Technology in Society 81 (2025) 102782

Contents lists available at ScienceDirect

Technology in Society

journal homepage: www.elsevier.com/locate/techsoc

Who's afraid of automation? Examining determinants of fear of automation in six European countries

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ARTICLE INFO

Keywords:
Technological change
Fear of automation
Technological unemployment
Labor market
Human resource management

ABSTRACT

This study develops an original conceptualization of *fear of automation* and examines its determinants, including the role of technology in the workplace (complementary or substitutive), task routineness, workers' exposure to technology, perceived lack of control over life, and position in the labor market. Using survey data from six Central EU countries—Austria, Czechia, Germany, Hungary, Poland, and Slovakia—we find that exposure to technology heightens fear of automation, as do task substitution and routineness. Younger, less-educated, and lower-income individuals, as well as those who perceive a greater lack of control, are more afraid of automation, while gender does not show a significant effect. In conclusion, we discuss how fear of automation may impact reskilling motivation in organizational practices.

1. Introduction

The fear of automation—the concern that machines will replace human labor—has resurfaced with each wave of technological change, reflecting historical anxieties that date back to the Industrial Revolution [1]. Work is a fundamental aspect of modern human life, providing not only income but also structure, routine, and a foundation for social relationships. It significantly contributes to an individual's identity, shaping who we are both personally and socially [2,3]. When work is disrupted, society can become unbalanced, as demonstrated by Jahoda and Lazarsfeld's [4] classic Marienthal study, which documented how mass unemployment in a 1930s Austrian village eroded social cohesion, undermined individual well-being, and destabilized community life.

The Fourth Industrial Revolution brings forth an increased potential for the automation of work due to the application of artificially intelligent machines. Moreover, the current wave of technological change has a wider scope and faster pace than its previous iterations. The combinatorial nature of the innovation process, focused on data and information, leads to an almost geometric progression in digital technologies. This growth holds the promise of automating not just physical tasks but, increasingly, cognitive ones as well, presenting both potential and risk. The recent development of multimodal Generative AI (GAI)—a form of artificial intelligence technology that can autonomously produce text, images, and even code—heralds yet another breakthrough, promising profound transformations in the labor market, particularly in creative and educational sectors [5]. The future of work seems more uncertain than ever, affecting even the authors of this article—cognitive workers in academia—who experience AI technologies encroaching upon their fundamental duties.

Just as the Luddites sought to destroy steam-powered looms two hundred years ago during the Industrial Revolution to protect their jobs, in 2023, Hollywood screenwriters and actors went on strike to defend their intellectual property from the threat of artificial intelligence algorithms generating text and images. But do workers in general fear automation as acutely? This was the primary question that shaped the design of our research. A preliminary analysis of survey data from over 6600 workers across six European countries (Austria, Czechia, Germany, Hungary, Poland, and Slovakia) collected at the turn of 2021 showed that, despite the extensive literature on risks of technological unemployment and growing media hype, for many workers this remains a rather baffling issue. A surprising 37 % of our respondents selected the "no opinion" option on the intentionally provocative statement intended to stimulate more decisive responses: "I feel that the development of new technologies and the associated automation of tasks will lead to mass unemployment within the next 10 years." Still, one in three participants agreed with the statement, mirroring the findings of Golin and Rauh [6],

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https://doi.org/10.1016/j.techsoc.2024.102782
Received 19 June 2024; Received in revised form 3 December 2024; Accepted 3 December 2024
Available online 4 December 2024

who reported that 35 % of respondents fear "displacement through technology".

In this article, we assume that as technology progresses faster than ever, more workers are likely to worry about automation. This underscores both the need to refine the conceptual frameworks used to describe and analyze this phenomenon and to conduct further systematic research on the determinants of fear of automation.

Consequently, we aim to make a twofold contribution to the literature. First, we join the ongoing effort to develop the notion of the "fear of automation," seeking to clarify to bring some clarity to the terminological abundance that borders on chaos, arising from inconsistent definitions and overlapping usage of terms like "technophobia," "technoparanoia," and "fear of automation" in recent studies. We begin with a psychological definition of fear and move towards a more sociological approach, treating fear as a phenomenon deeply rooted in culture and society, especially in late modernity. On this basis, we propose a theoretically grounded conceptualization of fear of automation, combining individual perception of the risk of automation within one's professional tasks, the feeling of job insecurity, and the belief that technological unemployment awaits us all.

Secondly, building on this conceptual development, we seek to assess the role of specific factors determining fear of automation. We construct our argument in two stages. Referring to the extensive literature on the impact of technology on the labor market, including approaches focusing on skill-biased and routine-biased technological changes, we first identify groups of workers who are objectively vulnerable—defined as those whose jobs involve routine and repetitive tasks that are highly susceptible to automation, as demonstrated by task-based risk assessments in the literature—and may justifiably fear the impact of automation on the security of their jobs. Next, we review studies that specifically focus on identifying the determinants of fear of automation. This step concludes with the formulation of hypotheses regarding the significance of several key factors identified in the literature in shaping fear of automation, namely exposure to technology, the nature of work tasks in relation to repetitiveness, perceived control over one's life, and labor market position. We also address the research gap by incorporating a personal dimension of technology exposure—a worker's experience with technology at workplace—going beyond generalized occupational and sectoral exposure. In the results section, we provide a data description summarizing the statistics of the selected variables. Next, we conduct econometric modeling to investigate the relationships between these variables and fear of automation more deeply. We find that an increase in each dimension of the digitalized work environment—personal (workplace technology experience), occupational (task routineness) and sectoral (technology exposure)—is associated with a heightened fear of automation. Furthermore, a lower sense of control over life, along with a weaker labor market position, is linked to higher fear of automation.

The discussion grounds the results of the study in the literature, particularly with reference to the theories of skill-biased and routine-biased task change under technological impact, and demonstrates its practical application within organizations undergoing digital transformation. The value of our study lies not only in providing new empirical evidence on the determinants of fear of automation, including a comprehensive perspective on the technological environment of a worker, but also in focusing on Central and Eastern European labor markets, which are underrepresented in the scholarly literature. Understanding the root causes of fear of automation can inform strategies to mitigate workers' concerns and develop organizational cultures that foster human-centered digital transformation.

2. Literature review

2.1. How to conceptualize fear?

Fear is an emotion known to every human being. The definition in the American Psychological Association Dictionary [7] states that fear is "a basic, intense emotion aroused by the detection of imminent threat, involving an immediate alarm reaction that mobilizes the organism."

The APA definition goes on to firmly differentiate fear from anxiety: the former is a response to a present and clearly identifiable threat, while the latter is oriented to a distant, uncertain, and more diffuse threat. People react to fear by seeking immediate solutions, while anxiety necessitates solutions that are broader and more adaptable [8]. This differentiation inspired the design of our questionnaire (Question 3 was originally designed to measure technological fear, while Question 4 was designed to measure technological anxiety; see Section 4, Table 1). Thus, we assumed that fear is connected with concrete mental representations—for example, the possibility of losing one's job in the foreseeable future—while anxiety is associated with distant, ambiguous, and dispersed threats, such as the risk of massive technological unemployment.

During the data analysis phase, we encountered recent critical literature in psychology challenging the widely accepted distinction between fear and anxiety and proposing new theoretical assumptions to merge these concepts. Critics such as Daniel-Watanabe and Fletcher [9] argue that the traditional definition of fear and the differentiation between fear and anxiety—fundamental to categorizing mental disorders—are inconsistent and oversimplified. They contend that these flaws stem from contradictory data, which arise due to the direct and often inappropriate application of animal research findings to human behavior.

Concurrently, we observed terminological confusion within the literature, as some authors, like McClure [10] with "technophobia" and Agogo [11] with "technoparanoia," use these terms to describe the fear of job loss due to machines. Technophobia, however, has a defined meaning in information systems literature and is closely related to computer anxiety, which refers to individual apprehension about using technology in daily life. Some authors consistently use the notion of

Table 1
Phrasing of the survey questions and the answers.

Question	Phrasing	Answer
1. Workplace technology experience	I feel that in my current job new technologies:	1 = Have no impact on my job tasks 2 = Support me in carrying out my job tasks 3 = Replace me in an increasing number of job tasks 4 = Replace me in so many job tasks that I feel I have to retrain
Components of *fear of automation* (dependent variable)		
2. Job insecurity	I fear that in the next 10 years I will lose job in the profession I am currently in.	1 = I strongly disagree 2 = I rather disagree 3 = I neither agree nor disagree 4 = I rather agree 5 = I strongly agree
3. (Belief in) task automation	I believe that tasks falling within my current professional responsibilities can be automated using new technologies within the next 10 years.	
4. (Belief in) technological unemployment	I feel that the development of new technologies and the associated automation of tasks will lead to mass unemployment within the next 10 years.	

Note: The questions were introduced by the following statement: "Now we would like to ask you about your attitude towards new technologies (Information Systems, Specialized Software, Algorithms, Robots), which are increasingly used in the economy." The questions were articulated in local languages; the translations of the words "feel" and "I believe" were kept close to the meaning of "in my opinion"; for example in Polish "uważam", "sądzę."

anxiety to refer to fears of machines replacing human labor [12]. Nevertheless, in recent years an increasing number of empirical studies have applied the notion of "fear of automation." Innocenti and Golin [13] equate it with the "perceived risk of unemployment due to automation effects;" Golin and Rauh [6] describe it as a "response to a perceived threat of job loss because of automation;" and Mulas-Granados et al. [14] open their paper by stating that "the fear of automation is turning into the collective angst of our times," implicitly defining it as a "negative perception of how automation will shape the future of their own work." Similarly, Långstedt et al. [15] assert that "advanced technologies are changing our working life in unpredictable ways. Consequently, a fear of technologically induced mass unemployment has re-emerged."

Given this growing body of work, we chose to consolidate technological fear and anxiety into a unified concept: fear of automation. We connected this concept with job insecurity, a well-established theme in the sociology of work [16] (see Section 4.1 *Description of measures*). We align with LeDoux's succinct definition of fear as the "conscious awareness that you are in harm's way" (Le Doux as cited in Ref. [17]), with the specific harm here being the risk of job loss to machines. In this way, fear of automation encompasses not only individual concerns about one's labor being replaced by automation technologies but also broader worries about technological unemployment.

2.2. Fear in late modernity

Building on the psychological differentiation between fear and anxiety, we now turn to a sociological perspective that views fear as an integral part of social life in late modernity. Adopting a comprehensive the notion of fear of automation allows us to move beyond an overly psychological framework and enhance our understanding with insights from the emerging sociology of fear.

Seen through sociological lenses, the ways and practices of fear are inherently social, shaped by cultural patterns of interactions, relations, structures, discourses, and imaginaries. Fear and society co-create each other: on the one hand, "society, in its different figurations, affective constellations, and various mechanisms, is involved in producing, forming, and representing fear" ([18]: 276). On the other hand, fear reproduces society, serving as an integration mechanism: when we fear something, we may unite to confront it or acknowledge a shared predicament. The sociological approach to fear considers not just an individual emotion but also the cultural matrix within which fear is realized [19].

The sociology of fear suggests that while fear has always been present in social life, it has assumed particular significance in late modern societies. Tudor ([19]: 238) observes that "fearfulness appears to have become a way of life in modern society," an observation supported by Sik [20], who describes fear as "a phenomenological texture of late modernity." Bauman [21] introduces the concept of "liquid fear," a constant sensation experienced by reflexive individuals aware of their vulnerability to unseen dangers in modern society. Other leading theorists of late modernity, like Beck and Giddens, link fear to the extensive scale, scope, and impact of socioeconomic and cultural transformations, emphasizing its amplification due to dwindling social trust—a consequence of deteriorating social integration mechanisms in late capitalism [22].

In this context, technological revolutions that reshape the labor market are seen as specific generators of an objectified fear that one's job may be usurped by intelligent machines. Furedi [23] suggests that the fear of automation is fueled by the rapid pace of technological progress, which exacerbates the feeling of a lack of control over the social and economic consequences of technology adoption. Furedi also notes that the prevalence of fear in contemporary society is partly driven by deliberate actions of those who benefit from it. He describes a culture of fear crafted by "fear entrepreneurs," who cultivate a discourse of fear within "markets of fear."

Fear of automation is a case in point [24]. For decades, the fear of automation has been flared up by publications arguing that technology and automation signal the end of mass employment [25]. The now-canonical definition of technological unemployment was proposed almost 100 years ago by John Maynard Keynes, who described it as the phenomenon where technology advances faster than the economy's ability to generate new jobs. Keynes warned that this could lead to widespread economic dislocation and social unrest if new employment opportunities were not created swiftly enough. In the 1990s, Aronowitz and DiFazio [26] warned of a "jobless future," and Rifkin [27] ominously discussed the "end of work." More recently, Suskind [2] worried about a world without work and Ford [28] revisited the concept of a "jobless future."

However persuasive, their narratives were painted with broad strokes of essayistic fervor. This is why it can be argued that the paper by Frey and Osborne [29], provocatively titled "The Future of Employment: How susceptible are jobs to computerization," had the most significant impact on the fearmongering discourse regarding technological unemployment. These two Oxford economists anchored the fear of automation to a specific and quite alarming figure, claiming that nearly half (47 %) of all jobs were at risk of "computerization." Their methodology has drawn significant criticism for overestimating technology's potential and neglecting the earlier approach developed by Harvard economists Autor, Levy, and Murnane [30], which proposed assessing the risk of automation based on specific tasks or clusters of tasks within professions, rather than evaluating entire occupations. From this perspective, in some areas, humans will enhance machine functions through training, interpreting, and maintaining them, while in others, machines will boost human capacities, reducing the need for humans to perform mundane or risky tasks [31,32]. The impact will not be so much the replacement of humans by machines as the complementing of human work by machine work, and vice versa, introducing a new division of labor without resulting in massive technological unemployment in the foreseeable future [33].

Nevertheless, Osborne and Frey's assertive claims caught the attention of influential fear entrepreneurs, particularly in the media. The BBC even developed an app allowing readers to check if robots could replace their jobs. Major consulting firms began producing reports forecasting massive job losses, creating a lucrative market of fear. For instance, a 2018 McKinsey report suggested that 375 million workers—about 14 percent of the global workforce—might need to switch occupational categories due to digitalization, automation, and AI advances [34]. As of 2024, the alarmist tone continues, with reports indicating that 12 million US workers alone may need to change jobs [35].

2.3. Who is vulnerable to automation?

Recent literature on the impact of automation technologies on overall employment offers no consistent evidence [36–39]. However, a balanced yet slightly optimistic view seems to prevail among labor market economists. In a comprehensive review of 127 empirical articles published between 1988 and 2021, Hötte et al. [40] concluded that massive technological unemployment is unlikely, as job creation from technological progress usually offsets job losses. Economic theory suggests that compensatory mechanisms, such as new roles and increased productivity, support labor demand in non-automated sectors. Additionally, technological innovation can boost labor demand by lowering production costs and consumer prices, potentially increasing output if demand rises due to higher income and lower prices [41].

While economists generally agree that massive technological unemployment is unlikely, they also recognize that technology's impact on the labor market will not be uniformly positive. In fact, technological changes are skill-biased [42,43]—both complementary and substitution effects occur simultaneously, but in relation to different groups of workers. Intelligent machines and systems complement the work of highly competent individuals, but may also exacerbate exclusion in labor markets, particularly among low-skill, production, and manufacturing workers. This can lead to a potential widening of the pay and status gap between different worker groups [44].

The number of positions in which harmonious complementarity between human and machine work can occur is actually limited, and workers whose employers want to pair them with machines generally possess such high competencies that they need not fear unemployment anyway [28]. Brynjolfsson and McAfee [45] highlights that employment security will be available to workers with a specific competence profile. Stephany and Teutloff [46] further reinforce the importance of skills and their complementarity in the context of AI-driven technological change. They find that skills that can be broadly complemented in diverse settings are associated with higher value, especially in the case of increased demand and applicability of AI skills.

A significant impact of Osborne and Frey's [29] publication was its authoritative identification of specific worker groups particularly vulnerable to the current automation phase: those in routine work. Routine work involves tasks that follow a clear, step-by-step procedure, whether physical or cognitive, and can be performed by workers at all skill levels, but is predominant among medium-skilled workers. According to their analysis, 47 % of the U.S. jobs are exposed to computerization, with the estimated automation risk for some traditionally secure white-collar jobs—including accountants, cashiers, bank customer service representatives, and sales administrators—reaching as high as 97 %. However, using a different, task-based, approach, Arntz, Gregory, and Zierahn [47] label only 9 % of jobs in OECD countries as automatable, while Nedelkoska and Quintini [48] demonstrate that 14 % of jobs are at high risk, with another 32 % facing significant changes due to automation. The differences in estimates between such studies were scrutinized by Lorenz et al. [49]. While they confirme that routine, computer-based tasks are more likely to be affected by automation, they also highlight the importance of within-occupation task heterogeneity and the selection of models employed to estimate automation risk. Binary models, like the one used by Frey and Osborne [29], which classify jobs as either high-risk or not, tend to overestimate the share of automatable jobs, when compared to studies utilizing fractional models, so models that yield a more detailed range of automation probabilities (such as Ref. [48]). This is because the binary models are sensitive to the threshold used to define high automation risk and produce bimodal distribution. In contrast, the distribution of automation risks in fractional models is bell-shaped, where the majority occupations fall between the extremes of low and high automation probability [49].

The focus on the impact of technology on employment, especially in routine tasks, has been expanded under the concept of routine-biased technological change by researchers such as Goos et al. [50]. Although debates persist over the precise definition of routineness and how to categorize tasks as routine or non-routine, the theory suggests significant shifts in the labor market. Autor [51] notes that employment in middle-skill occupations, which have the highest percentage of routine tasks, is declining relative to positions in low- and high-skill jobs. This phenomenon is referred to as job polarization. Furthermore, as demand for routine activities decreases, the returns to these tasks also diminish [52,53].

Additionally, recent developments in artificial intelligence gradually expand the assumptions of the routine task-based approach. As algorithms are becoming capable of solving problems requiring "tacit" knowledge, the spectrum of codifiable activities broadens, encompassing non-routine cognitive and creative tasks. Such advances may affect different groups of workers, mainly highly skilled individuals who have not previously been adversely affected or threatened [51], potentially raising the level of fear of losing their job to increasingly potent digital machines.

Interestingly, there seem to be no consensus as to who is more endangered by automation, men or women. For instance, Lorenz et al. [49] report that gender has no significant effect on automation risk, whereas Nedelkoska and Quintini [48] argue that women face a higher risk. Supporting the latter view, Roberts et al. [54] show that women can be twice as affected by automation, as they work in more routine-suffused jobs. Blanas et al. [55] contend that software and robots have reduced demand for low- and medium-skill workers, the young, and women in manufacturing, but increased demand for high-skill, older workers, and men in services. This supports the theory that automation replaces routine tasks, with some workers, especially women, transitioning away from these roles. Yet in her analysis of 10 key books on the future of work published between 2018 and 2020, Kelan [56] found that their authors are concerned about automation of jobs and tasks performed by man, particularly those who are middle-aged and low-skilled. Based on data for Canadian workers, Petersen et al. [57] also state that, with some exceptions, occupations characterized by low income and high employment of men are more susceptible to automation risk, particularly in some industry sectors. More specifically, Filippi et al. [58] find that European women face a slightly lower risk of substitution due to automation compared to men. However, in institutional contexts with higher gender equality, women tend to acquire non-automatable skills, which further decreases their risk of substitution.

Similarly, there is no consensus on the specific vulnerability of workers in different age groups to automation. At first glance, older workers appear more vulnerable to automation [59,60], but Nedelkoska and Quintini's [48] novel finding challenges this view. Their research shows that while the relationship between automation and age is U-shaped, jobs held by teenagers are at the highest risk.

In general, it is important to emphasize the lack of consensus in the scholarly literature regarding the specific factors determining the risk of automation, as meticulously described by Filippi et al. [58], who note that "the literature investigating how automation technologies affect employment is extremely complex, uncertain, and immature," and that the empirical results "are often inconsistent, creating uncertainty in the literature." This immaturity makes the formulation of hypotheses in our study more challenging. At the same time, it highlights the need for both conceptual effort and the empirical accumulation of results, both of which are addressed in our study, representing another small step toward the maturation of the literature on automation's impact on the labor market.

2.4. What determines fear of automation?

The literature reviewed thus far generally suggests that fear of automation is most likely experienced by less-skilled workers and those engaged in routine tasks. In this section, we explore the relatively few empirical studies that specifically examine which groups are particularly fearful of automation.

2.4.1. Exposure to technology

Several studies have explored how exposure to technology influences the development of automation fear. For example, although Klenert et al. [38] convincingly shows that robot use leads to an increase in aggregate employment in Europe, Mulas-Granados et al. [14] find that higher robot penetration increases people's apprehension toward technology. This is especially evident in the large-scale manufacturing and automotive sectors, where human labor is being noticeably replaced by robots [44,48]. In their study on the determinants of robot acceptance at work, Turja and Oksanen [61] observe that while countries with higher ICT exports and more cellular phones per capita demonstrated greater acceptance of robots, higher job-automation risks correlated with lower acceptance levels.

There is no agreement regarding whether awareness of automation risk leads to increased job insecurity. Nazareno and Schiff [62] find no direct relation between awareness of automation risk, job insecurity, and the lessened well-being of workers. On the other hand, Innocenti and Golin [13] argue that workers aware of automatability exhibit increased concerns about being replaced, a sentiment echoed by Yam et al. [63], who find that anticipation of robotic integration heightens job insecurity across all skill levels. Similarly, Dengler and Gundert [64] observe that workers in vulnerable occupations feel job insecurity even without personal experience with robots. Ligmont and Alexiou [65] extend this understanding by demonstrating that mere awareness of automation technologies in authoritarian organizational cultures particularly heightens employees' perceptions of job insecurity.

2.4.2. Sense of control

Willcocks ([25]: 297–298) broadly asserts that the fear of automation has "always been a psychological repository for some of our deepest anxieties, about future uncertainties and loss of control, including over our own creations." Significantly, individuals who believe in their ability to control their own lives and maintain freedom of choice tend to experience less anxiety about automation [13]. Interestingly, Di Nuzzi and Santoni [66] argue that fear of automation may stem from the feeling of a lack of direct control over machines. Admittedly, the sense of control over one's life may play the role of an anxiety buffer when facing the threat of automation [67]. Godollei and Beck [68] offer a general proposition that "people in jobs, industries, countries, or economic positions which afford them little control are more likely to be susceptible to fearful reactions". Their study shows that how much control people feel they have over automation strongly influences whether they see it as a threat to their job security or an opportunity to improve their work performance.

2.4.3. Labor market position

Several studies highlight that fear of automation, and more generally, technology-related job insecurity is linked with weaker labor market positions [69]. McClure [10] find that fear of robots, AI, and new technology, which he proposes to call technophobia, is strongly related to concerns over job security and financial instability. The study shows that technophobia prevails more among women, non-White minorities, and less educated individuals, pointing to a connection between automation fears, automation vulnerability (see Section 2.3), and socio-educational inequalities. Importantly, from the perspective of fear treated as a phenomenon specific for late capitalism, technophobes often report anxiety-related mental health issues, suggesting that such fears could contribute to a vicious cycle of escalating anxiety, particularly regarding employment and financial wellbeing. Innocenti and Golin [13] also find that women, younger workers, and low-income earners are more likely to fear unemployment due to automation. Mulas-Granados et al. [14], using data on 11,000 workers from both advanced and emerging economies, assert that "negative perceptions about automation are prevalent among workers who are older, poorer, more exposed to job volatility, and from countries with higher robot penetrations". Similarly, Ghimire et al. [70], interpreting the results of the survey in Atlanta, state that automation is feared more by older and poorer residents, as well as Black/African Americans. Provocatively, they conclude that those who did not take the risk of automation into account – less-educated and Hispanics or Latinos – are more likely to lose their jobs. Interestingly, Shoss [16] notes that workers in societies with greater overall inequality tend to see AI and robots as more threatening.

The scholarly literature does not present a consensus on the relationship between a worker's age and their apprehensions regarding automation. Generally, the relationship between age and job insecurity due to automation is described as U-shaped, with variations noted in different studies [14,64]. Several studies suggest that older workers, presumably due to more stabilized work positions, tend to be less afraid of automation [6,13]. On the other hand research led by Ivanov et al. [71] lends partial support to the hypothesis that younger individuals, likely due to their ease with technology, are less fearful of job displacement by machines. Furthermore, their study highlights a potential urban-rural divide, with non-metropolitan residents exhibiting heightened concern about job automation, which may reflect varying experiences with technology.

In general, more educated individuals in higher-paid occupations tend to exhibit lower levels of fear of automation [13,69]. Rodriguez-Bustelo et al. [72] also contend that education level significantly shapes perceptions of automation, with those holding higher education credentials exhibiting less fear and more proactive engagement with the potentialities of an automated future. Their study also notes an inverse relationship between job complexity and automation fear, indicating that roles involving diverse skills and higher complexity – that is, usually less routine engender optimism about automation's future. In a similar vein, Ivanov et al. [71] discovered that workers who feel confident about their skills are less anxious about automation and adapt better to technological advancements.

3. Research hypotheses

Our study design allows us to analyze how workers perceive technology's impact on their roles, specifically whether it substitutes for or complements their tasks. We aim to test the hypothesis that fear of automation increases among workers who have experienced changes in their job functions due to technological advancements. Drawing from routine-biased technological change theory, we investigate whether workers in roles with a higher proportion of routine tasks exhibit greater fear of automation. Additionally, we examine the relationship between overall exposure to technology within a sector and the level of fear experienced by workers.

Building on insights from our literature review, we hypothesize that fear of automation is heightened among workers who are structurally more vulnerable due to their precarious position in the labor market. Furthermore, we propose examining whether a sense of control over one's life acts as a buffer against fear of automation, aligning our discussion with the broader discourse on fear as a fundamental aspect of the contemporary human condition.

To determine the factors shaping fear of automation, we test the following hypotheses inspired by the literature review.

H1. A higher fear of automation is related to experiencing changes in work tasks due to the introduction of automation technologies. In other words, if a worker has already experienced their tasks being substituted or complemented by new technologies, the fear of automation is higher. In line with the literature review, we expect that the fear of automation will be greater when tasks are substituted rather than complemented.

H2. The more routine tasks a given job involves, the higher fear of automation.

H3. Fear of automation is higher the more intense workers' exposure to technology within their sector.

H4. Workers who perceive a greater lack of control over their lives exhibit a higher fear of automation.

H5. A higher fear of automation is related to a weaker position in the labor market, as defined by gender, age, education, and income.

4. Data and methods

The study uses data collected as part of the deliberately designed Central European Social Survey, conducted via the Computer-Assisted Web Interviewing (CAWI) method. The survey encompassed 11,000 individuals across six European Union countries: Austria, Czechia, Germany, Hungary, Poland, and Slovakia. The data collection period spanned from December 2021 to January 2022. To ensure a representative sample, a random quota sampling procedure was employed, meticulously reflecting each country's demographic composition among adults aged 18 and above. This procedure accounted for gender, age categories, and the size of the respondents' place of residence.

For the purposes of our analyses, we confine our sample to individuals actively engaged in the workforce. This includes full-time workers, part-time workers, interns, individuals on maternal or parental leave, and those who are self-employed. Our sample consists of 6634 workers from these six countries. To see the percentage distribution of gender, age, and place of residence among the confined sample; see Table A1 in the Appendix.

Of the six countries covered, Austria and Germany are the most heavily represented, while Slovakia has the lowest representation. Among our respondents, 61 % hail from Central and Eastern European (CEE) countries, namely Poland, Hungary, Czechia, and Slovakia. The gender distribution is roughly balanced, with 53 % of respondents being male. The majority (80 %) fall within the age range of 18–54, with a mean age of 43 years.

In terms of educational attainment, 40 % of workers graduated from upper-secondary school, while the remainder is nearly equally divided between those with primary or lower-secondary education and those with tertiary education. Regarding occupation, the most common roles among our respondents are Clerks (24 %), followed by Service workers and shop and market sales workers (19 %), Professionals (16 %), and Technicians and associate professionals (11 %). The largest proportion of respondents works in the "Other Services Activities" sector (14 %), followed by Manufacturing (13 %), Human Health and Social Work Activities (9 %), and Education (7 %). For detailed information on occupations and sectors, see Table A2 in the Appendix.

The perceptions of new technologies at work—a broad term relating to information systems, specialized software, algorithms, and robotic solutions—were probed through four questions presented in the Table 1. The first question addressed recent experiences with new technologies in the workplace, asking whether they were complementary (answer 2), substitutive (3 or 4) or had no impact on job tasks (answer 1). In the second question, respondents were asked about their job insecurity. The third surveyed beliefs regarding the automation potential of a worker's current job tasks. The last question inquired workers' beliefs about automation-induced mass technological unemployment. The time frame for Question 2, 3, and 4 spans the next ten years (see Table 1), and these three questions are used to construct our measure of fear of automation, as explained further in Section 4.1.

Before the development of the Central European Social Survey, which took place at the turn of the years 2020 and 2021, only a few studies had explored the theme of automation fears (e.g., [69,73–75]). As all the studies employed different questionnaires, there was no established standard in place for surveying people about their concerns regarding automation. The phrasing of our Questions 2 and 3 drew from the items developed by Brougham and Haar [74], whose focus encompassed a wider array of technologies in the context of automation, forming our umbrella term "new technologies", which refers to information systems, specialized software, algorithms, and robots. We followed their approach of disentangling questions on automation perceptions from job insecurity to identify workers who fear both automation and job loss, as well as those who expect automation without feeling job insecurity and vice versa. Furthermore, we added a time frame to our questions to increase the precision of the responses as automation technologies continuously expand their spectrum of capabilities. Later studies, such as by Innocenti and Golin [13], or Arntz et al. [76], similarly introduced time frames, which validate our approach.

4.1. Description of measures

The main measure of interest in this study—fear of automation—synthesizes the second, third, and fourth questions. The answers to these questions take values on a 5-point Likert scale, ranging from 1 (I strongly disagree) to 5 (I strongly agree), with 3 (I neither agree nor disagree) as the midpoint (see Table 1). Following the method of Dekker et al. [69], we calculate the mean value of the answers to these questions, resulting in a scale from 1 to 5. The lowest values depict workers who are not afraid of losing their job in the profession, do not expect their job tasks to be automated, and do not foresee mass technological unemployment. The highest values cover workers expecting job loss, automation, and mass technological unemployment.

For the purpose of further analyses allowing us to contextualize factors determining fear of automation, we construct three measures: (a) Workplace technology experience, which relates to direct individual experience with technology within their job duties; (b) Routine Task Intensity (RTI), which depicts how routine (repetitive, procedural) workers' job tasks are; and (c) Technology exposure, which refers to overall exposure to industrial robots within the respective sector.

The categorical variable Workplace technology experience is derived from Question 1 (see Table 1), and is used here to attest whether workers declare no impact of technology on their work (answer 1); a complementary effect, when technology supports them in performing their job tasks (answer 2); or a substitutive effect, when they feel that technology increasingly replaces them in their job tasks (answers 3 and 4).

Since our dataset lacks the information needed to construct our own Routine Task Intensity measure, we develop the measure using the OECD Survey of Adult Skills (PIAAC, 2012), guided by the task-based methodology of De La Rica et al. [53]. We then match the constructed measure to our dataset on the country-occupational level. Hence, each worker in our survey is assigned a RTI measure from PIAAC based on their occupation and country of living.

Other task-based methodologies often rely on the US-focused databases, such as the Dictionary of Occupational Titles or the Occupational Information Network (e.g., [77], [42]), which may not always capture the occupational task structures in other countries. Hence, the advantage of using the approach of De La Rica et al. [53] lies in ensuring cross-country heterogeneity of task measures. The validity of their approach was confirmed through statistical comparison with the O*NET measures as computed by Acemoglu and Autor [42], demonstrating significant positive correlations for the United States (notably the highest) as well as for other countries. Yet, the correlations for other countries differ, indicating a varying occupational task structure between countries [53] and the need to account for it.

The PIAAC dataset provides information on specific job tasks at an individual level, which we group into Abstract, Routine, and Manual tasks—a categorization necessary to construct the RTI measure. Abstract tasks involve complex cognitive activities requiring problem-solving, decision-making, social skills, or applying specialized knowledge. Routine tasks consist of repetitive and rule-based activities, which are measured here as the infrequency of tasks requiring autonomy, such as planning one's own activities, instructing and advising other people, or making speeches. Manual tasks involve working physically for extended periods or tasks requiring accuracy with hands or fingers. Table A3 in the Appendix presents the exact method of grouping the PIAAC questions into these categories as proposed by De La Rica et al. [53]. Within these three groups, responses to each question were provided on a 5-point scale indicating the frequency of performing a particular task.

To derive a single measure for each task group, we conduct Principal Component Analysis (PCA) on the Abstract and Routine task groups, and use the first PCA components for further analyses. In line with the methodology of De La Rica et al. (2020), we calculate the average for the Manual tasks, given that this category comprises only two items. Having single measures for Abstract, Routine, and Manual tasks, we calculate Routine Task Intensity (RTI) in accordance with Goos et al.'s [50] formula:

$$RTI = ln(RoutineTasks) - (ln(AbstractTasks) + ln(ManualTasks))$$

on a pooled dataset of the six analyzed countries. We calculate the means for ISCO 2-digit classification of occupations for each country, except for Austria, for which data is available only on the broadest level of aggregation (ISCO 1-digit). To tackle this issue, the measures for Austria were derived as the average of the other investigated countries' occupational measures. We match the calculated RTI from PIAAC with our survey using ISCO 2-digit occupational classification and country. The matched RTI measure is then standardized.

To obtain the Technology exposure measure, we use two datasets. The International Federation of Robotics (IFR) data provides information on the number of industrial robots operating in a given sector, country, and year. The data on the number of workers in a certain country-sector in 2020 was acquired from Eurostat's Labour Force Survey. Following de Vries et al. [78], we calculate the Technology exposure as the number of the operational stock of industrial robots (R) per one thousand workers (EMP) in country-sector pairs for 2020:

$$\text{Technology Exposure}_{c,s} = \frac{R_{c,s}}{\text{EMP}_{c,s}}$$

The sectoral matching between our dataset, Eurostat's Labour Force Survey and the calculated is presented in Table A4, Appendix. Similarly to Routine Task Intensity, the Technology exposure measure is standardized.

In addition to demographic variables such as gender, age, income, education, and country of residence, we include a variable assessing the perception of personal control over life events. The measure of the Perceived lack of control is based on a question worded: "Currently, I have a feeling that many things are happening in my life over which I have no influence", with responses ranging from 1 (strongly disagree) to 7 (strongly agree). Higher values signify a decreasing sense of control over one's own life.

4.2. Empirical specification

This study's main empirical approach focuses on the determinants of fear of automation. The construction of this measure enables the use of the OLS regression method. The model takes the following form:

$$y_{i,o,s,c} = \alpha + \beta_1 \text{Work\_tech\_experience}_i + \beta_2 \text{RTI}_{o,c} + \beta_3 \text{Tech\_exposure}_{s,c} + \beta_4 \text{Control}_i + \beta_5 X_i + \epsilon_i$$

where $y_{i,o,s,c}$ denotes the measure of the fear of automation of an individual i in occupation o, who works in sector s of country c. $Work\_tech\_experience_i$ represents an individual's Workplace technology experience (either complementary or substitutive). $RTI_{o,c}$ refers to the Routine Task Intensity measure for occupation o in country c and $Tech\_exposure_{s,c}$ covers exposure to robots in sector s of country c. $Control_i$ captures the Perceived lack of control over one's life. X_i is a vector of controls for gender, age, education, wage quintile, and country fixed effects. To address the issues arising from different levels of aggregation among independent variables, we employ clustered standard errors for occupations (ISCO 1-digit, 10 clusters) and sectors (NACE 1-digit, 21 clusters).

4.2.1. Robustness

The modeling approach outlined above presents two challenges to unbiased identification: potential self-selection into occupations with various levels of automation exposure and confounding effects related to perceived lack of control. Specifically, certain groups of workers are more likely to self-select into occupations with specific levels of automation exposure, as reflected by occupational Routine Task Intensity. For instance, men, highly educated individuals with advanced skills, and high-wage earners tend to be employed in less automatable jobs ([48]; for more details, see Section 2.3. Who is vulnerable to automation?). Similarly, workers' characteristics—such as age, wage, gender, or education—can influence their sense of control [79]. Given that fear of automation is also shaped by these factors, confounding arises in relation to workers' characteristics. To address these identification threats, we employ the Inverse Probability Weighting (IPW) method with respect to Routine Task Intensity and Perceived lack of control.

IPW is a statistical technique widely used to mitigate potential biases in observational studies by introducing weights that generate a pseudo-population. Within this pseudo-population, the variable of interest (often referred to as the treatment) and selection are independent of covariates, enabling more reliable estimation of its effect on the outcome variable. In essence, each observation is assigned a weight based on the inverse of the probability (or propensity score) of receiving the treatment or being selected, given the covariates. By applying these weights, the treated and untreated groups in the reweighted population achieve similar covariate distributions. This reduces self-selection and confounding by mimicking a randomized experiment [80].

The application of IPW involves several steps. First, the covariates for the Propensity Score (PS) model—the model explaining the treatment variable, i.e., RTI and Perceived lack of control—are identified based on insights from theory and relevant literature (e.g., [47,48,58,79]). In our study, the hypothesized individual covariates associated with self-selection into occupations with varying levels of automation exposure (RTI) include gender, age, education, and wage. The same set of confounders is introduced when estimating the PS model for Perceived lack of control. In both PS models, we also account for the country of origin.

In the second step, the PS model is estimated using a method suitable for the nature of the treatment variable. Then, the IPWs are derived using a formula consistent with the modeling approach. Since our variables of interest are continuous, we apply the IPW method for continuous variables as proposed formally by Naimi et al. [81] and implemented in R using the *ipw* package by Heiss [82]. The formula we use is as follows: $IPW = \frac{f_X(X;\mu_1,\sigma_1^2)}{f_{X|C}(X|C=c;\mu_2,\sigma_2^2)}$, where X is the continuous treatment variable, C denotes confounders, the numerator is the probability density function of X, and the denominator is the conditional probability density function of X given C. We apply the formula to two variables, yielding two sets of IPWs: one balancing the covariates for RTI, and the other balancing the covariates for the Perceived lack of control. To obtain a single weight, we multiply the IPWs calculated for these two variables of interest.

Third, extreme weights are inspected and addressed to improve the accuracy of the estimates [80,81,83,84]. We trim extreme weight values by replacing those below the 1st percentile with the 1st percentile value and those above the 99th percentile with the 99th percentile value.

Next, the balance of covariates across different treatment levels is assessed. To ensure that the covariates are balanced for the combined weight, we examine two balance tables: one for RTI and one for the Perceived lack of control. Both tables indicate that the covariates are balanced for the variables of interest, using 0.05 as the maximum allowable threshold for the absolute value of the balance measure (following Bishop et al. [80]). This suggests that confounding issues are mitigated in the outcome model. For more details, see the balance tables in Table 2.

Finally, having obtained the combined weights that balance the covariates for both RTI and Perceived sense of control, we apply them to the econometric models as a robustness check.

5. Results

5.1. Fear of automation: Descriptive

The measure of fear of automation takes values from 1 to 5. Fig. 1A displays the distribution of the measure among our respondents. We establish a threshold score of 3.67 or above to identify workers who fear automation, as this reflects individuals who must at least "rather agree" with two of the three components of the measure. Considering this, our analysis reveals that 15.9 % of workers experience fear of automation, as illustrated in Fig. 1B. This finding concurrently implies that the majority of workers are not afraid. This is echoed in the measure's mean of 2.71 and median of 2.67.

The relationships between the components of the measure of fear of automation are positive and statistically significant. As calculated using Gamma measure of association for ordinal variables, the association is the strongest between job insecurity and belief in technological

Table 2
Covariate balance before and after applying the combined IPWs.

	RTI		Perceived lack of control	
Covariate	Balance b. w.	Balance a. w.	Balance b. w.	Balance a. w.
Gender (Female)	0.047	0.001	0.03	−0.003
Age	−0.051	0.000	0.045	0.018
Age squared	−0.052	−0.001	0.042	0.019
Education				
Primary & Lower-sec	0.132	0.02	0.002	0.001
Upper-sec	0.086	0.012	0.013	−0.004
Tertiary	−0.226	−0.034	−0.016	0.003
Wage quintile				
1st	0.122	0.03	0.019	−0.005
2nd	0.052	0.003	0.026	0.006
3rd	0.01	0.004	−0.013	−0.005
4th	−0.076	−0.018	−0.017	0.003
5th	−0.108	−0.02	−0.016	0.000
Country				
DE	−0.011	0.007	−0.097	0.003
AT	−0.079	−0.012	−0.034	−0.006
CZ	−0.098	−0.031	0.077	0.005
HU	0.303	0.073	0.026	−0.002
PL	−0.16	−0.031	0.023	−0.004
SK	0.075	−0.002	0.017	0.004

Note: "Balance b.w." refers to the balance before weighting, while "Balance a.w." refers to the balance after weighting. The applied weight is calculated by multiplying the inverse probability weights (IPW) derived from two propensity score models: one for RTI and one for Perceived lack of control.

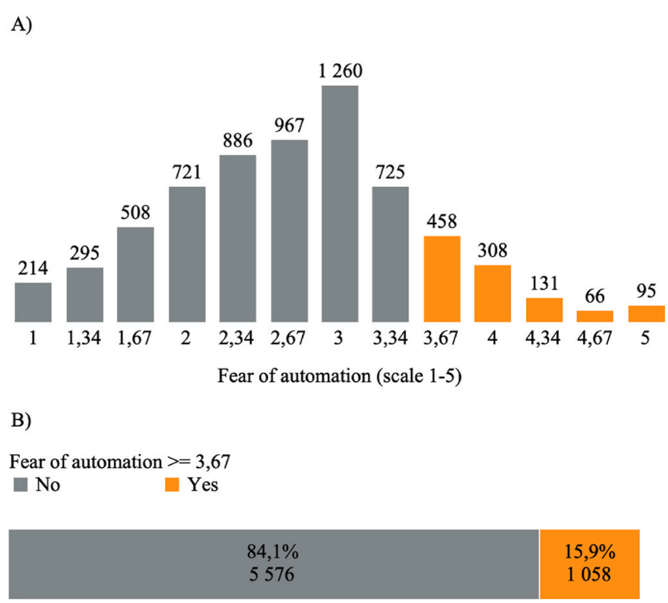

Fig. 1. The distribution of the measure of fear of automation.
Source: Own calculations.

Table 3
Associations between the components of our measure of fear of automation.

	Job insecurity	Task automation	Technological unemployment
Job insecurity	1		
Task automation	0.428***	1	
Technological unemployment	0.431***	0.283***	1

Note: Gamma measure of association; ~ $p < 0.1$, *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

unemployment. Similarly strong association is observed between job insecurity and belief in task automation (see Table 3). Hence, workers appear to often provide similar answers to these pairs of questions. To illustrate this, Fig. 2 shows the distribution of responses and the percentage of transitions between these two pairs of questions.

17.2 % of respondents are convinced that they will lose their job within 10 years, and 25.9 % believe that their tasks can be automated. One-third envisions mass technological unemployment (see Fig. 2). At the same time, half of the workers fearing job loss are convinced that their tasks can be automated, and 63.1%—that technology and automation will lead to mass unemployment in the future (see Fig. 2). More surprisingly, only one-third of people who expect task automation or mass unemployment fear losing their job (see Fig. 2).

Unsurprisingly, there are individuals who believe in the progress of task automation and its detrimental effect on society while not fearing job loss, as well as workers who fear job loss regardless of automation (see Fig. 2). The majority, however, offers similar answers to both pairs of questions. To see the exact cross-tabulation of the unaggregated responses to survey questions used to construct the fear of automation measure, refer to Appendix Figure A1.

An examination of correlations between the continuous variables of interest reveals that fear of automation is positively associated with Routine Task Intensity and Technology exposure, as displayed in Table 4. Similarly, when the Perceived lack of control rises, so does fear of automation.

We consider several factors that could explain the differences in fear of automation (see Table 5). Workers who have already experienced automation constitute the only group with the average fear measure that exceeds 3. Young adults (18–34), workers in the 1st wage quintile, and primary school graduates score not far behind (all around 2.85). Also, the measure's mean decreases as wages increase. Employees in Central and Eastern European countries report notably higher levels of fear, with Slovakia and Poland topping the list. Men score lower on average than women (see Table 5).

5.2. *Determinants of fear of automation*

Table 6 displays the results of our modeling approach described in Section 4.2. Empirical specification. The models are estimated for the sample covered by the Technology exposure measure (N = 6607). Models (1) and (2) are estimated without weights, while Models (3) and (4) incorporate Inverse Probability Weights, as described in Section 4.2.1. Robustness.

In the first model (Model (1)), we focus only on the main variables of interest: Workplace technology experience, Routine Task Intensity, Technology exposure, and Perceived lack of control. This allows us to isolate the direct relationships between these variables and fear of automation without the impact of covariates.

In the second model (Model (2)), we add control variables that account for workers' labor market position (gender, age, education, wage quintile) and country fixed effects, which help address the omitted variable bias. By comparing the estimates between Models (1) and (2), we observe low variability in the coefficients, suggesting that the core relationships are robust. However, as we are aware of issues related to self-selection and confounding with respect to RTI, Perceived lack of control and control variables (see Section 4.2.1. Robustness), we apply the combined Inverse Probability Weights to Model (3) and Model (4). Again, when we compare the estimates between the models, the variability is not high; however, there are shifts suggesting that confounding may be reduced through weighting. This makes Model (4), which reintroduces the control variables, our preferred specification for hypothesis testing.

As described in detail below, the obtained results support the majority of the hypotheses formulated in the study (see Section 3 Research hypotheses and Table 6).

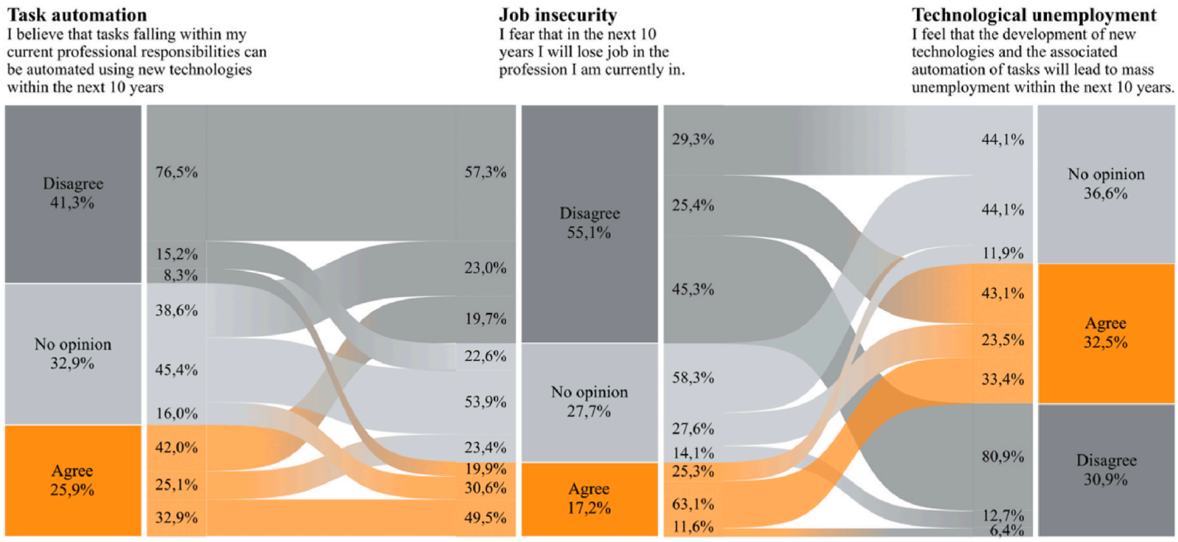

Fig. 2. Response distribution and percentage transitions between Questions 2 and 3 and Questions 2 and 4.
Note: Own calculations; the categories "Rather Agree" and "Strongly Agree" have been combined into "Agree," and "Rather Disagree" and "Strongly Disagree" into "Disagree".

Table 4
Correlations between continuous measures: Fear of automation, Routine Task Intensity (RTI). Technology exposure, and Perceived lack of control.

	Fear of automation (DV)	RTI	Technology exposure	Perceived lack of control
Fear of automation (DV)	1			
RTI	0.121***	1		
Technology exposure	0.023~	0.045***	1	
Perceived lack of control	0.122***	0.017	−0.005	1

Note: Pearson correlation coefficient; DV denotes the dependent variable; ~ $p < 0.1$, *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 5
Descriptive statistics (mean and standard deviation) for the measure of fear of automation across categorical independent variables.

Variable	Subgroup	Fear of automation Mean	St.dev.
Workplace technology experience	Complementary	2.70	0.80
	No impact	2.61	0.82
	Substitutive	3.22	0.84
Gender	Female	2.73	0.81
	Male	2.69	0.86
Education	Primary & Lower-sec	2.85	0.78
	Upper-sec	2.67	0.86
	Tertiary	2.62	0.85
Age group	18–34	2.85	0.85
	35–44	2.69	0.84
	45–54	2.68	0.83
	55+	2.58	0.80
Wage quintile	1st	2.87	0.82
	2nd	2.77	0.83
	3rd	2.71	0.81
	4th	2.58	0.84
	5th	2.63	0.86
Country	AT	2.46	0.86
	CZ	2.71	0.80
	DE	2.67	0.87
	HU	2.78	0.85
	PL	2.85	0.80
	SK	2.91	0.73

Source: Own calculations.

H1. supported. Any workplace technology experience, whether complementary or substitutive, correlates with higher levels of *fear of automation* compared to workers who report no impact of technology on their job, by 0.13 and 0.64, respectively (see Table 6, Model (4)). Hence, higher *fear of automation* is related to technology-induced changes in work tasks, with the experience of task substitution having a more pronounced effect on this fear.

H2. supported. The more routine tasks a job involves, the higher the *fear of automation*. Specifically, for each one standard deviation increase in *Routine Task Intensity*, *fear of automation* rises by 0.07 (see Table 6, Model (4)).

H3. supported. *Fear of automation* is higher the more intensive worker exposure to robots within a sector. There is a positive association between increased exposure to technology and the level of fear: a one standard deviation increase in the *Technology exposure* relates to a 0.02 increase in the measure of fear (see Table 6, Model (4)).

H4. supported. Employees declaring greater lack of control over events in their lives exhibit higher *fear of automation*. One level up the scale of *Perceived lack of control* is associated with a 0.05 increase in the level of *fear of automation* (see Table 6, Model (4)).

H5. partially supported. Higher fear of automation is related to a weaker position in the labor market for younger workers and those with lower income and education. While gender does not play a significant role in determining *fear of automation*, the relationship with age is negative (see Table 6, Model (4)). Moreover, higher educational levels are associated with lower levels of fear of automation. Upper-secondary and tertiary education levels decrease the fear by 0.13 and 0.19, respectively, compared to primary and lower-secondary education as the reference level. Wages demonstrate an inverse relationship with the fear.

5.3. *Limitations of the study*

The questionnaire was prepared by a diverse group of researchers from different disciplines, requiring compromises on the length and wording of the questions to ensure coherency. The limitations of the CAWI (Computer-Assisted Web Interviewing) method, well-documented

Table 6
Fear of automation: OLS regression analysis.

	(1)		(2)		(3)		(4)	
	No weights				IPW			
Workplace technology experience (ref = No impact)								
Complementary	0.10***	(0.01)	0.15***	(0.02)	0.08***	(0.01)	0.13***	(0.02)
Substitutive	0.59***	(0.05)	0.64***	(0.03)	0.59***	(0.06)	0.64***	(0.04)
Routine Task Intensity	0.10***	(0.02)	0.06***	(0.02)	0.08***	(0.02)	0.07***	(0.02)
Technology exposure	0.01**	(0.004)	0.01**	(0.01)	0.02~	(0.01)	0.02***	(0.01)
Perceived lack of control	0.06***	(0.01)	0.05***	(0.004)	0.05***	(0.01)	0.05***	(0.004)
Gender (ref = Male)								
Female			−0.003	(0.02)			−0.02	(0.03)
Age			−0.01*	(0.01)			−0.01*	(0.01)
Age squared			0.0001	(0.0001)			0.0001	(0.0001)
Education: (ref = Primary & Lower-sec)								
Upper-sec			−0.12***	(0.02)			−0.13***	(0.04)
Tertiary			−0.20**	(0.06)			−0.19*	(0.08)
Wage quintile: (ref = 3rd)								
1st quintile			0.12**	(0.05)			0.12*	(0.05)
2nd quintile			0.04	(0.04)			0.06	(0.05)
4th quintile			−0.10**	(0.03)			−0.10*	(0.04)
5th quintile			−0.04	(0.04)			−0.04	(0.03)
Constant	2.61***	(0.04)	3.23***	(0.14)	2.12***	(0.08)	2.62***	(0.20)
Country FE	No		Yes		No		Yes	
Observations	6607		6607		6607		6607	
R^2	0.08		0.14		0.07		0.13	
Adjusted R^2	0.08		0.14		0.07		0.13	

Note: Dependent variable: fear of automation (scale 1–5). All models: OLS regressions with standard errors clustered at the ISCO 1D and NACE 1D level. Models estimated for the sample covered by the Technology exposure measure; Model (1) and Model (2) are estimated without weights; Model (3) and Model (4) are estimated with Inverse Probability Weights; ~ $p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; GVIF for Model (2) does not indicate multicollinearity (see Table A5, Appendix).

in academic literature, include its dependence on internet access—excluding those without online connectivity—and the unsupervised nature of responses, potentially compromising data reliability. Despite these challenges, CAWI's strength lies in its efficiency in quickly gathering data from a wide respondent base.

The key limitation of this study is its dependence on survey data from a select group of European countries. Future research should expand its scope to include a wider array of countries to enhance the generalizability of the results across the European economy, or to enable grounded cross-national comparisons that consider various stages of economic development. Moreover, there is a pressing need for longitudinal research to observe the progression of attitudes toward automation, especially as technological progress accelerates. This article does not thoroughly explore the causal factors behind the differing levels of automation fear observed across countries. Addressing this deficiency calls for detailed case studies that factor in the unique aspects of labor markets and the impact of public policy measures. Additionally, while the initial sample of respondents is representative in terms of gender, age, and place of residence's size, the sampling procedure did not account for the occupational structures of the studied countries. Hence, the generalizability of the results is limited after restricting the sample to working individuals. When interpreting and applying the results, one should consider the occupational structure described in Table A2 in the Appendix.

6. Discussion

Our study shows that approximately one in six workers fears automation. The literature offers various explanations of this fact, from most radical to quite optimistic. Perhaps fear of automation is like fear of death: so many buffers guard us from experiencing it that we forget to fear the inevitable march onward by the machines [67]. Or maybe people tend to associate automation risk with other people's jobs, not their own, and remain unconcerned even when directly threatened by automation [62]. The argument might also favor Khogali and Mehid [24], who claim that the overall impact of AI on employment is likely to be positive. However, we maintain that in our technologized society, amid the rapid development of Generative Artificial Intelligence, fear of automation will grow, driven by media hype and the narrative of ubiquitous consulting firms, making research on its determinants a necessity.

We make several contributions to the literature on the fear of automation and, more broadly, to research on technology's impact on the labor market. First, we propose an original approach to the conceptualization of fear of automation. As evidenced in the suggested construction of our measure, we emphasize that such fear is a social phenomenon, deeply embedded in the economic context. The way we study and describe technologically stimulated transformations in the labor market, as an academic community, also becomes an element of the social perception of fear. We do not assert that this conceptualization is definitive or exhaustive; instead, we view it as a contribution to ongoing discussions and encourage other researchers to critique and expand upon it.

Second, our analysis of the factors determining the fear of automation shows the importance of occupational task structure and exposure to technology, thereby validating insights by Dengler and Gundert [64], Innocenti and Golin [13] and Mulas-Granados et al. [14]. The perception that technologies are replacing human roles in the workplace exacerbates fear of automation; likewise, even beneficial engagement with technologies at the workplace and the sense that one's industry is undergoing digitalization also heighten this fear.

Support for H1 (relating fear to changes in work tasks) and H3 (relating fear to sectoral exposure to technology) highlight an intriguing paradox: rather than alleviating fears, familiarity with technology at work and within the sector appears to heighten concerns about automation. People in jobs with higher occupational task content sensitive to automation and in sectors more saturated with robots are more afraid of automation. This conclusion needs to be tested further, particularly as it does not align with the results of qualitative studies such as Nazareno and Schiff [62].

Our analysis shows that workers become more aware of the potential of automation when they encounter technology in their workplaces, even if it only complements their tasks. This suggests that the presence of automation, regardless of its function, prompts workers to reflect on its broader implications for job security. As a result, we offer a more nuanced understanding of how different forms of technological change influence workers' perceptions. To the best of our knowledge, our study is unique in examining the relationship between task substitution, task complementarity, and fear of automation.

Third, our research also contributes to theories highlighting the skill-biased and routine-biased character of technological impact on the labor market. The confirmation of H2 (fear of automation is related to job routineness) aligns with the theory that repetitive, routine tasks heighten workers' fear of automation, as these tasks are most susceptible to automation [30]. With regard to skill-biased technological change, we find that more educated individuals fear automation less.

Furthermore, our observations align coherently with existing scholarly literature (e.g., Ref. [13,69]), substantiating that individuals occupying more precarious positions in the labor market indeed exhibit elevated levels of automation fear. Younger, those with lower educational attainment, and those receiving lower compensation experience a heightened sense of fear towards automation. While finding support for H5 (regarding the relationship between fear of automation and labor market position) was expected in terms of age, income and education, the lack of significant gender difference was surprising given analyses stating that automation may disproportionately affect women in the labor market [54]. This suggests the need for further research into gender-related perceptions of automation risk.

Last but not least, our research shows that the belief in having less control over one's own life heightens fear of automation, closely aligning with the findings of Innocenti and Golin [13]. We have accounted for the possibility that this belief may correlate with an individual's socioeconomic status, but it can also be influenced by organizational factors. This is a promising and much-needed research direction, enriching the theoretical conceptualization of fear of automation as shaped by multiple factors.

We believe that our study's insights into the determinants of fear of automation can be instrumental for organizational leaders and policymakers. Given the paradox that increased familiarity with technology seems to heighten, rather than alleviate, automation fears, how should organizations and policymakers address this issue to better support their workforce? It may be argued that, when carefully managed, fear of automation can motivate employees to engage in training and acquire new professional skills. Workers may internalize the need to take action to maintain employability in changing labor markets [68]. However, as some studies suggest [6], workers often prefer redistribution and government support programs to individually addressing these challenges through training or career changes. Such instrumental manipulation of workers' fear of automation may not only be unethical—manifesting as structural violence and deepening workplace inequalities—but could also, in the long term, harm human-centered digital transformation. Fear of automation can shape employee attitudes toward digital transformation, potentially leading some to resist the process or, in extreme cases, engage in acts of sabotage, for example when digitalization destabilizes standard working time or employment relationships [84]. Understanding the factors contributing to fear of automation is crucial to better address the psychological and practical challenges posed by the growing integration of technology in the workplace. Furthermore, this understanding can inform sustainable human resource management practices that balance technological advancements with workers' well-being and adaptability, fostering a more inclusive digital transition [85].

In conclusion, we would like to emphasize the importance of, and the need for, future research on perceived control over one's fate in relation to fear of automation, a factor was only peripherally addressed in our study that requires further analysis. The workplace is a central aspect of contemporary life, and its organizational culture can influence perceptions of reduced control, particularly when intersecting with personal and socioeconomic characteristics. Enhancing employees' agency and involvement in decision-making during the implementation of new technologies, thereby their sense of control, could be a key strategy for mitigating the fear of automation. Furthermore, policy measures should focus on enhancing technology awareness and demonstrating its complementary role to human labor. It is essential to develop targeted reskilling and upskilling programs for younger, less educated, and lower-income workers to align with labor market demands and industry-specific needs. Additionally, encouraging job redesign to integrate technology as a supportive tool can help transform workplace dynamics and reduce anxiety associated with automation. Incorporating participatory design into the deployment of new technologies can also improve workers' sense of control and acceptance. Tailoring these strategies to the unique contexts of Austria, Czechia, Germany, Hungary, Poland, and Slovakia will maximize the effectiveness of interventions.

During the preparation of this work the author(s) used LLM in order to proofread the text. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Renata Włoch: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Katarzyna Śledziewska:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Satia Rożynek:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Funding acquisition, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Excellence Initiative – Research University: The study used data from the Central European Social Survey as part of the funding provided by the Excellence Initiative – Research University (2020–2026).

Appendix

Table A1
Percentage distribution of gender, age categories and place of residence by country

		AT	CZ	DE	HU	PL	SK
Gender	Male	52.7	51.0	52.1	55.8	52.1	53.4
	Female	47.3	49.0	47.9	44.2	47.9	46.6

(*continued on next page*)

Table A1 (*continued*)

		AT	CZ	DE	HU	PL	SK
Age category	18–34	30.0	28.7	24.4	30.1	30.5	32.9
	35–44	25.6	28.1	24.5	28.1	28.5	28.2
	45–54	26.6	25.4	24.8	25.3	23.8	18.9
	55+	17.8	17.8	26.2	16.5	17.1	20.0
Place of residence	Large city	31.5	31.5	37.8	30.3	35.0	22.2
	Suburban area	11.2	9.4	17.0	8.5	6.0	6.6
	Small town	22.1	33.2	30.3	29.8	27.7	32.6
	Rural village	31.7	25.3	14.7	31.0	30.9	38.0
	Isolated house outside a village	3.5	0.6	0.2	0.4	0.5	0.8

Note: Calculated for the sample of working individuals, N = 6634.

Table A2
The occupational and sectoral structures of the study's sample of working individuals

Occupational structure ISCO 08, 1-digit			Sectoral structure NACE Rev. 2, 1-digit		
	Title	%		Title	%
0	Armed forces	1.9	A	Agriculture, Forestry and Fishing	2
1	Legislators, senior officials and managers	3	B	Mining and Quarrying	0.7
2	Professionals	16	C	Manufacturing	12.5
3	Technicians and associate professionals	11.2	D	Electricity, Gas, Steam and Air Conditioning Supply	1.6
4	Clerks	24.1	E	Water Supply; Sewerage, Waste Management and Remediation Activities	1.7
5	Service workers and shop and market sales workers	19.3	F	Construction	6.1
6	Skilled agricultural and fishery workers	1.7	G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	5.9
7	Craft and related trades workers	9.2	H	Transportation and Storage	6.5
8	Plant and machine operators and assemblers	5.5	I	Accommodation and Food Service Activities	3.4
9	Elementary occupations	7.7	J	Information and Communication	4.8
	NA	0.4	K	Financial and Insurance Activities	4.2
			L	Real Estate Activities	0.9
			M	Professional, Scientific and Technical Activities	2.9
			N	Administrative and Support Service Activities	3.6
			O	Public Administration and Defence; Compulsory Social Security	6.8
			P	Education	7.1
			Q	Human Health and Social Work Activities	9
			R	Arts, Entertainment and Recreation	2.6
			S	Other Service Activities	14.2
			T	Activities of Households as Employers; Undifferentiated Goods and Services Producing Activities of Households for Own Use	1.8
			U	Activities of Extraterritorial Organizations and Bodies	1.6

Source: Own calculations, N = 6634.

Table A3
Grouping of PIAAC items into Abstract, Routine and Manual tasks

Task group	PIAAC item	Variable
Abstract	Face complex problems	F_Q05b
	Use more advanced math or statistics such as calculus, complex algebra, trigonometry, or use regression techniques	G_Q03h
	Read articles in professional journals or scholarly publications	G_Q01d
	Planning the activities of others	F_Q03b
	Persuading/influencing people	F_Q04a
Routine	Planning your own activities (inverse)	F_Q03a
	Organising your own time (inverse)	F_Q03c
	Instructing, training or teaching people, individually or in groups (inverse)	F_Q02b
	Making speeches or giving presentations (inverse)	F_Q02c
	Advising people (inverse)	F_Q2e
Manual	Working physically for a long period	F_Q06b
	Using skill or accuracy with hands or fingers	F_Q06c

Source: De La Rica et al. [53].

Table A4
Sectoral matching between our questionnaire, Eurostat (NACE Rev. 2, 1-digit) and IFR data

NACE Rev. 2, 1 digit Our questionnaire; Eurostat		IFR data	
A	Agriculture, forestry and fishing	A-B	Agriculture, forestry, fishing
B	Mining and quarrying	C	Mining and quarrying
C	Manufacturing	D	Manufacturing
D	Electricity, gas, steam and air conditioning supply	E	Electricity, gas, water supply

(*continued on next page*)

Table A4 (*continued*)

NACE Rev. 2, 1 digit Our questionnaire; Eurostat		IFR data	
E	Water supply; sewerage, waste management and remediation activities	E	Electricity, gas, water supply
F	Construction	F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	90	All other non-manufacturing branches
H	Transportation and storage	90	All other non-manufacturing branches
I	Accommodation and food service activities	90	All other non-manufacturing branches
J	Information and communication	90	All other non-manufacturing branches
K	Financial and insurance activities	90	All other non-manufacturing branches
L	Real estate activities	90	All other non-manufacturing branches
M	Professional, scientific and technical activities	P	Education/research/development
N	Administrative and support service activities	90	All other non-manufacturing branches
O	Public administration and defense; compulsory social security	90	All other non-manufacturing branches
P	Education	P	Education/research/development
Q	Human health and social work activities	90	All other non-manufacturing branches
R	Arts, entertainment and recreation	90	All other non-manufacturing branches
S	Other service activities	90	All other non-manufacturing branches
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	90	All other non-manufacturing branches
U	Activities of extraterritorial organizations and bodies	90	All other non-manufacturing branches

Source: Jurkat et al. [86].

Table A5
Generalized Variance Inflation Factor (GVIF) for Model (2), Table 6.

	GVIF	Df	GVIF^(1/(2*Df))
Routine Task Intensity	1.23	1	1.11
Workplace technology experience	1.08	2	1.02
Technology exposure	1.07	1	1.03
Perceived lack of control	1.02	1	1.01
Gender	1.13	1	1.06
Age	42.64	1	6.53
Age squared	42.57	1	6.52
Education	1.48	2	1.10
Wage quintile	1.26	4	1.03
Country	1.59	5	1.05

Note: Multicollinearity among the independent variables in the model is not detected, except between Age and Age Squared, which is expected since Age Squared is derived from Age.

A)

Job insecurity
I fear that in the next 10 years I will lose job in the profession I am currently in.

Task automation
I believe that tasks falling within my current professional responsibilities can be automated using new technologies within the next 10 years.

	1	2	3	4	5
1	780	257	155	50	43
2	380	678	261	102	32
3	300	542	991	269	79
4	192	396	367	312	69
5	64	68	64	63	120

B)

Job insecurity
I fear that in the next 10 years I will lose job in the profession I am currently in.

Technological unemployment
I feel that the development of new technologies and the associated automation of tasks will lead to mass unemployment within the next 10 years.

	1	2	3	4	5
1	352	53	42	12	11
2	585	667	218	82	27
3	438	633	1 071	224	64
4	270	519	421	397	68
5	71	69	86	81	173

C)

Task automation
I believe that tasks falling within my current professional responsibilities can be automated using new technologies within the next 10 years.

Technological unemployment
I feel that the development of new technologies and the associated automation of tasks will lead to mass unemployment within the next 10 years.

	1	2	3	4	5
1	258	81	49	54	28
2	343	576	335	278	47
3	342	369	1 302	348	69
4	249	366	428	550	82
5	93	61	67	106	153

Fig. A1. Cross-tabulation of the responses to survey questions used to construct the fear of automation measure.
Source: Own calculations.

Data availability

The authors do not have permission to share data.

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