sector, or organization. The potential impact of these different technologies can influence an individual's perception of automation risk. As we did not differentiate between various forms of automation in our questionnaire, we are uncertain which specific types of automation respondents had in mind. To address this limitation, future research should differentiate between various technologies, skill requirements, and learning activities.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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ORCID iD

Giedo Jansen https://orcid.org/0000-0002-8800-5708

Supplemental material

Supplemental material for this article is available online.

Notes

1. Sometimes, as opposed to formal learning, 'non-formal learning' is used as common term for education that is organized but does not produce a formal credential. In such distinctions, formal learning is referred to as activities that produce a diploma or credential, and non-formal is education that does not.
2. As learning participation is a binary variable, generalized SEM or GSEM would be appropriate (Long and Freese, 2006). However, to ease interpretation of the coefficients, we estimated normal SEM models. The generalized model can be found in Appendix A online; substantive conclusions remain the same.

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Author biographies

Giedo Jansen is Associate Professor Regulation of Work at the University of Amsterdam, AIAS-HSI. His research is multidisciplinary and spans various academic disciplines, including sociology, political science and labor relations. His research focuses on how technological innovations (such as automation, digitalization, and the rise of AI) transform work structures and power relations.

Suzanne Janssen works as an Assistant Professor at the University of Twente, at the Department of Technology, Human, and Institutional Behavior. Her research focuses on practices of work, communication, and collaboration in the context of intelligent technologies in organizations (e.g., robots, AI). She is interested in the dual role of technology in the work of professionals, and the transformative role of technologies in organizations.

Mark Levels is Professor of Health, Education and Work at Maastricht University. He is program director of the research program Health, Skills, and Inequality at the Research Centre for Education and the Labor Market (ROA). One of his main research lines explores the impact of artificial intelligence on work and society.

Marie-Christine Fregin is Research Leader at Maastricht University's Research Centre for Education and the Labour Market (ROA). Her research focuses on Artificial Intelligence and how AI implementation affects workers' tasks, skills requirements, productivity, well-being, and sustainable employability. She works with transdisciplinary teams to study the impact of AI at the interface of science, industry, and politics.