Navigating Uncertainty: How Experience Shapes Perception and Politics in the AI Era

Valentina González-Rostani* Tobias Tober†

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Abstract

How do individuals perceive technological risk, particularly job insecurity, in the era of AI-driven change? This paper explores how people navigate the uncertainty created by the pace of technology and experts' unclear predictions about its impact on jobs. We focus on three perceptions: techno-optimists, techno-pessimists, and those exposed to rapid technological change, examining their demographic characteristics and implications for political coalition-building. Using data from three original surveys, including open-ended responses, we show that personal and vicarious experiences shape these perceptions, with exposed workers occupying a middle ground between optimism and pessimism. Contrary to the view that high-skilled workers are less vulnerable, we find that perceived employment risks rise with the use of complex technologies like programming languages. Exposed workers and pessimists share political traits, such as support for illiberal policies, while optimists lean toward liberal policies. These results deepen our understanding of how technological risk perceptions influence politics.

Key words: automation, subjective risks, policy preferences, open-ended responses.

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*Princeton University, gonzalezrostani@princeton.edu.
†University of Konstanz, tobias.tober@uni-konstanz.de.

1 Introduction

The rapid pace of technological change, particularly advancements in automation and artificial intelligence (AI), is transforming labor markets across the globe. Economist and former US Treasury Secretary Larry Summers described this shift during an interview on Bloomberg Television on April 7, 2023, as follows:

> "I think it's coming for the cognitive class. [...] And I have to say that a lot of people who have been quickest to say that structural change is just something you have to live with and accept as part of modernity when it was happening to other people, people who maybe wore uniforms to work, are now going be seeing it happening to them, and it will be interesting to see how they respond."

This quote highlights a key issue: the accelerating speed of technological innovation means that workers face substantial uncertainty about how rapid technological change will affect their job security in the future. This uncertainty is further reinforced by the fact that even experts increasingly acknowledge that predictions about technology's future impact on labor markets are highly speculative due to the fast pace of change (Autor 2022, 2024). These predictions vary widely and offer limited guidance for workers, as demonstrated by the contrasting estimates presented by Frey and Osborne (2017) and Arntz, Gregory, and Zierahn (2017). Given this context of uncertainty, how do individuals form beliefs about the future impact of technology on their employment? How do these beliefs shape their perceptions of technological change and influence their political attitudes?

Building on a growing body of political science research that examines the perception of technological risk and political behavior (e.g., Borwein et al. 2025; Busemeyer and Tober 2023; Gallego et al. 2022; Magistro et al. 2025), this article systematically studies how individuals form these perceptions of risk. Specifically, we explore three types of technological perceptions — exposed, pessimists, and optimists — and analyze who holds these views and the implications of these risk formations and perceptions for political coalition building.

We contribute to the literature on subjective concerns about technological risks and policy preferences in two ways. First, we theorize that both personal and vicarious experiences with rapid technological change play a crucial role in shaping perceptions of job insecurity. Building on recent advances in behavioral economics (Bordalo et al. 2023; Bordalo et al. 2024), we draw on models of selective memory, which suggest that individuals use recalled experiences to simulate future scenarios. We argue that, in the face of uncertainty regarding expert predictions and information about technological change, individuals rely on their own experiences. These experiences help them form beliefs about future risks associated with technology, amplifying employment fears by making automation appear more immediate and disruptive. Consequently, those directly exposed to advanced technologies are more likely to perceive heightened job insecurity, as they witness their rapid advancement and impact first-hand.

Our second contribution is to distinguish and measure two additional categories beyond the role of experience: techno-optimists and techno-pessimists. While optimists view technology as a driver of progress and pessimists focus on its risks, exposed workers recognize both the benefits and threats of technology — acknowledging the potential for job loss while also appreciating technological advancements. We measure these groups using a set of both close-ended and open-ended questions. Studying these categories (not just the exposed ones) is essential to understanding the potential for building political coalitions. In particular, the divisions between optimists, pessimists, and exposed workers may shape support for certain policies. Exposed workers, for example, may support policies similar to those favored by pessimists, even though they acknowledge technology's benefits. Yet, optimists, usually more ideologically liberal may be more prone to some liberal policies that could potentially serve as source for compensation for the exposed group.

We empirically test these expectations using three original surveys. First, we analyze a 25-country survey (2020) and a six-country survey (2022) to examine the determinants of technological job insecurity, applying item response theory (IRT) modeling to capture its multidimensional nature while accounting for individual-level variables like workplace technology use and macro-level factors. Second, we conduct an in-depth US analysis (2023) to analyze optimists, pessimists, and exposed individuals. This includes assessing their perceptions of technological change using open-ended responses and automated topic classification, as well as analyzing their group characteristics and political attitudes.

Our findings provide empirical support for our theoretical expectations. The results from our first study using cross-sectional data show that concrete experiences with rapid technological change in the workplace are a significant predictor of technology-related job insecurity. Contrary to the assumption that high-skilled workers are insulated from these risks, our analyses reveal that engagement with complex technologies — such as programming languages and robotics — strongly correlates with job insecurity. Our second, US-centered study further corroborates that individuals exposed to rapid technological change recognize both its risks and benefits. We also find that the exposed group differs from optimists and pessimists in terms of higher education levels and lower routine-task intensity. Politically, however, the exposed group shares many characteristics with techno-pessimists, including a higher likelihood of supporting illiberal and ethnocentric policies typically endorsed by right-wing populist leaders. In contrast, optimists support trade liberalization, offshoring, and immigration while rejecting populist and ethnocentric views. Exposed workers and pessimists have clear potential for coalition-building, and there is also some room for agreement between optimists and pessimists, particularly on policies like taxing the rich, which pessimists support strongly and optimists weakly.

Our study has three key empirical strengths that enhance our understanding of technology perceptions. First, we provide a large-N cross-sectional overview of tech perceptions with original data collection, improving on prior research that has relied mainly on one or two cases (e.g., Bicchi, Kuo, and Gallego 2024; Gallego et al. 2022). Second, we employ Item Response Theory (IRT) modeling to infer tech perceptions and identify their underlying causes, addressing the multidimensionality of technological change, while previous studies often rely on a single survey item to measure subjective job insecurity (e.g., Ahrens 2024; Cusack, Iversen, and Rehm 2006; Margalit 2013; Marx 2014). Third, we use multiple indicators to measure optimism and pessimism, incorporating open-ended responses that offer a richer, less constrained understanding of individuals' perceptions of technological change. This approach demonstrates that open-ended responses, though underutilized in our field, can effectively explore perceptions of contentious issues (Margalit and Raviv 2024; Roberts et al. 2014; Ferrario and Stantcheva 2022; Zollinger 2024). Methodologically, our work contributes to discussions on the use of Large Language Models (LLMs) (e.g., Le Mens and Gallego 2025; González-Rostani, Incio, and Lezama 2024) by validating OpenAI for summarizing topics and classifying short responses.

This paper proceeds as follows. Section 2 situates our approach within the existing literature. Section 3 develops our theoretical argument, emphasizing the role of experience in shaping technological job insecurity, perceptions of technological change, and political attitudes. Section 4 details our three original data sources and measurement choices, while Section 5 outlines our statistical modeling strategy. Section 6 presents the empirical results of our analyses. Finally, Section 7 summarizes our contributions and implications of these findings.

2 Motivation

Summers' introductory quote highlights two key shifts in how scholars perceive the effects of rapid technological change on the labor market. First, while automation once primarily affected low- and middle-skilled workers, high-skilled occupations — such as doctors, software engineers, and financial traders — are now increasingly vulnerable (e.g., Acemoglu et al. 2022; Eloundou et al. 2023; Autor 2024). Second, technological innovation, once seen as "lifting all boats" (Acemoglu and Johnson 2023, 14), is now recognized to impose significant economic burdens on those directly affected by rapid technological change (e.g., Bessen et al. 2023; Moll, Rachel, and Restrepo 2022). This shift has been described as moving "from unbridled enthusiasm to qualified optimism to vast uncertainty" (Autor 2022).

How do citizens politically respond to these labor market transformations? Political science research has begun to address this important question. One line of work focuses on electoral behavior (for an overview, see Gallego and Kurer 2022), with most studies suggesting that those negatively affected by technological change tend to support populist right-wing parties (e.g., Anelli, Colantone, and Stanig 2021; Kurer 2020; Milner 2021; Gonzalez-Rostani 2024a) and experience political alienation (e.g., Gonzalez-Rostani 2024b). A related strand examines how technological change shapes policy preferences, showing that concerns over labor market disruptions increase demand for social policy compensation (Busemeyer et al. 2023; Busemeyer and Tober 2023; Kurer and Häusermann 2022), redistribution (Thewissen and Rueda 2019), and protectionism aimed at limiting technological change (Bicchi, Kuo, and Gallego 2024; Gallego et al. 2022) or restricting globalization (Wu 2023; Chaudoin and Mangini 2025; Gonzalez-Rostani 2024c).

Despite their insights, these studies face a common challenge: empirically capturing an individual's labor market vulnerability to technological change. Much of the political science literature, following traditional economic approaches, relies on 'objective' risk measures. These include robot adoption as a proxy for industrial automation, task-based indicators assessing routine-task intensity (RTI), and measures of cognitive task demands. While these approaches are justified, they inherently depend on predefined assumptions about how technological change unfolds — contrasting with the substantial uncertainty mentioned earlier. Moreover, from a political perspective, subjective perceptions of risk may be just as crucial as objective measures, as political attitudes are likely to shift only when individuals feel at risk, rather than merely being statistically vulnerable (cf. Ahrens 2024; Cusack, Iversen, and Rehm 2006).

A growing body of research has used subjective perceptions of technological risk — especially fears of technology-driven unemployment — to examine links with voting behavior and policy preferences (Borwein et al. 2025; Busemeyer et al. 2023; Busemeyer and Tober 2023; Busemeyer, Stutzmann, and Tober 2024; Gallego et al. 2022; Kurer 2020; Kurer and Häusermann 2022). However, this approach faces identification challenges, often relying on single-question measures that overlook the multidimensional nature of tech perceptions, making it difficult to isolate their impact on political attitudes and behavior. Studies also show that objective risk measures and subjective perceptions often correlate weakly, with workers in low-risk, non-routine roles — such as programming —reporting high job insecurity (Gallego et al. 2022; Kurer and Häusermann 2022). If subjective risk perceptions weakly reflect experiences with technological change, their link to political outcomes remains unclear. This article addresses this gap by examining whether they stem from personal or vicarious experiences.

We also examine the complex relationship between individuals and technological change by analyzing optimists, pessimists, and those exposed to rapid transformation. This helps identify potential political coalitions and policy divides posed by technological change. The literature mostly focuses on those harmed (Anelli, Colantone, and Stanig 2021; Kurer 2020; Milner 2021), with few exceptions on beneficiaries (e.g., Gallego, Kurer, and Schöll 2022). While insightful, these studies often oversimplify the complex relationship between individuals and technology — some are optimistic, others pessimistic despite no exposure, and those exposed may hold mixed views.

In summary, while much research focuses on objective technological threats and policy preferences, a gap remains in understanding subjective perceptions — optimism, pessimism, and exposure — how they form, and who holds them. This article addresses this gap.

3 Experience, Perceptions and Political Attitudes

This section outlines our theoretical expectations. We first examine how experiences with rapid technological change shape job insecurity. We then explore how these experiences influence perceptions of technological progress and policy preferences. We distinguish three perspectives — optimistic, pessimistic, and exposed — along with their expected characteristics and differences.

3.1 The Role of Experience in Shaping Technological Job Insecurity

We emphasize the pivotal role of personal and vicarious experiences with rapid technological change in shaping perceived vulnerabilities. These experiences amplify subjective risk by making potential labor market disruptions more tangible and salient, often evoking a sense of being overwhelmed by the speed of technological innovation. We base this argument on recent advances in behavioral economics, which suggest that individuals form beliefs about novel future risks — such as AI as a potential employment risk — by selectively recalling statistical information and experiences (Bordalo et al. 2024; Bordalo et al. 2023). This literature draws on psychological research showing that memory plays a key role in the mental simulation of future events (e.g., Dougherty, Gettys, and Ogden 1999).

Conceptualized in a stylized way, individuals assess the probability of a future event — such as job loss due to technological change — based on a combination of objective information from experts or the news (e.g., expert forecasts of AI-related job losses) and experiences from themselves or their social circle. When these experiences resemble the target event, they become more retrievable, influencing future expectations (Bordalo et al. 2023; Bordalo et al. 2024). Thus, workers with direct or indirect exposure to technological change are likely to rely on these experiences when estimating job loss risk.

This effect is reinforced by the fact that reliable statistical data on automation's employment impact is scarce, with expert predictions varying widely (e.g., Frey and Osborne 2017; Arntz, Gregory, and Zierahn 2017), and AI introducing unprecedented uncertainty (Autor 2022). Moreover, recent research suggests that statistical information has, on average, a much smaller impact on beliefs than qualitative stories (Graeber, Roth, and Zimmermann 2024). Consequently, personal experiences, narratives from peers, and media likely exert an outsized influence on perceptions of technological job insecurity.

In particular, we expect significant differences in how workers perceive technological change based on their exposure to basic versus complex technologies. Those using only basic tools like laptops may feel less job insecurity, as limited exposure to automation makes disruptions seem distant and gradual. In contrast, workers engaging with complex technologies (e.g., AI tools) — despite lower objective automation risk (Arntz, Gregory, and Zierahn 2017; Gallego et al. 2022) — likely perceive higher job insecurity. Their direct interaction with automation highlights rapid progress, reinforcing concerns about job displacement. Additionally, they are more likely to recall concrete examples from peers, industry trends, or media, further amplifying their sense of vulnerability.

The latest wave of technological change, driven by AI, machine learning, and advanced algorithms, provides a compelling example of how exposure to advanced technology shapes perceptions of job insecurity. While *ChatGPT* shocked the public in 2022 by performing non-routine cognitive tasks (Eloundou et al. 2023), AI had already been widely adopted in business sectors. A 2018 Forrester Research survey found that 37% of software firms worldwide used AI tools (Chandler 2020), and by 2019, 30% of US firms using robotics had integrated AI (Acemoglu et al. 2025). This early adoption suggests that workers exposed to advanced technology are more attuned to automation's rapid pace, heightening perceptions of job insecurity.

In sum, we argue that personal and vicarious experiences with rapid technological change in the workplace amplify technological job insecurity. Thus, contrary to the assumption that working with sophisticated tools ensures job security, direct exposure to these technologies increases perceived risk by making their disruptive potential and the speed of technological change more salient.

Hypothesis 1 *Individuals with concrete experiences of rapid technological change in the workplace will be more likely to perceive heightened technological job insecurity.*

3.2 Three Perceptions of Rapid Technological Change

We have claimed concrete experiences with technological change shape job security perceptions, especially among workers exposed to advanced technologies. But does this mean that those with such experiences generally perceive technological innovation negatively? We argue that exposed individuals represent a third, often overlooked perspective — one that blends elements of both pure techno-optimism and pure techno-pessimism, as illustrated in Figure 1. This does not mean that all exposed workers fall into this category — some may be purely optimistic or purely pessimistic — but rather that a significant portion of individuals who have experienced rapid technological change occupy a middle ground between these extremes.

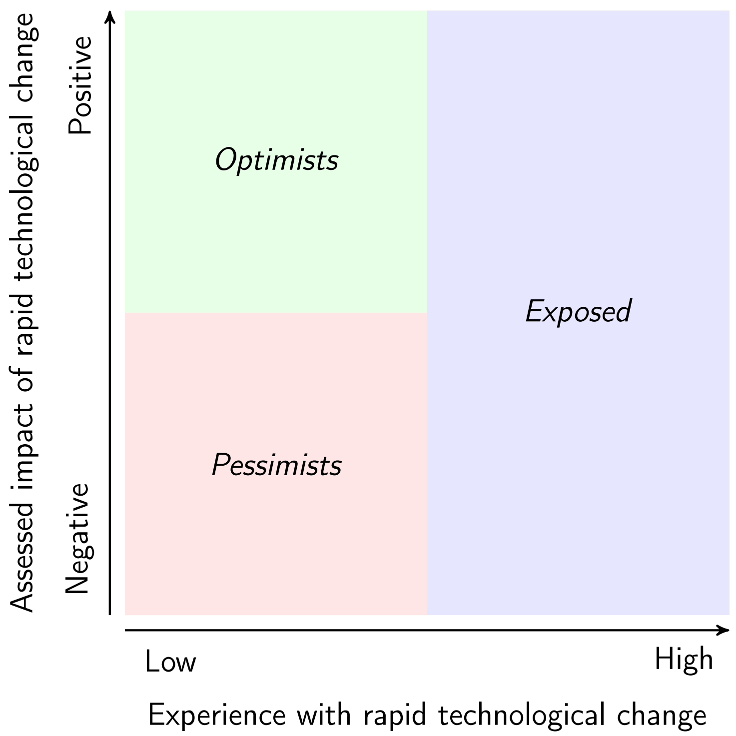

Figure 1: Assessed Impact of and Experience with Rapid Technological Change.

While optimists tend to see technological change as a driver of progress, emphasizing its potential to boost productivity, flexibility, and safety, pessimists tend to view it with apprehension, focusing on risks to employment, autonomy, and societal cohesion (cf. Brynjolfsson and McAfee 2014). Research suggests key differences between optimists and pessimists, whether in relation to technological change specifically or structural transformations more generally. Optimists are more likely to be male, politically liberal, and higher-income earners, whereas pessimists are more likely to be female, politically conservative, and lower-income earners (Jost et al. 2003; Lauterbach et al. 2023; Novozhilova, Mays, and Katz 2024; Steenvoorden and Harteveld 2018).

We expect that exposed individuals with concrete experiences of rapid technological change fall somewhere between pure optimism and pessimism. As argued above, exposed workers — like pessimists — may fear technology-induced job loss. At the same time, however, they — like optimists — are likely to recognize the benefits of rapid technological innovation, as they often work in highly technologized sectors, have firsthand experience with complex technologies, and are generally tech-savvy. Thus, we predict that exposed individuals will likely express mixed feelings about rapid technological innovation, acknowledging both its risks and benefits.

As for group characteristics, we anticipate that exposed individuals are more likely to be male, reflecting historical employment patterns in which women have been underrepresented in science, technology, engineering, and mathematics (STEM) fields (Brussevich et al. 2018). Moreover, we expect exposed workers to have higher education levels due to the training required for complex technologies and to work in roles with lower routine-task intensity, given the association of advanced technologies with non-routine tasks. While less certain about income and ideology, we expect exposed workers to have higher earnings due to specialized skills and to be more politically moderate than techno-pessimists. To summarize, our hypotheses are as follows:

Hypothesis 2a *Individuals who are male, have higher incomes, and hold liberal ideological orientations are more likely to be technology optimists.*

Hypothesis 2b *Individuals who are female, have lower incomes, and hold conservative ideological orientations are more likely to be technology pessimists.*

Hypothesis 2c *Individuals who are male, have higher levels of education, and work in jobs with low routine-task intensity are more likely to be exposed to rapid technological change.*

3.3 Political Attitudes

We conclude by outlining the policy preferences linked to three perspectives on rapid technological change, extending beyond the well-documented notion of "technological protectionism," (e.g., Bicchi, Kuo, and Gallego 2024; Gallego et al. 2022). Recent research suggests that politicians may target exposed workers without explicitly discussing automation risks. For example, Gonzalez-Rostani (2024a) shows that Donald Trump employed pro-worker distributive politics and advocated for illiberal policies (e.g., tariffs, border controls) in regions with high concentrations of vulnerable workers. On the voter side, Borwein et al. (2024) find that while overall support for protecting workers from technological disruption is lower than for other types of shocks, policy appeals centered on workers' protections resonate with those who feel threatened by technological change. In this section, we analyze how these perspectives relate to the rise of right-wing populism and economic nationalism by discussing the policy preferences of optimists, pessimists, and exposed groups.

We expect technology optimists to associate rapid technological change with economic growth and innovation, making them more inclined to support trade liberalization and offshoring due to the economic advantages of global markets (Colantone and Stanig 2018; Kaltenthaler, Gelleny, and Ceccoli 2004). Their optimism and social trust — key drivers of support for freer trade — may further reinforce this pro-trade stance (Kaltenthaler and Miller 2013). At the same time, they will be less likely to endorse anti-immigrant or ethnocentric views. As a result, optimists should be less inclined to align with populist platforms, which emphasize anti-globalization and anti-immigration rhetoric (Norris and Inglehart 2019).

In contrast, pessimistic individuals are likely to view technological change as a threat closely tied to economic insecurity, which has been well-documented as a driver of support for populist leaders, such as Donald Trump, whose platforms emphasize protectionism, anti-immigration policies, and cultural nationalism (Gidron and Hall 2017). Moreover, concerns about adapting to new technologies, as highlighted in technostress research, could lead to frustrations with self-efficacy (D'Arcy et al. 2014; Tarafdar, Pullins, and Ragu-Nathan 2015), which may increase their susceptibility to populist rhetoric (Gonzalez-Rostani 2024b). Pessimistic individuals would also be more likely to favor immigration restrictions, perceiving immigrant inflows as intensifying labor market competition (Mutz 2018; Scheve and Slaughter 2001). They would similarly be less likely to support global trade and offshoring, associating these with job losses and economic dislocation, and more inclined to favor redistributive policies over tax cuts, reflecting their precarious economic position (Thewissen and Rueda 2019; Bicchi, Kuo, and Gallego 2024).

Individuals with direct or vicarious experience of technological change may recognize both its benefits and risks, positioning their policy preferences between optimists and pessimists. Heightened economic anxiety — particularly fears of job loss — suggests their attitudes will more closely align with pessimists. Thus, we expect exposed individuals to be receptive to populist appeals for restrictive policies, such as tariffs aimed at reversing globalization, and to adopt anti-immigration and ethnocentric views (Wu 2022; Anelli, Colantone, and Stanig 2021; Gonzalez-Rostani 2024c; Inglehart and Norris 2016).

Based on these arguments and prior empirical findings, we propose the following hypotheses.

Hypothesis 3a *Technology optimists are less likely to support populist politicians and hold ethnocentric views but more likely to favor liberal policies, including support for trade, offshoring, and immigration.*

Hypothesis 3b *Technology pessimists are more likely to support populist politicians and hold ethnocentric views, while also favoring protectionist policies — opposing trade, offshoring, and immigration while supporting higher taxes.*

Hypothesis 3c *Individuals exposed to rapid technological change are more likely than technology optimists — but less so than pessimists — to support populist politicians, hold ethnocentric views, and favor protectionist policies, including opposition to trade, offshoring, and immigration while supporting higher taxes.*

4 Data and Measurement

To test our framework, we use three data sources. First, for cross-sectional analysis, we draw on the *DigiWelfare* survey, implemented through Kantar Public in 2022 across Germany, Japan, Poland, Spain, Sweden, and the US. The quota-sampled dataset (age, gender, and education) includes 19,800 respondents (3,300 per country).

Second, we complement this analysis with the OECD's *Risks that Matter* (RTM) survey, collected in 2020, which examines public perceptions of economic and social risks. The dataset includes 25,814 respondents from 25 countries.[1] In collaboration with the OECD, we integrated self-designed items on subjective risk perceptions, identical to those in the *DigiWelfare* survey. We include the RTM analysis in the appendix as a complementary section, as it predates widespread AI awareness and was conducted during the pandemic, when lockdowns may have biased risk perceptions due to increased technology use and heightened job insecurity fears.

Finally, for a focused analysis of optimists, pessimists, and those directly exposed to technological change, we collected a US survey in 2023 via CloudResearch with 3,300 respondents. This dataset provides a more granular perspective on individual attitudes toward automation and job displacement.

1. Countries include Austria, Belgium, Canada, Chile, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Lithuania, Mexico, the Netherlands, Norway, Poland, Portugal, Slovenia, South Korea, Spain, Switzerland, Turkey, and the US.

4.1 Subjective Perception of Technology

We analyze three key subjective perceptions of rapid technological change, using them both as response variables and explanatory factors: technological job insecurity, technology optimism, and technology pessimism.

Technological job insecurity. Political science research commonly measures subjective job insecurity using a single survey item (e.g., Ahrens 2024; Cusack, Iversen, and Rehm 2006; Margalit 2013; Marx 2014), though some exceptions exist (e.g., Anderson and Pontusson 2007). However, job insecurity is inherently multidimensional — "perceptual, future-oriented, and uncertain" (Shoss 2017, 1917) — and is best captured through multiple indicators that reflect individuals' perceptions, emotions, and beliefs about employment stability.

Thus, we assess technology-related job insecurity through three specific items in our cross-sectional analysis. Respondents evaluate, on a five-point Likert scale, the likelihood that their job within five years will be replaced by robots, software, algorithms, or artificial intelligence; be displaced by someone offering a similar service via an internet platform; or be lost due to insufficient technological skills. These items allow us to capture the extent of perceived technological integration in the workplace with greater specificity. For descriptive statistics on three items, refer to Figures A5-A7 and Tables A1-A2 in the Appendix.

Pessimism and optimism. In our US-based analysis, we classify individuals' attitudes toward automation as pessimistic or optimistic using both closed- and open-ended survey responses. Closed-ended questions assess agreement with specific statements on a five-point Likert scale. Respondents are categorized as pessimistic or optimistic if they score 4 or higher on at least one relevant statement or if their open-ended response aligns accordingly.

Pessimism is measured through three statements: (1) "With more and more robots everywhere, my chances of finding another job are small," reflecting employment concerns; (2) "Increased automation and the use of robots will mean less and less work for people," capturing societal anxieties; and (3) "I am personally worried that what I do now in my job will be automated," addressing direct fears of job displacement.[2]

Optimism is assessed using two statements: "Robots can do many jobs better than people" and "Robots will help American companies keep pace with foreign competitors," emphasizing productivity and competitiveness. We present further descriptive information on optimists and pessimists in Figures A9-A10 in the Appendix.

To broaden our analysis, we incorporate open-ended responses, allowing respondents to describe their workplace experiences and views on automation. In our study, two independent coders classified responses as pessimistic, optimistic, or mixed. We also employ the OpenAI API for classification in two steps. First, OpenAI identifies recurring themes across responses. Then, using these themes, it categorizes each response accordingly. Further details on text analysis methods and OpenAI's validation — showing 89% accuracy against human coders — are in Appendix A.5.2.[3]

4.2 Policy Preferences

In our US analysis, we examine the link between technology perceptions and policy preferences, coding responses as binary variables to facilitate interpretation. Support for Trump's 2024 candidacy is coded as 1 for respondents answering "probably" or "definitely" in favor. Economic nationalism is measured by agreement (values above 4 on a five-point scale) with "American people should always buy American-made products." Pro-offshoring sentiment is coded as agreement (above 4) with reducing taxes on companies that move jobs overseas. Trade favorability is based on an index assessing trade's benefits — economy, workers, companies, consumers, and the respondent's family — with above-median scores coded as favorable. Opposition to taxing the top 1% is captured by

2. Additional measures, such as perceived job replaceability, are included. See Appendix A.4 for details.

3. See Appendix A.5 for coding details, including keyword lists and sample quotations.

responses favoring lower taxes (above 4). Finally, anti-immigration sentiment is coded as 1 for those favoring significant cuts to legal immigration (above 4). Appendix A.4.1 provides details on wordings and coding.

4.3 Experience With Rapid Technological Change

We argue above that personal or vicarious experiences with rapid technological change are an important factor shaping perceptions of technological change and policy preferences. In the subsequent analyses, we rely on two different measurement approaches to capturing these experiences.

Technology use at workplace. In our cross-sectional analyses, we capture experience with rapid technological change through two survey items measuring the frequency of digital information and communication technology (ICT) use, such as computers, laptops, or tablets, and interaction with complex technologies, such as robots or specialist software. Specialist software refers to programs requiring advanced skills, such as programming languages, rather than widely used applications like Microsoft Office. The *DigiWelfare* survey also includes items assessing specific technological competencies, contributing to the tasks-at-low-risk-of-automation (TLRA) index from Gallego et al. (2022). See Table A3 in the Appendix for descriptive statistics on work-related technology use.

Speed of change and job loss. We argue in Section 3.1 that workers using complex technologies are more likely to perceive job insecurity due to the rapid pace of technological change and experiences — direct or vicarious — of job displacement. To assess these factors in our US analysis, we incorporate two key measures: technological integration speed and job loss due to technology.

The first measure captures perceived workplace adoption speed of new technologies, assessed on a five-point scale: "How fast have new technologies been incorporated into your work?" The second measure identifies personal or secondhand experiences of job loss due to automation: "Did you or anyone close to you lose their job because of technology?" (No = 0, Maybe = 1, Yes = 2). For analysis, we recode this as a binary variable, with Yes coded as 1 (indicating direct or vicarious job loss) and zero otherwise.

4.4 Contextual Variables

We control for demographic factors, including age, gender, education, income, and race (the latter only for the US sample). Objective vulnerability to automation is measured using RTI scores (Goos, Manning, and Salomons 2014), based on ISCO-08 classifications. Political orientation is assessed via an 11-point left-right scale (*DigiWelfare* survey) or past party support (US sample). Country-level controls in the *RTM* analysis include OECD unemployment insurance generosity, technological development (Cisco Digital Readiness Index), and national unemployment rates.

5 Statistical Modeling

Testing our theoretical expectations involves three key modeling choices: (1) examining technological job insecurity as a function of workplace technology use and other factors, (2) identifying the determinants of technology perception categories, and (3) assessing how group membership influences policy preferences. Across all analyses, we prioritize relative theoretical plausibility over causal identification (see Spirling and Steward 2024).

Modeling technological job insecurity. Technological job insecurity is a latent construct that cannot be directly observed, posing a challenge in cross-sectional analysis. Even when defined as fears related to automation, the internet, and insufficient skills, its dimensions and aggregation remain unclear. To address this, we use Bayesian IRT modeling to estimate technological job insecurity from three survey items, inferring latent values that likely generated the observed data. This approach also assesses whether workplace technology use influences unemployment fears while accounting for other explanatory factors.

We use a one-parameter ordered logistic (1POL) specification for both the DigiWelfare and RTM datasets.[4] The DigiWelfare specification is:

$$\begin{aligned}
\text{JobInsecurity}_{ri} &\sim \text{Categorical}(\mathbf{p}_{ri,\kappa}) \\
\text{logit}(\mathbf{p}_{ri,\kappa}) &= \phi_{ri} + \theta_r + \xi_i \\
\phi_{ri} &= \beta_1 \, \textbf{TechnologyUse}_{ri} + \beta_2 \mathbf{x}_{ri} + \beta_3 \, \text{Country}_{c-1} + \kappa_k + \epsilon_{ri} \\
\kappa_k &\sim t(3, 0, 2.5) \\
\theta_r, \xi_i &\sim t(4, 0, 1) \\
\beta_{1,2,3} &\sim \text{Uniform}(0, 1),
\end{aligned} \tag{1}$$

where $\text{JobInsecurity}_{ri}$ denotes the categorical response of the respondent r to item i on the three items of the survey about job insecurity related to technology. The cumulative logit-link function constrains predictions to probabilities between 0 and 1. The vector $\mathbf{p}_{ri,\kappa} = \{p_{ri,1}, p_{ri,2}, p_{ri,3}\}$ contains the relative probabilities of each response value k (ranging from 1 = *very unlikely* to 3 = *likely*) below the maximum response value of *very likely*, which has a cumulative probability of 1. θ_r represents the person parameter, and ξ_i the item parameter. The linear model, ϕ_{ri}, incorporates workplace technology use ($\text{TechnologyUse}_{ri}$), individual-level controls ($\mathbf{x}_{ri}$), country fixed effects (Country_{c-1}), response-value-specific intercepts (κ_k), and an error term (ϵ_{ri}). The RTM survey's broader coverage allows for cross-country analysis, extending the specification to include country-level random effects and controls (see Appendix A.2.3).

Following Gelman (2008), continuous variables are centered and scaled by twice their standard deviation for better convergence and coefficient comparability, weakly regulariz-

4. Comparing the fits of an empty 1POL model and an empty 2POL model, which includes a parameter that discriminates between different job-insecurity items, using leave-one-out cross-validation (Vehtari, Gelman, and Gabry 2017) indicates that the 2POL model has greater expected predictive accuracy as measured by the expected log pointwise predictive density (elpd) in the context of the DigiWelfare data. However, the difference between the models is relatively small ($\Delta_{\text{1POL,2POL}} epld = 30.1$) compared to its standard error ($SE_{\text{1POL,2POL}} = 11.4$). Moreover, the correlation between the person parameters of both models is perfect ($\rho_{\theta_{r,\text{1POL}}, \theta_{r,\text{2POL}}} = 1$), suggesting no advantage in using the more complex 2POL model with these data. We thus retain the 1POL model (cf. Bürkner 2021, 27–28).

ing student-t priors are applied to intercepts and variance parameters, and flat priors are used for regression coefficients. Estimation is conducted using the `brms` package (Bürkner 2017) with MCMC sampling (12,000 iterations, 6,000 burn-in) to ensure convergence and reliable posterior inference.

Modeling technology perceptions and their impact on policy preferences. Our US-centered analysis models three technology perceptions — optimistic, pessimistic, and exposed — both as response variables and predictors of policy preferences. Their determinants are analyzed in relation to demographic, socioeconomic, and political factors, as specified in the following equation:

$$\begin{aligned}
\text{TechPerception}_{r,tp} &\sim \text{Bernoulli}(Pr(\text{Membership}_{r,tp})) \\
\text{logit}(\text{Membership}_{r,tp}) &= \gamma_1 \, \text{Gender}_{r,tp} + \gamma_2 \, \text{Race}_{r,tp} + \gamma_3 \, \text{Income}_{r,tp} + \gamma_4 \, \text{Education}_{r,tp} \\
&\quad + \gamma_5 \, \text{RTI}_{r,tp} + \gamma_6 \, \text{Age}_{r,tp} + \gamma_7 \, \text{Republican}_{r,tp} + \alpha_{r,tp} + \epsilon_{r,tp} \qquad (2) \\
\alpha_{r,tp} &\sim t(3, 0, 2.5) \\
\gamma_{1,2,3,4,5,6,7} &\sim \mathcal{N}(0, 1),
\end{aligned}$$

where the probability of respondent r belonging to one of our three groups of technology perceptions, $\text{TechPerception}_{r,tp=\{Optimists,Pessimists,Exposed\}}$, is modeled as a logit function of that person's gender, race, income, education, RTI score, age, and political orientation.

To examine policy preferences, we estimate the following model:

$$\begin{aligned}
\text{Policy}_{r,p} &\sim \text{Bernoulli}(Pr(\text{Support}_{r,p})) \\
\text{logit}(\text{Support}_{r,p}) &= \delta_1 \, \text{Optimists}_{r,p} + \delta_2 \, \text{Pessimists}_{r,p} + \delta_3 \, \text{Exposed}_{r,p} \\
&\quad + \mu \, \mathbf{c}_{r,p} + \alpha_{r,p} + \epsilon_{r,p} \qquad (3) \\
\alpha_{r,p} &\sim t(3, 0, 2.5) \\
\delta_{1,2,3}, \mu &\sim \mathcal{N}(0, 1).
\end{aligned}$$

Here, policy support depends on technology perceptions and $\mathbf{c}_{r,p}$, a vector of control variables identical to Equation 2. Both models use normal priors for explanatory variables and student-t priors for intercepts. We estimate them using 8,000 MCMC iterations, with 4,000 burn-in.

6 Results

To recapitulate, our measures of technological exposure, combined with proxies for subjective risks, allow us to assess the association between high technology use and technological job insecurity (Hypothesis 1). The cross-sectional design facilitates comparisons of job vulnerabilities across different institutional and technological contexts. Then, our US survey, which includes open-ended responses, provides deeper insights into individual perceptions of technology. By incorporating subjective perceptions (optimism, pessimism, and exposure) alongside other indicators, we refine group distinctions (Hypotheses 2a-c) and analyze the link between technological perceptions and policy preferences (Hypotheses 3a-c).

6.1 Technological Experience and Job Insecurity

What drives technological job insecurity? We investigate this question using data from the 2022 DigiWelfare survey. Figure 2 presents our findings, examining three measures of workplace technology use and risk: (1) basic and complex technology use, (2) specific complex technologies, and (3) a model incorporating RTI scores as an objective measure of automation vulnerability.

The base model shows an inverse U-shaped relationship between basic technology use and perceived technological job insecurity. Compared to non-users, concerns peak among those using basic technologies monthly before declining with frequent use. This non-linearity suggests regular users feel more proficient and less vulnerable. These findings align with prior research showing frequent ICT users share policy preferences with those benefiting from technological change (Busemeyer et al. 2023; Busemeyer and Tober

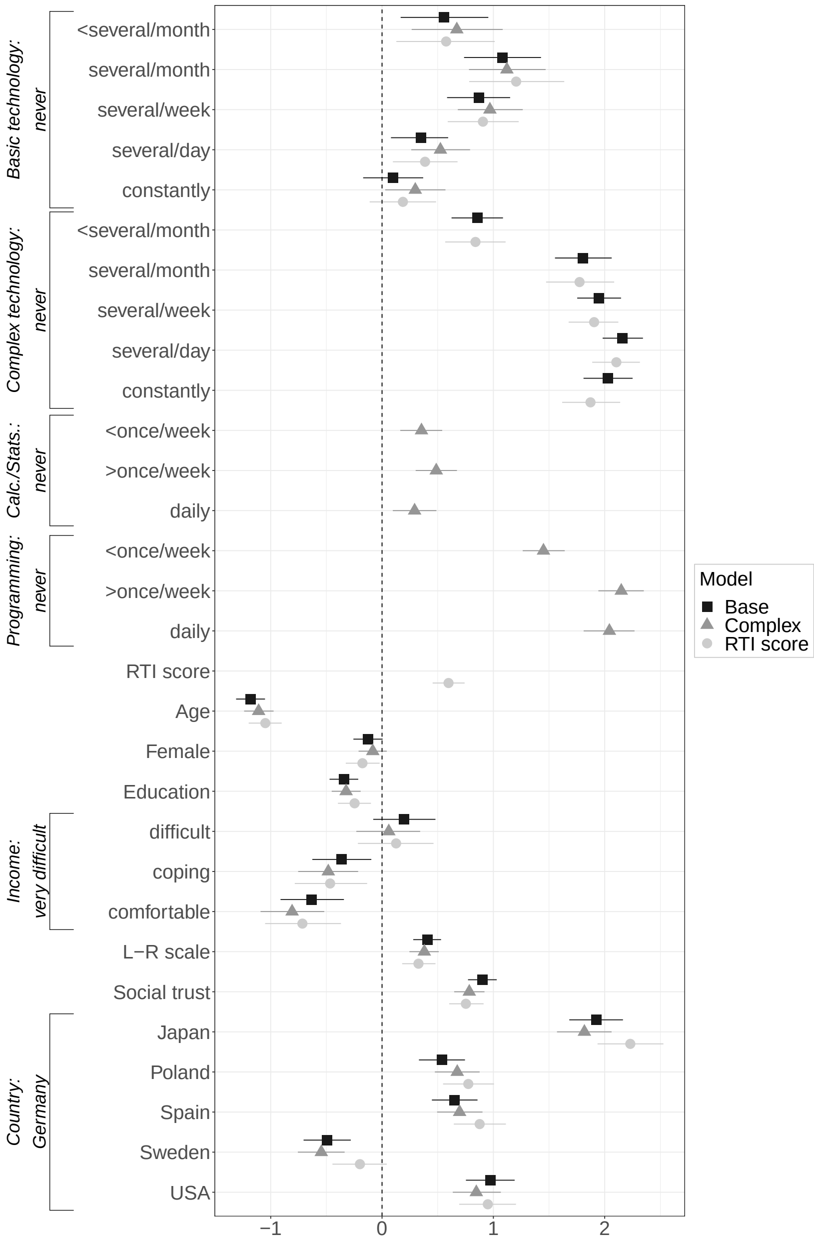

Figure 2: Determinants of Technological Job Insecurity (DigiWelfare Survey).

Note: Estimated results based on Equation 1. The dependent variable, technological job insecurity, reflects the perceived likelihood of job loss within five years due to automation (robots, software, algorithms, AI), competition via an online platform, or insufficient skills. Three models are estimated, each varying in how experience with rapid technological change is measured: (1) use of basic and complex technologies, (2) use of specific complex technologies, and (3) RTI scores as an objective measure of automation vulnerability. Data comes from the DigiWelfare Survey across six countries fielded in 2022.

2023). Panel A in Figure 3 illustrates this trend: the probability of viewing tech-induced unemployment as "very unlikely" drops from 70% to 44%, while seeing it as "unlikely" rises from 28% to 50%.

For those with experience using complex technologies, the effects on technological job

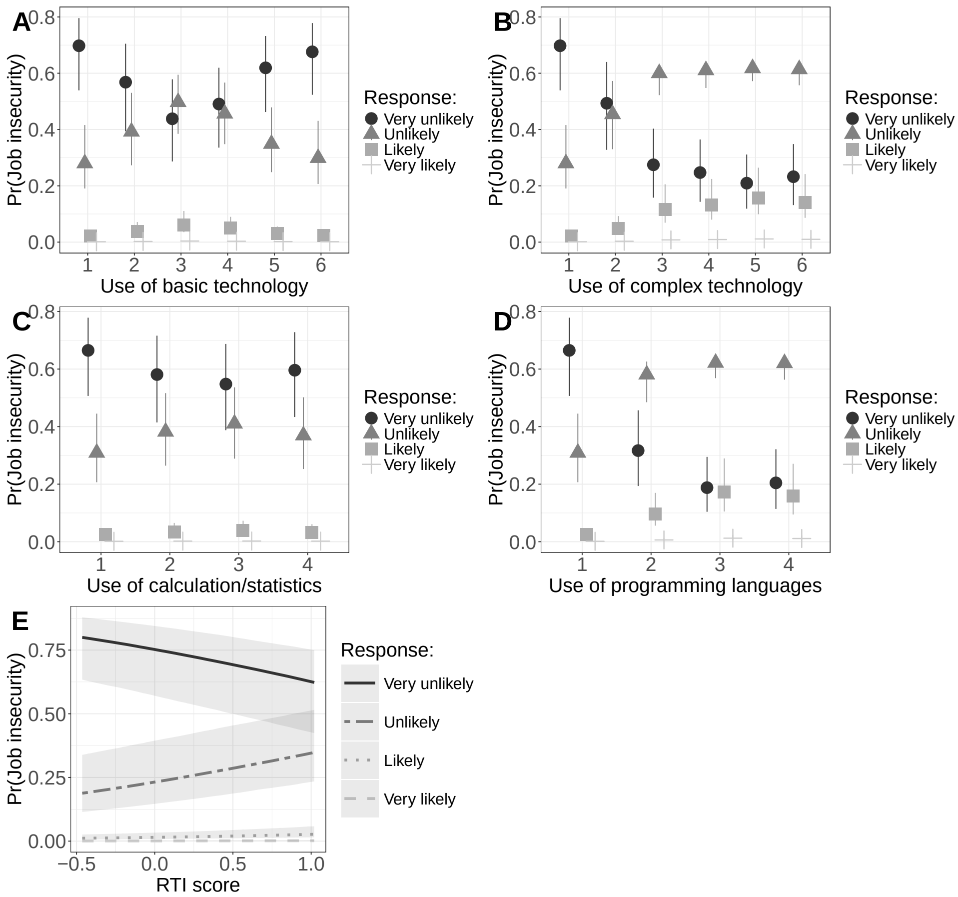

Figure 3: Predicted Probabilities (DigiWelfare Survey).

Note: Predicted probabilities based on Equation 1, varying by technology use and automation vulnerability. Panels A–D show the relationship between different types of technology use and the perceived risk of job loss. The x-axis represents the frequency of use, where 1 = never and higher values indicate more frequent use (up to 6 = constantly/most of the day for basic/complex technologies and 4 = usually daily for calculation/statistics and programming languages). The y-axis represents the probability of selecting each level of subjective risk, ranging from "Very Unlikely" to "Very Likely." Panel E illustrates the effect of RTI scores, an objective measure of automation vulnerability, where higher scores indicate greater routineness of tasks and thus higher exposure to automation risk. Data comes from the DigiWelfare Survey across six countries fielded in 2022.

insecurity are stronger than for basic technologies. Users engaging with these technologies less than or several times a month report greater perceived risk than non-users, with no decline among daily users. Panel B in Figure 3 shows that the probability of viewing tech-induced unemployment as "very unlikely" drops from 80% among non-users to 20% among very frequent users, while seeing it as "unlikely" rises from 28% to over 60%. These technologies also heighten expectations of near-term unemployment. Further examining complex technologies like programming and statistics underscores the role of experience in shaping technological job insecurity. Both are key predictors, with stronger effects for programming. Panel D in Figure 3 shows that experience with programming software mirrors the overall effect of complex technology use. These results support Hypothesis 1, which posits that individuals experiencing rapid workplace technological change, such as daily technology use, are more likely to perceive heightened technological insecurity.

Once we incorporate RTI scores, our main results hold. Higher scores are associated with greater perceived technological risk, though the effect is smaller than that of technology use (Figure 2). Panel E in Figure 3 shows that the probability of viewing tech-induced unemployment as "very unlikely" declines from 80% at the lowest RTI scores to 62% at the highest, while seeing it as "unlikely" rises from 19% to 35%. The probabilities of "likely" or "very likely" responses remain low and unchanged across RTI scores.

Turning to sociopolitical determinants, we learn that older, better educated, and financially secure individuals are better equipped to navigate uncertainties associated with technological change. As anticipated, respondents with a more conservative ideology (i.e., a rightward self-placement on the political spectrum) report higher levels of technological job insecurity. Overall, while socio-political factors play a role in shaping these perceptions, their effects are generally weaker than those of technology use. These findings further reinforce Hypothesis 1.

Finally, country fixed effects estimates indicate lower technological job insecurity in welfare states like Sweden and higher levels in liberal systems like the US. Japan stands out with the largest effect, likely due to cultural differences in response patterns, reflected in a high share of "don't-know" responses.[5]

As a robustness check, Figure A2 in the Appendix compares the base model results for technology use with three alternative specifications: (1) a model adjusting likelihood contributions using survey weights, (2) a model incorporating major occupational groups based on ISCO-08, and (3) a model controlling for the offshorability index from Blinder (2009) as a measure of globalization risk. The estimates indicate that these adjustments do not significantly alter the findings for basic and complex technology use.

Moreover, we replicate our analysis using the OECD's RTM survey, with full results

5. Figure A1 in the Appendix further confirms that Japanese respondents and those with lower subjective income are more likely to select "don't-know."

presented in Figure A3 based on Equation A1 in the Appendix. Panel A in Figure 4 supports our previous findings from the DigiWelfare survey, showing that the predicted probability of considering technology-related job loss likely increases substantially — from approximately 21% to 39% — as the use of complex technology increases.

As a supplementary analysis, Panel B presents predicted probabilities from a model that draws on an additional survey item from the RTM data, which asks respondents whether they agree with the statement that the pace of technology introduction in the workplace is overwhelming (with full results shown in Figure A4, based on Equation A2 in the Appendix). The estimated impact of complex technology use on this variable closely mirrors the previous pattern, with the predicted probability of agreeing with the statement increasing from 18% among workers who never use complex technologies to 25% among those who use them several times a month or more often.

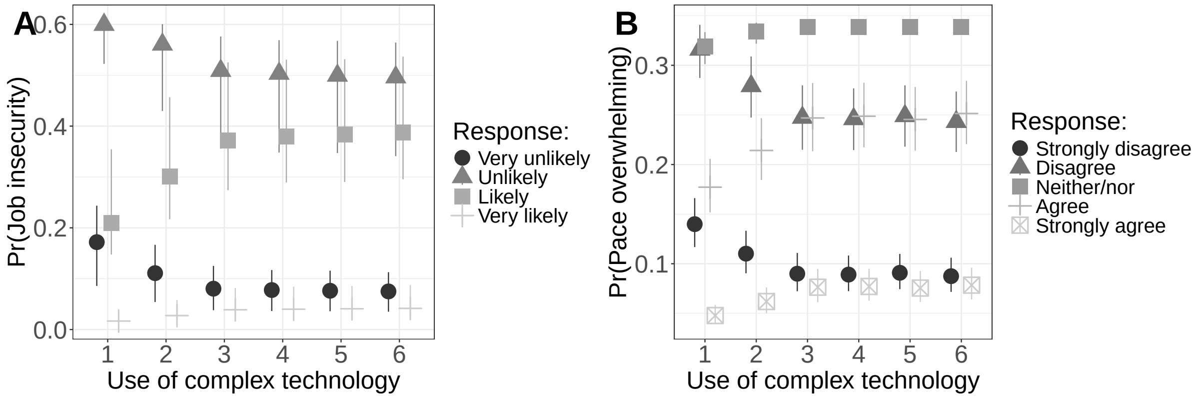

Figure 4: Predicted Probabilities (RTM Survey).

Note: Predicted probabilities of technological job insecurity (Panel A) based on Equation A1 in the Appendix and experiencing the pace of technology introduction in the workplace as overwhelming (Panel B) based on Equation A2 in the Appendix, varying by complex technology use. Data comes from RTM survey across 25 countries fielded in 2020.

Overall, our findings support Hypothesis 1, showing that personal experience with rapid workplace technological change — particularly through complex technologies like programming software — is strongly linked to heightened job insecurity across diverse country contexts. Our analysis indicates that these experiences outweigh other explanatory factors, reinforcing the theory that concrete experiences amplify concerns. These findings align with studies on AI's disproportionate impact on workers with programming skills (Eloundou et al. 2023; Hui, Reshef, and Zhou 2024; Webb 2020) and challenge claims that cognitively demanding tasks mitigate job insecurity (Gallego et al. 2022). Instead, our results suggest that workers performing these tasks often feel overwhelmed by the pace of change.

6.2 Perceptions of Rapid Technological Change, Its Determinants, and Policy Preferences

So far, we have examined how direct experience with rapid technological change heightens job insecurity. Now, we shift focus to its broader influence on attitudes toward technology and related policies. This section provides an in-depth analysis of subjective perceptions in the US, distinguishing between optimists, pessimists, and those directly exposed to technological change. We first identify key themes from respondents' open-ended answers to highlight dominant concerns in each group. Next, we explore the socio-political determinants of these perspectives, addressing questions like "Who is excited?" and "Who is afraid?" Finally, we examine how these perceptions shape policy preferences.

What do people have in mind when thinking about technological change? Figure 5 presents the key themes from open-ended responses across optimists, pessimists, and those exposed to technological change. We used OpenAI's API to identify the central themes and generate summaries; we then employed a prompt-based approach to classify the open-ended responses according to these themes.

Optimists emphasize technology's efficiency, productivity gains, and role in supplementing — rather than replacing — human labor. Respondents highlight how digital tools reduce mundane tasks and improve work quality. One participant, for example, lauded digital tools that "help do things faster, it's great. And decreasing the overall amount of work people need to do is a good thing." Another offered a similar sentiment, noting that, "I am a sales associate and having the technology to look up inventory without having to physically check it is a good thing for me." A legal worker noted, "Digitizing files and OCRing them has been a wonderful improvement because research is faster and less tedious," while an accountant added, "Having computer programs to do a lot of the bookkeeping frees up my time to take on more clients." These examples illustrate how optimism is tied to tangible workplace improvements.

Pessimists, in contrast, focus on job displacement and broader societal risks. Nearly 40% express concerns about automation replacing workers. One manufacturing employee laments, "We are slowly being replaced by robots, one machine at a time." A service worker echoes this concern, warning, "It is slowly taking over all service work. Janitors, clerks—nearly all retail and food service jobs are at risk. We are about to have a HUGE percentage of the US population in dire poverty. Learn to code? Good luck—some AI can already code better and faster than any human." Another respondent, after describing how technology has become more accurate and integrated into their workplace, concluded, "I guess I will have to learn a new job, but I'm getting older and don't want to start all over."

Beyond job loss, pessimists also voice distrust in AI's accuracy, frustration with automated systems, and ethical concerns about replacing human interaction with machines. For example, one respondent underscored the value of human interaction, stating, "I work in customer service, and some of the things I do have to be person-to-person, but people really get annoyed when the call is started with an AI."

The exposed group shares some of the pessimists' concerns — particularly about job displacement — but maintains a more nuanced perspective. Roughly 15% worry about the future of work, yet nearly 20% recognize technology's benefits for efficiency and productivity. A common theme is ambivalence: exposed individuals acknowledge AI's advantages but remain aware of its risks. As one respondent explains, "I have mixed feelings, I have been working on putting some AI tools to use improve and streamline some of my work, I can see a lot of potential. But I can also see how my own work is in danger of being replaced entirely... the results won't be quite as good but certainly would be cheaper than paying me. All in all I feel like I need to embrace AI and find ways

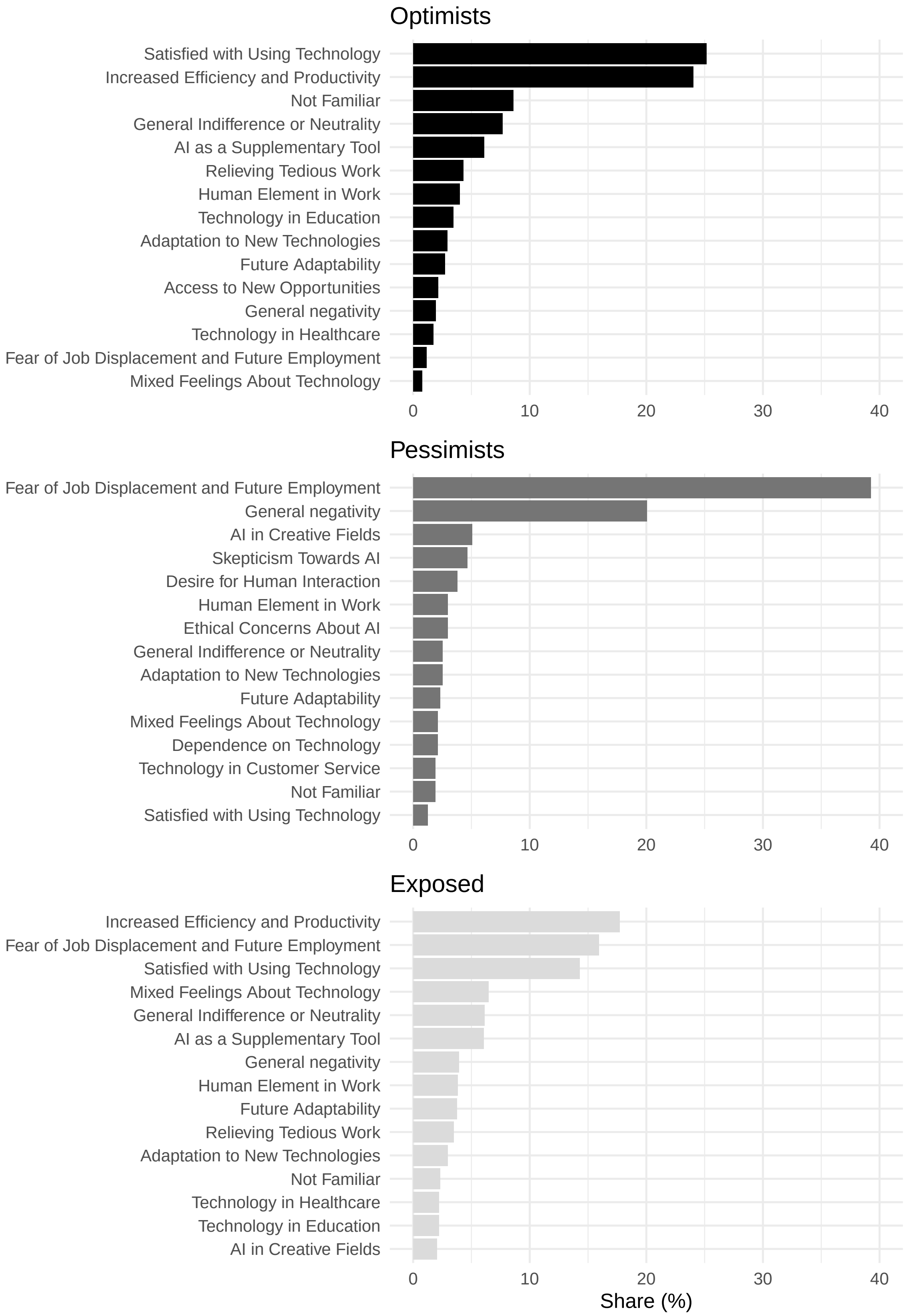

Figure 5: Top 15 Topics in Open-Ended Responses on Technology's Role

Note: This figure shows the share of each topic across groups, classified using OpenAI's API. 'Optimists' and 'Pessimists' are identified through hand-coding of open-ended responses. The 'Exposed' group is defined based on closed-ended questions about feeling overwhelmed by technological change and experiencing or witnessing job displacement due to technology. Data comes from the US sample.

to work -with- it, because there's no use working -against- it." Another IT professional highlights the pressure to constantly adapt, stating, "I think there are both pros and cons to AI tools. I like that AI would help with monotonous tasks and free up time for workers, but I am worried about a complete takeover." Similarly, an IT support technician expresses both appreciation and exhaustion, explaining, "I personally like technology but I also feel somewhat exhausted as various technologies are introduced and deprecate other established ones. It's not possible to remain static as if you don't learn the latest and greatest you will fall behind and be replaced." Unlike pessimists, exposed individuals often see technology as an inevitable force they must navigate rather than resist.

These findings align with our theoretical framework. While optimists and pessimists adopt polarized views, exposed individuals — those with direct experience of rapid technological change — occupy a middle ground. Their perspectives reflect both opportunity and vulnerability, reinforcing our argument that real workplace exposure shapes nuanced attitudes toward technological change.

Who is most likely to be optimistic, pessimistic, or exposed to technology? The results presented thus far show that individuals perceive technology in diverse ways. We now turn to examining the socio-political characteristics of each group. Figure 6 displays the results from three Bayesian logistic regressions based on Equation 2, highlighting how demographic, socioeconomic, and political factors relate to individuals' perceptions of technological change.

Men, high-income earners, and individuals in non-routine occupations, such as managerial or professional roles, are more likely to be optimists. Republicans, by contrast, are underrepresented in this group, supporting Hypothesis 2a. These findings align with prior research suggesting that individuals with greater economic security and job flexibility are more likely to embrace technological change, as they are better positioned to benefit from it. Access to resources, such as income and occupational stability, enhances adaptability to economic disruptions, making these individuals more optimistic about

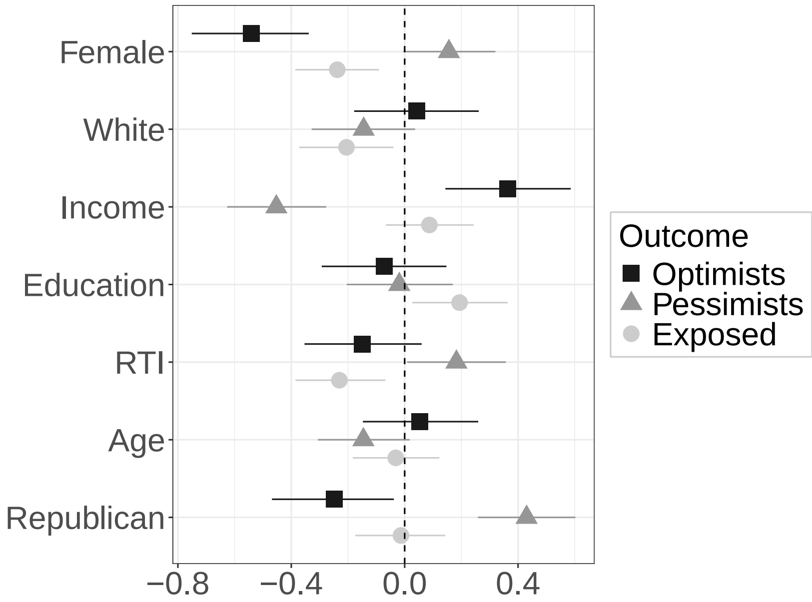

Figure 6: Characteristics of Optimists, Pessimists, and Exposed.

Note: Estimated results based on Equation 2. 'Optimists' are individuals who either strongly agree that robots benefit America, or that robots outperform humans in jobs, or are classified as optimists based on open-ended responses. 'Pessimists' are those who either strongly agree with statements reflecting sociotropic concerns, or worry about technology's future impact, or are classified as concerned. 'Exposed' individuals either feel overwhelmed by technological change or have witnessed job displacement due to technology. Income, education, RTI, and age (non-dummy variables) are standardized for comparability. Data comes from the US sample.

technological innovation.

Women, younger individuals, lower-income earners, and those in routine occupations, such as clerical or service jobs, are more likely to be pessimists. Moreover, Republicans are overrepresented in this group. These results are consistent with Hypothesis 2b. Economic insecurity and job precarity appear to drive their concerns, as those in routine-based roles face higher risks of automation-driven job displacement. Additionally, younger respondents may perceive technological change as a looming threat to their career prospects, while lower-income individuals may feel more vulnerable to automation-induced labor market shifts. These findings suggest that economic and occupational uncertainty contribute to a more negative outlook on technological advancement.

Finally, men, individuals in non-routine occupations, and those with higher levels of education are more likely to be in the exposed group, regardless of their stance on technology. These results support Hypothesis 2c and reinforce our argument that exposure to technological change extends beyond routine tasks, affecting a broader range of workers, including those in high-skilled, knowledge-based roles. As AI enables more complex decision-making and automation expands into professional fields, exposure to technological change is no longer confined to traditionally automatable jobs (Autor 2024). Instead, workers across industries must continuously adapt, reinforcing the importance of direct experience in shaping nuanced attitudes toward technology.

Perceptions of technological change and policy preferences. We now shift from examining the determinants of tech perceptions to analyzing their effects on policy preferences. This approach allows us to assess how subjective experiences of technological change influence broader political attitudes. Figure 7 presents the estimated effects of optimism, pessimism, and exposure on policy preferences, including trade favorability, ethnocentrism, support for anti-immigration policies, and taxation, based on Equation 3.

As expected (Hypothesis 3a), optimists are significantly more likely to support trade and pro-immigration policies, reflecting their confidence in technological advancements and openness to global economic integration. Additionally, technological enthusiasm is weakly associated with lower ethnocentrism, lower support for Trump, and reduced opposition to taxing the rich.

Pessimists are more likely to oppose trade and offshoring policies, reflecting concerns about job displacement and economic insecurity driven by globalization and technological change. They also exhibit strong ethnocentric attitudes, favoring policies that prioritize national interests and protect domestic workers, such as anti-immigration measures. Additionally, technological pessimism strongly predicts support for Trump. Pessimists also favor protective economic measures, including higher taxation on the rich, to safeguard their financial security, supporting Hypothesis 3b.

Finally, the exposed group occupies a middle ground, generally aligning with pessimists but with weaker effects. Some associations disappear entirely, such as opposition to offshoring and higher taxes on the rich, while others persist but with reduced strength, including support for anti-immigration policies, ethnocentrism, and Trump. These re-

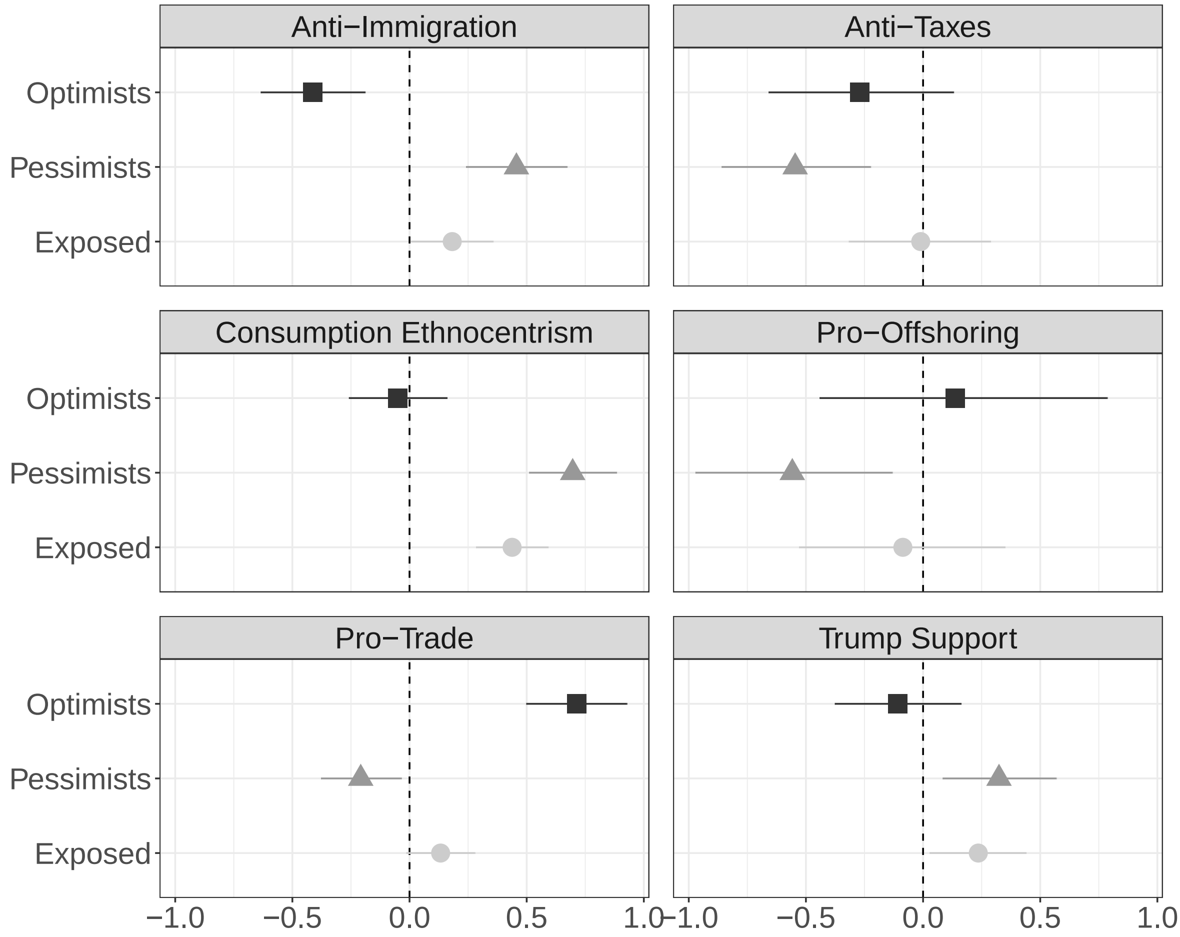

Figure 7: Policy Preferences of Optimists, Pessimists, and Exposed.

Note: Estimated results based on Equation 3 for six policy preference outcomes: support for anti-immigration, anti-tax, offshoring, trade, Trump, and consumption ethnocentrism. The main independent variables capture technology perceptions and experiences included in all models: 'Optimists' are individuals who either strongly agree that robots benefit America or that robots outperform humans in jobs or are classified as optimists based on open-ended responses. 'Pessimists' are those who either strongly agree with statements reflecting sociotropic concerns, or worry about technology's future impact, or are classified as concerned. 'Exposed' are individuals who either feel overwhelmed by the pace of technological change or have witnessed job displacement due to technology. All specifications include control for gender, race (white), party (Republican), and standardized non-dummy variables: income, education, RTI, and age. Data comes from the US sample.

sults support Hypothesis 3c and align with prior research linking automation exposure to increased support for illiberal policies (e.g., Wu 2023; Gonzalez-Rostani 2024c).

7 Final Remarks

This study contributes to the growing literature on technological change and policy preferences by emphasizing the role of workplace exposure in shaping job insecurity. Using data from three original surveys, we identify three distinct groups — optimists, pessimists, and the exposed — and challenge the assumption that high-skilled workers are insulated from technological risks. Our findings show that engagement with complex technologies, such as programming and robotics, is strongly linked to job insecurity, likely due to the overwhelming pace of technological change.

A key insight from these results is that the current wave of technological change differs from previous waves. Even high-skilled workers, traditionally viewed as secure, now experience heightened job insecurity. This suggests a direct link between working with complex technologies and feeling vulnerable to rapid innovation, challenging previous assumptions about skill level and job security. Recognizing these subjective risk perceptions is essential for understanding the political implications of a quickly evolving work environment.

Our exploration of the three subjective perspectives —optimism, pessimism, and exposure— reveals that optimists value technology's efficiency and productivity, pessimists fear job displacement and the future of work, and the exposed occupy a middle ground, sharing similar fears but expressing mixed feelings about technology. Our correlational analysis indicates that optimists tend to be high-income, male, and politically liberal, supporting pro-globalization policies, while pessimists are more likely to be lower-income, female, and conservative, advocating for protectionist measures. The exposed group, typically male and highly educated, supports some protectionist policies, though less intensively than pessimists.

An important implication of these findings is that the rapid pace of AI may create common ground between the exposed and pessimists, driving policy demands. The exposed — those overwhelmed by technological change or directly displaced — could align with pessimists concerned about broader societal impacts. Notably, this coalition may now include cognitive workers at the forefront of technological development, increasing support for illiberal policies. While less likely, coalitions between optimists and pessimists remain possible; for example, optimists may support taxing the rich, a key demand of pessimists, to finance compensation policies. Another implication is that the stark divide between optimists and pessimists in their policy preferences could serve as fertile ground for political polarization. While this topic has been largely unaddressed in the current political arena, this divide offers an opportunity for politicians to exploit these differences, potentially deepening political divisions in the future.

Future research should explore under what conditions high-skilled workers overwhelmed by AI form coalitions with pessimists, traditionally lower-educated and working-class individuals. Investigating shifts from optimism to pessimism — when and why they occur — could also yield valuable insights. Furthermore, expanding our open-ended analyses to policy preferences, rather than relying on constrained survey options, may provide a deeper understanding of individual attitudes. Finally, on the supply side, a natural next step would be to explore how politicians can activate workers' experiences, even without directly addressing job automation.

References

Acemoglu, Daron, Gary W Anderson, David N Beede, Cathy Buffington, Eric E Childress, Emin Dinlersoz, Lucia S Foster, et al. 2025. Automation and the workforce: a firm-level view from the 2019 annual business survey. In *Technology, productivity, and economic growth,* edited by Susanto Basu, Lucy Eldridge, John Haltiwanger, and Erich Strassner. National Bureau of Economic Research Studies in Income and Wealth. Chicago: University of Chicago Press.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo. 2022. Artificial intelligence and jobs: evidence from online vacancies. *Journal of Labor Economics* 40 (S1): S293–S340.

Acemoglu, Daron, and Simon Johnson. 2023. *Power and progress: our thousand-year struggle over technology and prosperity.* London: Basic Books.

Ahrens, Leo. 2024. Labor market risks and welfare preferences: a bounded rationality approach. *Socio-Economic Review* 22 (1): 327–348.

Anderson, Christopher J., and Jonas Pontusson. 2007. Workers, worries and welfare states: social protection and job insecurity in 15 OECD countries. *European Journal of Political Research* 46 (2): 211–235.

Anelli, Massimo, Italo Colantone, and Piero Stanig. 2021. Individual vulnerability to industrial robot adoption increases support for the radical right. *Proceedings of the National Academy of Sciences* 118 (47): e2111611118.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. 2017. Revisiting the risk of automation. *Economics Letters* 159:157–160.

Autor, David. 2022. *The labor market impacts of technological change: from unbridled enthusiasm to qualified optimism to vast uncertainty.* Working Paper, 30074.

Autor, David. 2024. *Applying AI to Rebuild Middle Class Jobs.* Working Paper, 32140.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge. 2023. What happens to workers at firms that automate? *The Review of Economics and Statistics,* 1–45.

Bicchi, Nicolas, Alexander Kuo, and Aina Gallego. 2024. Unpacking technological risks: different sources of concern and policy preferences. *Political Studies,* 1–24.

Blinder, Alan. 2009. How many US jobs might be offshorable? *World Economics* 10 (2): 41–78.

Bordalo, Pedro, Giovanni Burro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer. 2024. Imagining the future: memory, simulation, and beliefs. *The Review of Economic Studies,* 1–32.

Bordalo, Pedro, John J Conlon, Nicola Gennaioli, Spencer Y Kwon, and Andrei Shleifer. 2023. Memory and probability*. *The Quarterly Journal of Economics* 138 (1): 265–311.

Borwein, Sophie, Bart Bonikowski, Peter Loewen, Beatrice Magistro, and Blake Lee-Whiting. 2024. Who Can Assert Ownership Over Automation? Workplace Technological Change, Populist and Ethno-nationalist Rhetoric, and Candidate Support. *Political Behavior* 46 (4): 2191–2214.

Borwein, Sophie, Bart Bonikowski, Peter John Loewen, Blake Lee-Whiting, and Beatrice Magistro. 2025. Perceived technological threat and vote choice: evidence from 15 european democracies. *West European Politics* 48 (3): 534–561.

Brussevich, Mariya, Era Dabla-Norris, Christine Kamunge, Pooja Karnane, Salma Khalid, and Kalpana Kochhar. 2018. Gender, technology, and the future of work. *Staff Discussion Notes* 18:1–36.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* W. W. Norton & Company.

Bürkner, Paul-Christian. 2017. Brms: an r package for bayesian multilevel models using stan. *Journal of Statistical Software* 80:1–28.

———. 2021. Bayesian item response modeling in r with brms and stan. *Journal of Statistical Software* 100:1–54.

Busemeyer, Marius R, Mia Gandenberger, Carlo Knotz, and Tobias Tober. 2023. Preferred policy responses to technological change: survey evidence from OECD countries. *Socio-Economic Review* 21 (1): 593–615.

Busemeyer, Marius R., Sophia Stutzmann, and Tobias Tober. 2024. Digitalization and the green transition: different challenges, same policy responses? *Regulation & Governance* forthcoming.

Busemeyer, Marius R., and Tobias Tober. 2023. Dealing with technological change: social policy preferences and institutional context. *Comparative Political Studies* 56 (7): 968–999.

Chandler, Simon. 2020. How AI is making software development easier for companies and coders. *Forbes.*

Chaudoin, Stephen, and Michael-David Mangini. 2025. Robots, Foreigners, and Foreign Robots: Policy Responses to Automation and Trade. *The Journal of Politics.*

Colantone, Italo, and Piero Stanig. 2018. Global Competition and Brexit. *American Political Science Review* 112 (2): 201–218.

Cusack, Thomas, Torben Iversen, and Philipp Rehm. 2006. Risks at work: the demand and supply sides of government redistribution. *Oxford Review of Economic Policy* 22 (3): 365–389.

D'Arcy, John, Ashish Gupta, Monideepa Tarafdar, and Ofir Turel. 2014. Reflecting on the "Dark Side" of Information Technology Use. *Communications of the Association for Information Systems* 35 (1).

Dougherty, Michael R. P., Charles F. Gettys, and Eve E. Ogden. 1999. MINERVA-DM: a memory processes model for judgments of likelihood. *Psychological Review* 106 (1): 180–209.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock. 2023. *GPTs are GPTs: an early look at the labor market impact potential of large language models,* 2303.10130.

Ferrario, Beatrice, and Stefanie Stantcheva. 2022. Eliciting People's First-Order Concerns: Text Analysis of Open-Ended Survey Questions. *AEA Papers and Proceedings* 112:163–169.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. The future of employment: how susceptible are jobs to computerisation? *Technological Forecasting and Social Change* 114:254–280.

Gallego, Aina, Alexander Kuo, Dulce Manzano, and José Fernández-Albertos. 2022. Technological risk and policy preferences. *Comparative Political Studies* 55 (1): 60–92.

Gallego, Aina, and Thomas Kurer. 2022. Automation, digitalization, and artificial intelligence in the workplace: implications for political behavior. *Annual Review of Political Science* 25 (1): 463–484.

Gallego, Aina, Thomas Kurer, and Nikolas Schöll. 2022. Neither left behind nor superstar: ordinary winners of digitalization at the ballot box. *The Journal of Politics* 84 (1): 418–436.

Gelman, Andrew. 2008. Scaling regression inputs by dividing by two standard deviations. *Statistics in Medicine* 27 (15): 2865–2873.

Gidron, Noam, and Peter A. Hall. 2017. The politics of social status: economic and cultural roots of the populist right. *The British Journal of Sociology* 68 (S1): S57–S84.

Gonzalez-Rostani, Valentina. 2024a. Elections, Right-wing Populism, and Political-Economic Polarization: The Role of Institutions and Political Outsiders. *The Journal of Politics.*

———. 2024b. Engaged robots, disengaged workers: Automation and political alienation. *Economics & Politics* 36 (3): 1703–1730.

———. 2024c. The Path from Automation to Right-Wing Populism.

González-Rostani, Valentina, José Incio, and Guillermo Lezama. 2024. Social media versus surveys: A new scalable approach to understanding legislators' discourse. *Legislative Studies Quarterly,* 1–9.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. Explaining job polarization: routine-biased technological change and offshoring. *American Economic Review* 104 (8): 2509–2526.

Graeber, Thomas, Christopher Roth, and Florian Zimmermann. 2024. Stories, statistics, and memory. *The Quarterly Journal of Economics* 139 (4): 2181–2225.

Hui, Xiang, Oren Reshef, and Luofeng Zhou. 2024. The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market. *Organization Science* 35 (6): 1977–1989.

Inglehart, Ronald F., and Pippa Norris. 2016. Trump, Brexit, and the rise of populism: Economic have-nots and cultural backlash.

Jost, John T., Jack Glaser, Arie W. Kruglanski, and Frank J. Sulloway. 2003. Political conservatism as motivated social cognition. *Psychological Bulletin* 129 (3): 339–375.

Kaltenthaler, Karl, and William J. Miller. 2013. Social Psychology and Public Support for Trade Liberalization. *International Studies Quarterly* 57 (4): 784–790.

Kaltenthaler, Karl C., Ronald D. Gelleny, and Stephen J. Ceccoli. 2004. Explaining Citizen Support for Trade Liberalization. *International Studies Quarterly* 48 (4): 829–851.

Kurer, Thomas. 2020. The declining middle: occupational change, social status, and the populist right. *Comparative Political Studies* 53 (10): 1798–1835.

Kurer, Thomas, and Silja Häusermann. 2022. Automation risk, social policy preferences, and political participation. In *Digitalization and the welfare state,* edited by Marius R. Busemeyer, Achim Kemmerling, Kees Van Kersbergen, and Paul Marx, 139–156. Oxford: Oxford University Press.

Lauterbach, Ann S., Tobias Tober, Florian Kunze, and Marius R. Busemeyer. 2023. Can welfare states buffer technostress? income and technostress in the context of various OECD countries. *PLOS ONE* 18 (12): e0295229.

Le Mens, Gaël, and Aina Gallego. 2025. Positioning political texts with Large Language Models by asking and averaging. *Political Analysis,* 1–9.

Magistro, Beatrice, Sophie Borwein, R. Michael Alvarez, Bart Bonikowski, and Peter John Loewen. 2025. Attitudes toward artificial intelligence (AI) and globalization: Common microfoundations and political implications. *American Journal of Political Science* n/a (n/a): 1–19.

Margalit, Yotam, and Shir Raviv. 2024. Does support for redistribution mean what we think it means? *Political Science Research and Methods* 12 (4): 870–878.

Margalit, Yotam M. 2013. Explaining social policy preferences: evidence from the great recession. *The American Political Science Review* 107 (1): 80–103.

Marx, Paul. 2014. The effect of job insecurity and employability on preferences for redistribution in western europe. *Journal of European Social Policy* 24 (4): 351–366.

Milner, Helen V. 2021. Voting for populism in europe: globalization, technological change, and the extreme right. *Comparative Political Studies* 54 (13): 2286–2320.

Moll, Benjamin, Lukasz Rachel, and Pascual Restrepo. 2022. Uneven growth: automation's impact on income and wealth inequality. *Econometrica* 90 (6): 2645–2683.

Mutz, Diana C. 2018. Status threat, not economic hardship, explains the 2016 presidential vote. *Proceedings of the National Academy of Sciences* 115 (19).

Norris, Pippa, and Ronald Inglehart. 2019. *Cultural backlash: Trump, Brexit, and authoritarian populism.* Cambridge University Press.

Novozhilova, Ekaterina, Kate Mays, and James E. Katz. 2024. Looking towards an automated future: u.s. attitudes towards future artificial intelligence instantiations and their effect. *Humanities and Social Sciences Communications* 11 (1): 1–11.

Roberts, Margaret E., Brandon M. Stewart, Dustin Tingley, Christopher Lucas, Jetson Leder-Luis, Shana Kushner Gadarian, Bethany Albertson, and David G. Rand. 2014. Structural Topic Models for Open-Ended Survey Responses. *American Journal of Political Science* 58 (4): 1064–1082.

Scheve, Kenneth F., and Matthew J. Slaughter. 2001. Labor Market Competition and Individual Preferences Over Immigration Policy. *The Review of Economics and Statistics* 83 (1): 133–145.

Shoss, Mindy K. 2017. Job insecurity: an integrative review and agenda for future research. *Journal of Management* 43 (6): 1911–1939.

Spirling, Arthur, and Bradon Steward. 2024. What good is a regression? inference to the best explanation and the practice of political science research. *The Journal of Politics.*

Steenvoorden, Eefje, and Eelco Harteveld. 2018. The appeal of nostalgia: the influence of societal pessimism on support for populist radical right parties. *West European Politics.*

Tarafdar, Monideepa, Ellen Bolman. Pullins, and T. S. Ragu-Nathan. 2015. Technostress: negative effect on performance and possible mitigations. *Information Systems Journal* 25 (2): 103–132.

Thewissen, Stefan, and David Rueda. 2019. Automation and the welfare state: technological change as a determinant of redistribution preferences. *Comparative Political Studies* 52 (2): 171–208.

Vehtari, Aki, Andrew Gelman, and Jonah Gabry. 2017. Practical bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing* 27 (5): 1413–1432.

Webb, Michael. 2020. *The impact of artificial intelligence on the labor market,* SSRN Scholarly Paper 3482150, Rochester, NY.

Wu, Nicole. 2022. Misattributed blame? attitudes toward globalization in the age of automation. *Political Science Research and Methods* 10 (3): 470–487.

———. 2023. "restrict foreigners, not robots": partisan responses to automation threat. *Economics & Politics* 35 (2): 505–528.

Zollinger, Delia. 2024. Cleavage Identities in Voters' Own Words: Harnessing Open-Ended Survey Responses. *American Journal of Political Science* 68 (1): 139–159.

A Online Appendix

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A.1 DigiWelfare Survey

Conducted in June and July 2022 by Kantar Public, this survey was based on quota sampling (gender, age, and education) in Germany, Japan, Poland, Spain, Sweden, and the United States, with 3,300 respondents per country (19,800 in total). The survey includes questions on technology-related fears of job loss, individual use of technology at work, and additional person-specific information.

A.1.1 Measurement and Question Wording

This appendix provides details on the data sources, survey items, and measurement strategies used in this study.

Technological Job Insecurity. To measure technology-related employment insecurity, three survey items were included in both datasets. Respondents were asked: *How likely do you think it is that the following will happen to your job over the next five years?*

1. *My job will be replaced by a robot, computer software, an algorithm, or artificial intelligence.*
2. *My job will be replaced by a person providing a similar service on an internet platform.*
3. *I will lose my job because I am not good enough with new technology or because I will be replaced by someone with better technological skills.*

Scale: Responses were recorded on a four-point scale ranging from (1) *very unlikely*, (2) *unlikely*, (3) *likely*, to (4) *very likely.*

Technology Use at Work. To capture workplace technology use, both surveys included two items:

1. *How often do you use digital information and communication technologies (ICT), such as computers, laptops, or tablets, in your work?*

2. *How often do you use or have you used complex technology in your job, such as robots or specialist software? By "specialist software," we mean software requiring specialized training or advanced computing/programming skills, excluding common applications like Microsoft Office.*

Scale: Responses were recorded on a six-point scale ranging from (1) *never*, (2) *less than several times a month*, (3) *several times a month*, (4) *several times a week*, (5) *several times a day*, to (6) *constantly, most of the day.*

Tasks at Low Risk of Automation (TLRA) Index. The DigiWelfare survey also included questions on performing specific high-tech tasks: *Thinking about your current job, how frequently do you perform the following tasks:*

1. *Calculations and statistics.*

2. *Programming languages (e.g., SQL, Java, C#, Python).*

Scale: Responses were recorded on a four-point scale: (1) *never*, (2) *less than once a week*, (3) *at least once per week*, and (4) *usually daily.*

Objective Vulnerability to Automation. Objective vulnerability to automation is measured using Routine Task Intensity (RTI) scores based on the International Standard Classification of Occupations 2008 (ISCO-08). These scores use detailed task-level data to quantify the routine content of occupations. RTI scores were only applied to the DigiWelfare survey, as the RTM survey lacked sufficiently detailed occupational data.

Demographic Variables. Control variables include age, gender, education, and income. Education is measured in years (DigiWelfare) or a nine-level factor variable (RTM). Income is recorded as subjective income categories (DigiWelfare) or logged disposable household income (RTM). Additional measures include political orientation and generalized trust, captured in DigiWelfare using 11-point scales for left-right political alignment and trust in others.

A.1.2 Results

A.2 RTM Survey

A.2.1 Survey Description

The second data source is OECD's *Risks that Matter* (*RTM*) survey from September and October of 2020, which studies the public perceptions of a broad range of economic and so-

Figure A1: Bayesian 1PL IRT model with residual category as response variable (1=*don't know*, 0=otherwise).

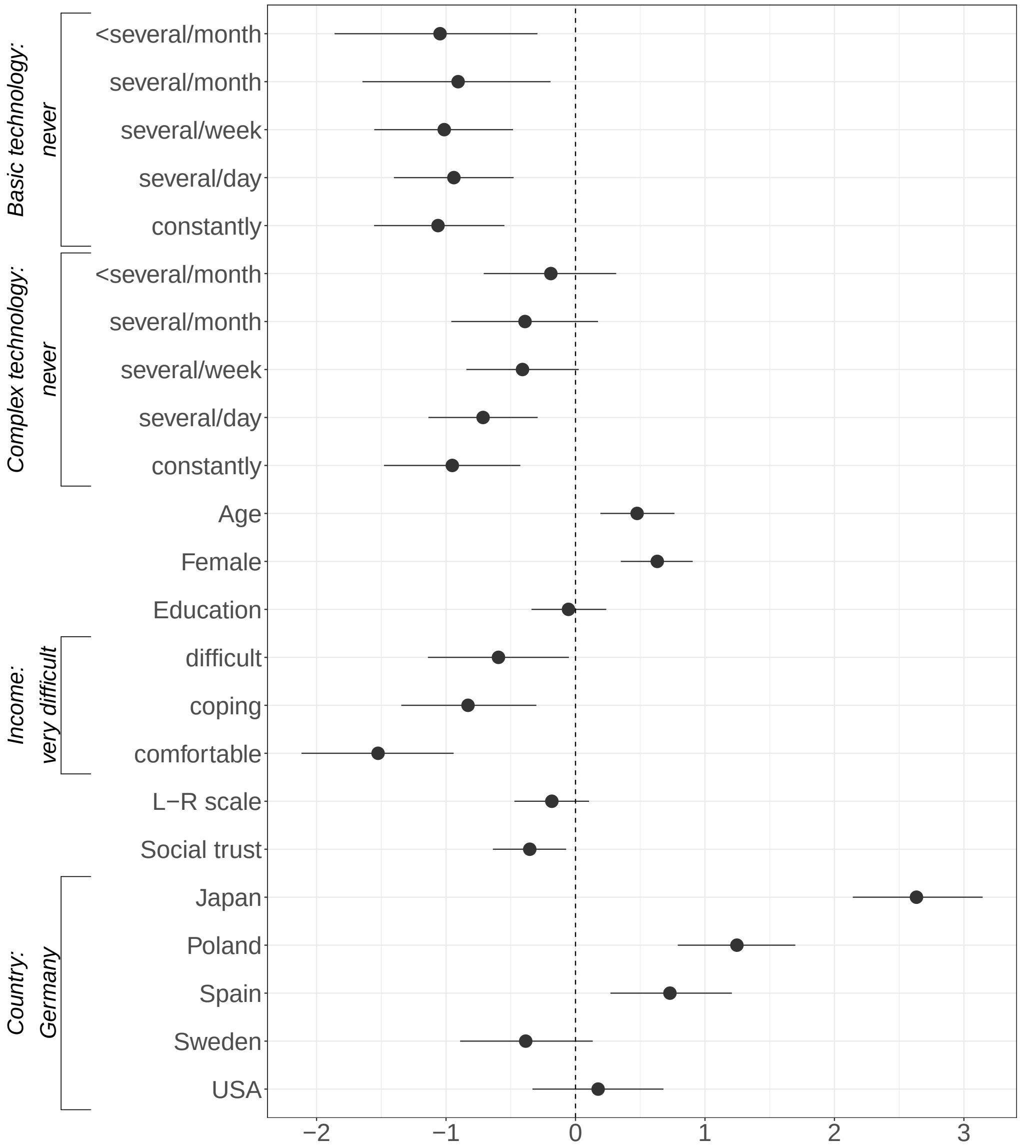
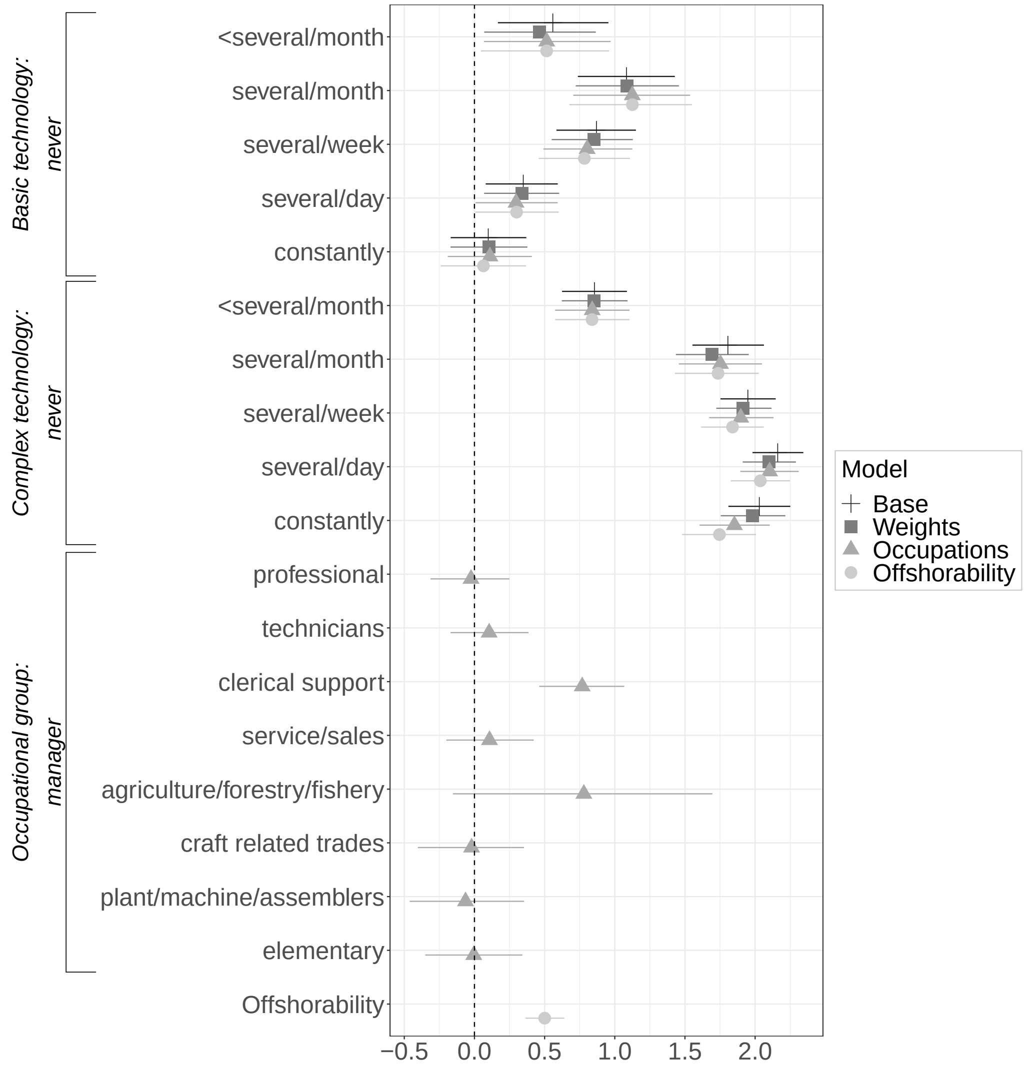


Figure A2: Comparing base model, model with survey weights, model with major occupational groups as defined by ISCO-08, and model with job offshorability index from Blinder (2009) as a measure of globalization risk. Other individual-level variables included but not shown.



cial risks. The survey was fielded by the survey contractor Respondi Ltd. based on quota sampling (gender, age, education, income, and employment status) and covers 25,814 individuals in the following 25 countries: Austria, Belgium, Canada, Chile, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Lithuania, Mexico, the Netherlands, Norway, Poland, Portugal, Slovenia, South Korea, Spain, Switzerland, Turkey, and the United States. Through a research collaboration with the OECD, the same set of self-designed items on subjective risk perceptions as used in the DigiWelfare survey were included in RTM survey as well. Moreover, The RTM survey also contains some of the same self-designed questions on respondents' job-related technology use. While the limited space that was provided to external researchers in the survey questionnaire implies that not all theoretical considerations at the individual level can be tested with the RTM data, the larger country sample allows for a more meaningful test of the potential impact of contextual factors than would be possible with the smaller country sample of the DigiWelfare survey alone.

A.2.2 Measurement and Question Wording

Country-Level Variables. The larger country sample in the RTM survey allows for a hierarchical modeling approach that explicitly accounts for control factors at the country level. We consider the following three country-level variables:

1. **Welfare State Generosity:** Measured using the OECD's 2020 data on the proportion of previous in-work household income maintained after 12 months of unemployment.

2. **Technological Advancement:** Measured through the Cisco Digital Readiness Index, combining metrics on internet usage, mobile cellular subscriptions, and cloud services for 2020.[6]

3. **Economic Context:** Captured by the national unemployment rate for 2020, sourced from the OECD Main Economic Indicators database.

Feeling Overwhelmed by Pace of Technology Introduction in the Workplace. In addition, the RTM survey also included a question on how respondents feel about the pace of technological change in the workplace: *To what extent do you agree with the following statement: I feel that the pace at which new technologies are introduced in my workplace is overwhelming.*
Scale: Responses were recorded on a five-point scale: (1) *strongly disagree*, (2) *disagree*, (3) *neither agree nor disagree*, (4) *agree*, and (5) *strongly agree.*

A.2.3 Specification

The RTM data allow for the inclusion of a broader set of countries, enabling a closer examination of cross-country variation. The model includes country-specific variance

6. For more details, see https://www.cisco.com/c/m/en_us/about/corporate-social-responsibility/research-resources/digital-readiness-index.html#/Technology%20Adoption (accessed on October 25, 2023).

components and additional country-level variables:

$$
\begin{aligned}
\text{JobInsecurity}_{rci} &\sim \text{Categorical}(\mathbf{p}_{rci,\kappa}) \\
\text{logit}(\mathbf{p}_{rci,\kappa}) &= \phi_{rci} + \theta_{r|c} + \omega_c + \xi_i \\
\phi_{rci} &= \beta_1\, \textbf{TechnologyUse}_{rci} + \beta_2 \mathbf{z}_{rci} + \lambda \mathbf{z}_{ci} + \kappa_k + \epsilon_{rci} \\
\kappa_k &\sim t(3, 0, 2.5) \\
\theta_{r|c}, \omega_c, \xi_i &\sim t(4, 0, 1) \\
\beta_{1,2}, \lambda &\sim \text{Uniform}(0, 1).
\end{aligned}
\tag{A1}
$$

This model introduces a country-variance component, ω_c, with $\theta_{r|c}$ denoting person-specific variance within country c. Additionally, it includes country-level controls ($\mathbf{z}_{ci}$) alongside a reduced set of individual-level controls ($\mathbf{z}_{rci}$). Priors remain consistent with Equation 1. The estimation of the Bayesian IRT RTM model is based on 8,000 MCMC iterations, including a burn-in of the first 4,000 iterations.

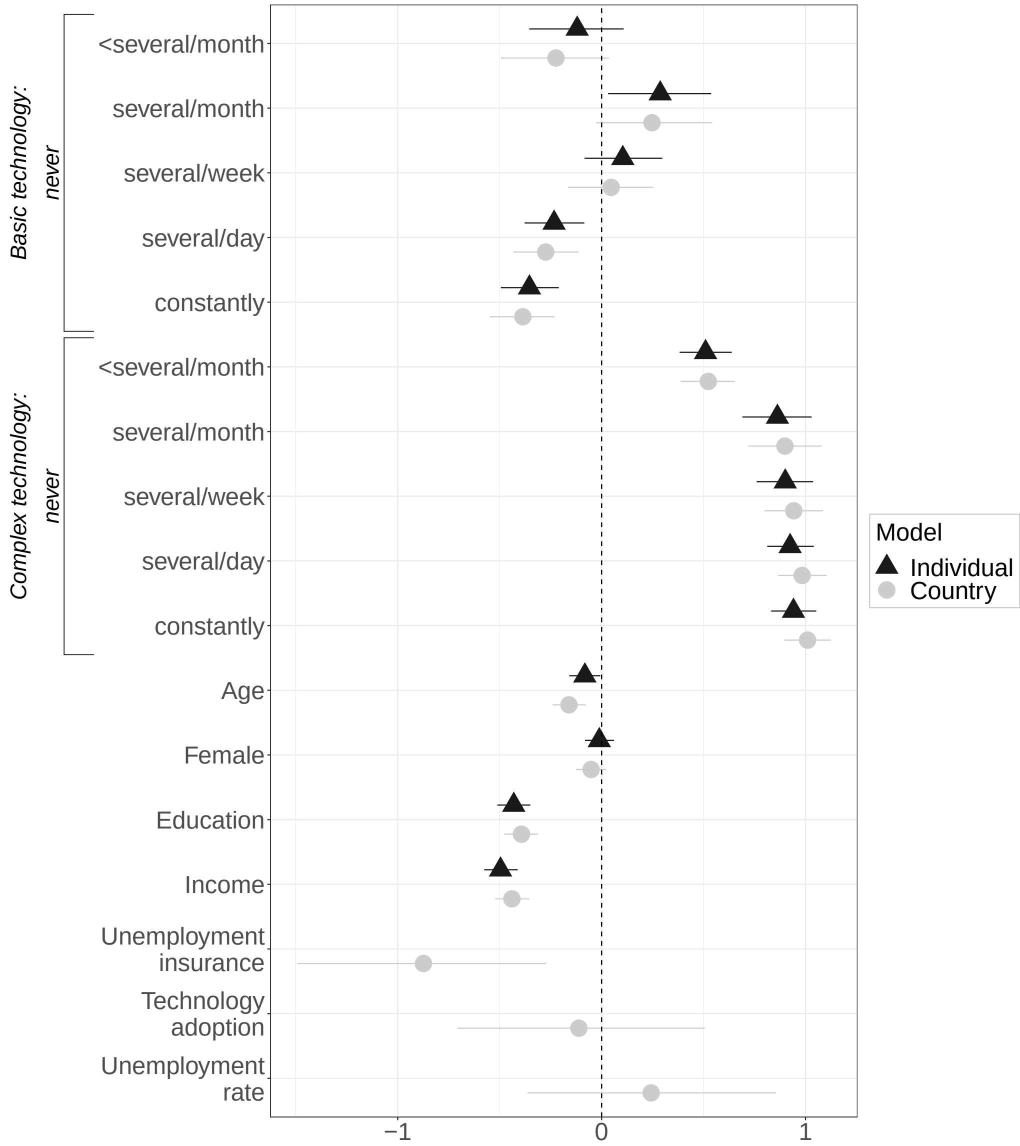
As a supplementary analysis, we use the RTM data to examine how technology use correlates with feelings of being overwhelmed by the pace of technological change in the workplace. We estimate the following Bayesian ordered logistic mixed-effects model, based on 12,000 MCMC iterations, with 4,000 used as burn-in:

$$
\begin{aligned}
\text{PaceOverwhelming}_{rc} &\sim \text{Categorical}(\mathbf{p}_{rc,\kappa}) \\
\text{logit}(\mathbf{p}_{rc,\kappa}) &= \beta_1\, \textbf{TechnologyUse}_{rc} + \beta_2 \mathbf{z}_{rc} + \lambda \mathbf{z}_{ci} + \omega_c + \kappa_k + \epsilon_{rc} \\
\kappa_k &\sim t(3, 0, 2.5) \\
\omega_c &\sim t(4, 0, 1) \\
\beta_{1,2}, \lambda &\sim \mathcal{N}(0, 1).
\end{aligned}
\tag{A2}
$$

Variable Scaling and Priors. To facilitate convergence and interpretability, continuous variables are centered and scaled by two times their standard deviation (Gelman 2008). Weakly regularizing priors are applied to intercepts, variance components, and fixed parameters, as specified in Equations A1 and A2.

A.2.4 Results

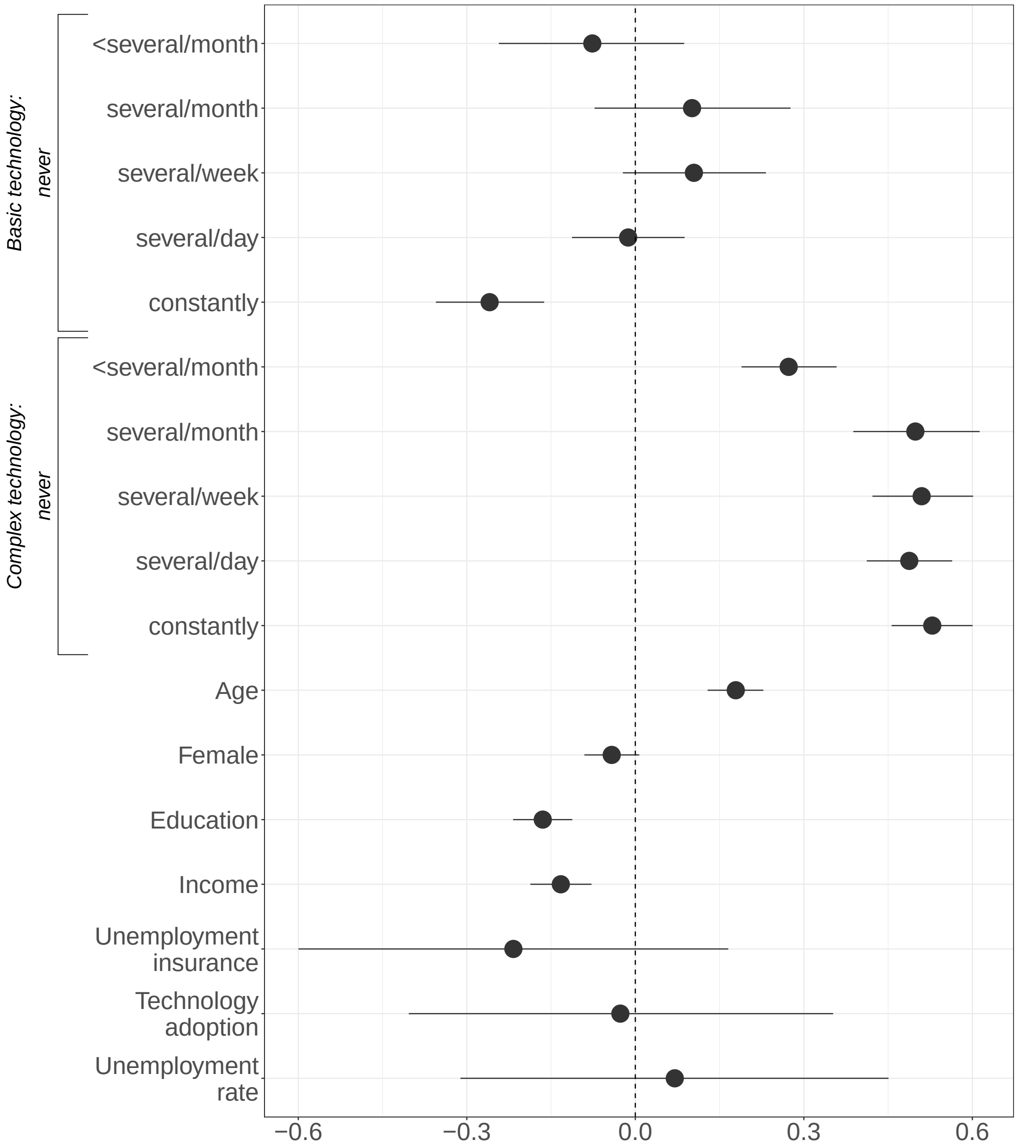
Figure A3: Job insecurity: Estimates based on Equation A1.



A.3 Descriptives: Cross-Sectional Surveys

Table A1 reports the polychoric correlations between the three measures of subjective risk and displays the frequency distributions of the four answer categories (ranging from *very unlikely* to *very likely* from left to right). The bar plots reveal a right-skewed distributional pattern, which is slightly less pronounced in the case of the RTM survey, with the second category (*unlikely*) being always the median in the RTM survey compared to the median of 'very unlikely' in the case of the DigiWelfare survey. Across both surveys and all risk items, the last category (*very likely*) indicating strong expectations of technology-related unemployment within the next five years is by far the least chosen category. The three

Figure A4: Pace overwhelming: Estimates based on Equation A2.



risk measures are strongly positively correlated (although, again, slightly less in the RTM survey), pointing to common underlying factors. The three measures also exhibit high degrees of internal consistency (Cronbach's α equals 0.88 in the DigiWelfare and 0.81 in the RTM data) and unidimensionality (the variation explained by the first component of a principle component analysis equals 80 percent in the DigiWelfare and 72 percent in the RTM survey).

Table A1: Distributions of and polychoric correlations between three measures of subjective risk (DigiWelfare survey | RTM survey).

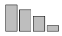
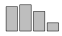
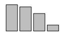
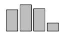
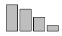
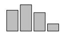
Subjective risk of	Automation	Internet	Skills
Automation	 | 		
Internet	0.79 | 0.72	 | 	
Skills	0.77 | 0.64	0.77 | 0.63	 | 

Figure A5 shows the proportion of individuals who expect technology-related unemployment (i.e., those individuals who think that the proposed scenarios are *likely* or *very likely*) due to the three types of risk over the next five years in both surveys. The percentage of respondents perceiving risks is lower in the DigiWelfare survey than in the RTM survey, with 29-32 percent reporting subjective risk in the DigiWelfare survey compared to 35-39 percent in the RTM survey.

Figure A6 plots the percentage of perceived risks for each country in the two samples. The descriptive results suggest that the higher average percentage of technology-related unemployment fears in the RTM survey is partly explained by the responses from individuals living in emerging market economies like Chile, Mexico, and Turkey, which exhibit very high levels of subjective risk. However, the levels of perceived risks are also higher in those countries in the RTM survey that are included in the DigiWelfare survey as well (i.e., Germany, Poland, Spain, and the United States), with the differences being exceptionally stark in the case of Poland (roughly 16-20 percentage points higher in the RTM survey than in the DigiWelfare survey).

The proportion of respondents choosing the residual category (*don't know/can't choose*) is considerably higher in the DigiWelfare survey (16-18 percent) than in the RTM survey (6-8 percent), as shown in Table A2. However, as shown in Figure A7, when these residual responses are included as baseline, the share of individuals perceiving risk drops only slightly more in the DigiWelfare survey (about 5-6 percentage points) than in the RTM survey (about 4-5 percentage points).

Figure A5: Percentage of respondents perceiving risk across surveys.

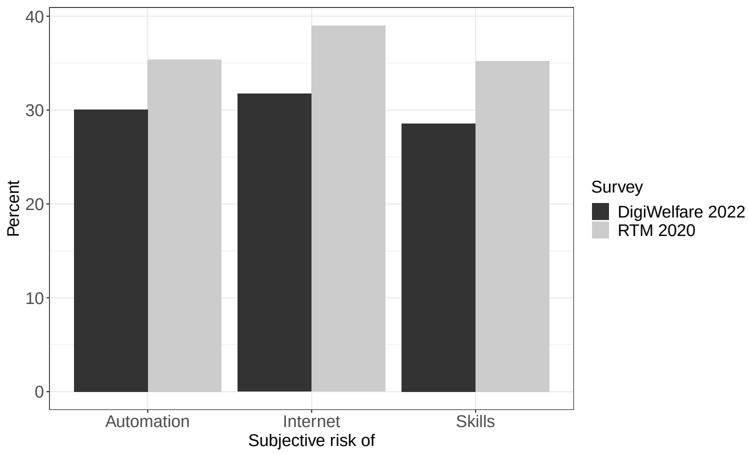


Figure A6: Percentage of respondents perceiving risk across surveys and countries.

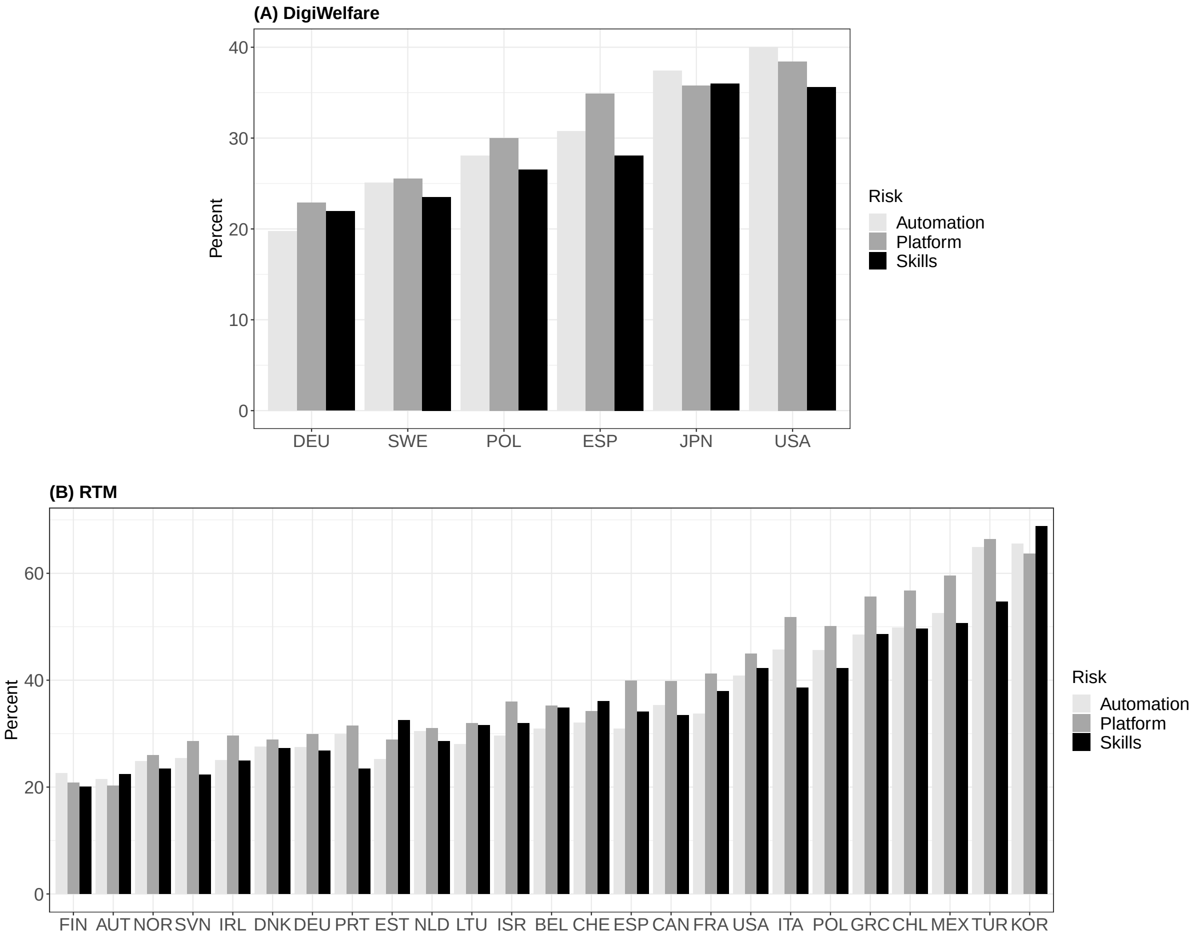


Table A2: Response distribution across three items on technological risk in percent (note: percentage points do not sum up to 100 due to rounding).

Survey *Country*	Risk	Very unlikely	Unlikely	Likely	Very likely	Don't know
DigiWelfare	Automation	33	27	18	7	16
	Platform	29	27	19	7	18
	Skills	33	27	17	7	16
Germany	Automation	45	26	13	4	12
	Platform	41	26	15	5	14
	Skills	44	24	14	5	13
Japan	Automation	16	27	20	6	31
	Platform	14	28	20	4	34
	Skills	14	28	20	5	32
Poland	Automation	28	32	19	5	15
	Platform	26	31	21	5	18
	Skills	26	34	17	5	17
Spain	Automation	34	27	20	7	12
	Platform	26	27	24	6	17
	Skills	33	30	18	7	13
Sweden	Automation	42	24	16	7	11
	Platform	40	23	16	7	14
	Skills	44	23	14	7	12
USA	Automation	29	23	22	13	13
	Platform	28	25	21	13	14
	Skills	33	24	18	13	12
RTM	Automation	29	31	23	10	6
	Platform	25	31	26	9	8
	Skills	27	34	24	9	7

Figure A7: Percentage of respondents perceiving risk across surveys, excluding and including the residual category.

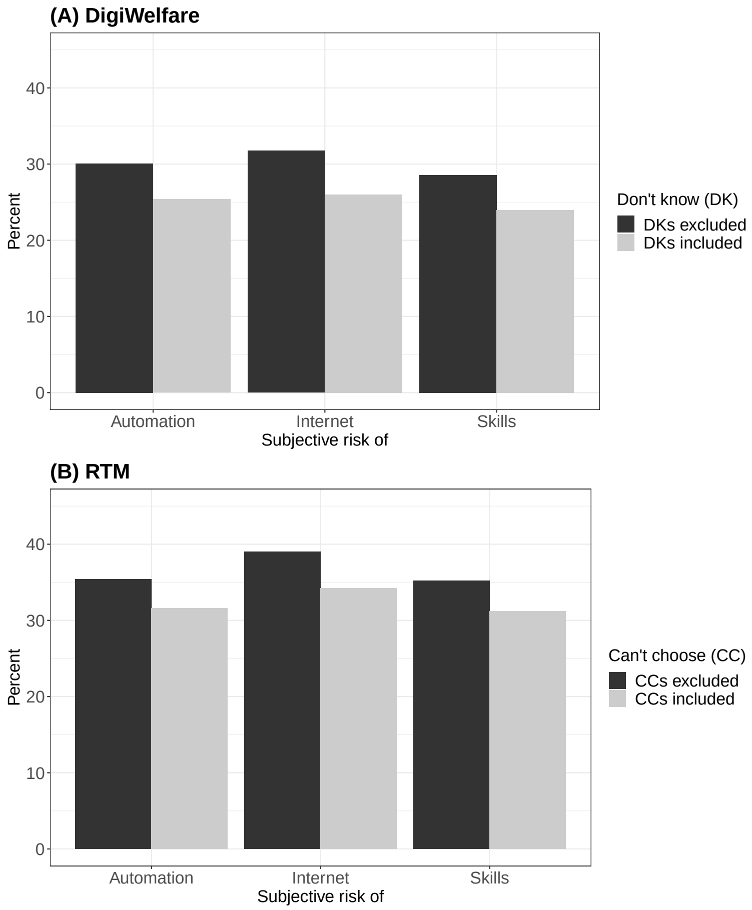
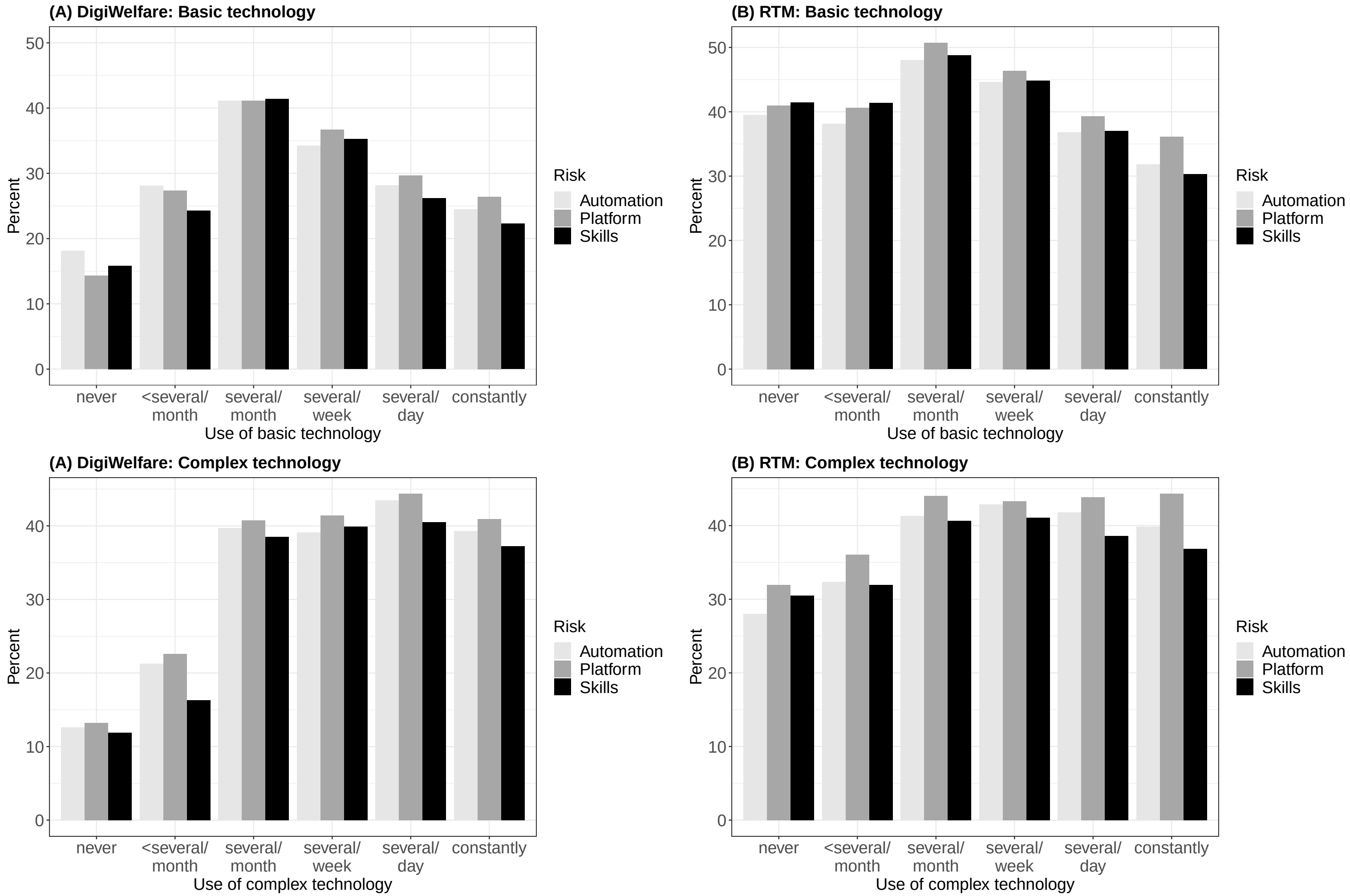


Table A3: Frequency of the use of various technologies in percent (note: percentage points do not sum up to 100 due to rounding).

Frequency of use	Basic technology		Complex technology	
	DigiWelfare	RTM	DigiWelfare	RTM
Never	16	10	47	40
Less than several times a month	4	3	8	11
Several times a month	5	3	6	5
Several times a week	14	7	13	9
Several times a day	34	25	16	16
Constantly, most of the day	26	50	9	19
Frequency of use	**Calculation/statistics**		**Programming**	
	DigiWelfare	RTM	DigiWelfare	RTM
Never	34		66	
Less than once a week	22		14	
At least once per week	25		12	
Usually daily	20		9	

Figure A8: Descriptive relationship between technology use and subjective technological risk.



A.4 US Sample

A.4.1 Question Wording and Scales for Policy Preferences

This section provides the exact wording of the survey questions and the response scales used to measure policy preferences in the US analysis. All responses were transformed into binary variables for analysis.

- **Support for Donald Trump (Dummy)**
  - **Question:** If Donald Trump runs again for president, would you vote for him in 2024?
  - **Scale:** Definitely not (1) to Definitely (4).
  - **Coding:** Responses of 3 ("Probably") and 4 ("Definitely") were coded as 1; all others were coded as 0.
- **Consumption Ethnocentrism (Dummy)**
  - **Question:** How much would you agree with the following statement: "American people should always buy American-made and brand products instead of imports from other countries"?
  - **Scale:** Strongly disagree (1) to Strongly agree (5).
  - **Coding:** Responses of 4 ("Agree") and 5 ("Strongly agree") were coded as 1; all others were coded as 0.
- **Pro-Offshoring Sentiment (Dummy)**
  - **Question:** Do you think the federal government should raise taxes on American companies that offshore jobs to foreign countries?
  - **Scale:** Strongly disagree (1) to Strongly agree (5).
  - **Coding:** Responses of 4 ("Agree") and 5 ("Strongly agree") were coded as 1; all others were coded as 0.
- **Trade Favorability Index (Dummy)**
  - **Question:** Generally, have increasing amounts of trade with other countries been good or bad for the following groups? *Groups:* American economy, workers, companies, consumers, you and your family.
  - **Scale:** Very bad (1) to Very good (5).
  - **Coding:** Responses were combined into an index, and scores above the median were coded as 1; all others were coded as 0.
- **Against Taxing the Rich (Dummy)**
  - **Question:** Do you think the federal government should increase or decrease the taxes paid by the wealthiest 1% of Americans, or keep the level about the same?

  - **Scale:** Increase a lot (1) to Decrease a lot (5).
  - **Coding:** Responses of 4 ("Decrease somewhat") and 5 ("Decrease a lot") were coded as 1; all others were coded as 0.

- **Anti-Immigration Sentiment (Dummy)**
  - **Question:** Do you think the federal government should increase or decrease the number of legal immigrants allowed into the United States, or keep this number about the same?
  - **Scale:** Increase a lot (1) to Decrease a lot (5).
  - **Coding:** Responses of 4 ("Decrease somewhat") and 5 ("Decrease a lot") were coded as 1; all others were coded as 0.

A.4.2 Question Wording and Scales for Technology Perceptions

This section outlines the survey questions and response scales used to measure perceptions and experiences with technology. The responses were designed to capture subjective views on the pace of technological adoption, concerns about job displacement, and attitudes toward automation and AI.

- **Pace of Technological Integration (Ordinal)**
  - **Question:** How fast have new technologies been incorporated in your work?
  - **Scale:** Extremely slow (1), Somewhat slow (2), Average (3), Somewhat fast (4), Extremely fast (5).

- **Job Loss Due to Technology (Binary)**
  - **Question:** Did you or anyone close to you lose their job because of technology?
  - **Scale:** No (0), Maybe (1), Yes (2).
  - **Coding:** Responses were recoded into a binary variable where "Yes" was coded as 1, and all other responses as 0.

- **Perceived Risk of Job Automation (Ordinal)**
  - **Questions:** How much do you agree with the following statements?
    - My job is likely to be replaced by robots and artificial intelligence in the upcoming 5–10 years.
    - With more and more robots everywhere, my chances of finding another job are small.
    - Increased automation and the use of robots will mean less and less work for people.
    - I am personally worried that what I do now in my job will be automated.
  - **Scale:** Strongly disagree (1), Somewhat disagree (2), Neither agree nor disagree (3), Somewhat agree (4), Strongly agree (5).

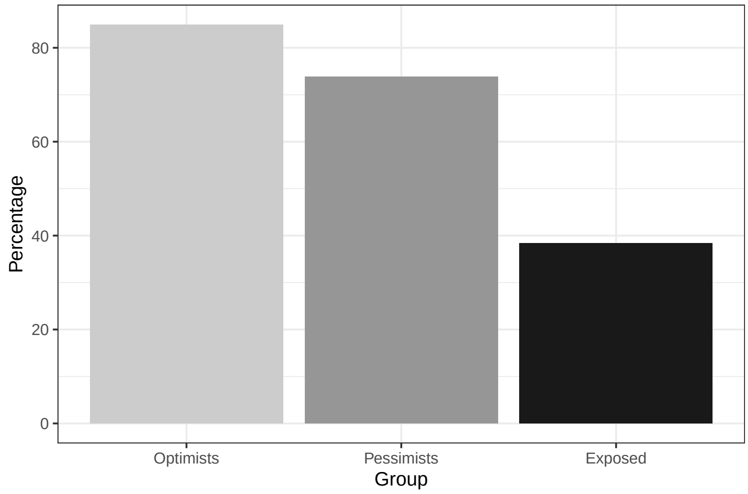
- **Perceived Benefits of Technology (Ordinal)**
  - **Questions:** How much do you agree with the following statements?
    - Robots can do many jobs better than people.
    - Robots will help American companies keep pace with foreign competitors.
  - **Scale:** Strongly disagree (1), Somewhat disagree (2), Neither agree nor disagree (3), Somewhat agree (4), Strongly agree (5).
- **Open-Ended Question About Technology Experience**
  - **Question:** Can you briefly share your experience with technology at work with us? Do you like or dislike having these machines or AI tools?
  - **Response Type:** Open-ended.

A.4.3 Operationalization

The variables Optimists, Pessimists, and Exposed are constructed as follows:

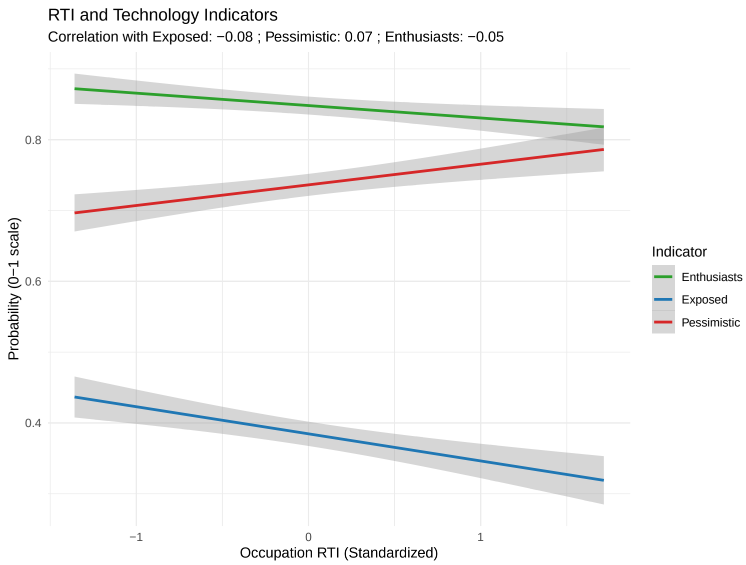
- Optimists: This variable captures individuals who expressed enthusiasm for technology. It is constructed as a dummy variable, where a value of 1 indicates that at least one of the following conditions was met: strongly agreeing with statements about robots benefiting America or performing jobs better than people, or being classified as enthusiasts based on their open-ended responses.
- Pessimists: This variable represents individuals with significant concerns about technology. It is constructed as a dummy variable, where a value of 1 indicates that at least one of the following conditions was met: strongly agreeing with statements reflecting sociotropic concerns, worries about the future impact of technology, or being classified as concerned based on their open-ended responses.
- Exposed: This variable identifies individuals more likely to experience technological disruptions. It is constructed as a dummy variable, where a value of 1 indicates that at least one of the following conditions was met: scoring high on the question about losing a job due to automation or perceiving technological change as too fast.

Figure A9: Percentage of optimists, pessimists, and exposed.



A.4.4 Descriptives

Figure A10: Correlation between subjective perceptions and RTI risk.



A.5 Open-Ended Responses

A.5.1 Examples

Here are some of the themes identified among open-ended responses with keywords and examples.

Example of themes that were mainly pessimistic

- **Fear of Job Displacement and Future Employment**
  - **Keywords:** "job is not safe," "replacing," "obsolete," "fired," "layoffs," "reduces hours," "makes jobs scarce," "unemployment."

- "I dislike having them because my job is not safe in the future."

- **Adaptation to New Technologies**
  - **Keywords:** "changing so fast," "evolving," "rapid pace," "overwhelming," "difficult to keep up."
  - "Things are changing so fast. I am 58 and hopefully this will be my last job because I have become too old to adapt to all the changes."

- **Human Element in Work**
  - **Keywords:** "less human," "impersonal," "lacks empathy," "mechanical," "no human interaction."
  - "It's very sanitizing and eliminates connections with customers that causes me to dislike it."

- **Skepticism Towards AI**
  - **Keywords:** "doesn't work well," "not accurate," "prone to errors," "unreliable," "crashes."
  - "We have limited AI tools at work but i have found that for the most part someone always needs to go behind and correct mistakes they have made when they are used."

- **AI in Creative Fields**
  - **Keywords:** "stolen works," "AI-generated art," "destroys creativity," "replaces artists."
  - "The problem is a lot of the 'creative' AI have been trained on stolen works."

- **Technology in Customer Service**
  - **Keywords:** "customers hate it," "prefer humans," "difficult to use," "confusing."
  - "i do not like the automated system we use for hospital billing. there are so many prompts it is difficult to actually speak to a real person and the attempt to have the customer use the automated system is challenging for most. it is far better to speak to an actual person but it is cheaper for the hospital to use this system rather than fully staff the department. Customers do not like it at all. they want to actually speak with a human."

- **Dependence on Technology**
  - **Keywords:** "less value," "diminish my worth," "dependent on AI," "takes decision-making away."
  - "AI tools have become commonplace in my line of work. I have become significantly more concerned about my job security in recent years. I don't think I'll be replaced anytime soon, but the threat is there, and AI tools diminish my value to the organization."

- **Technological Inequality and Redistribution**
  - **Keywords:** “benefit the rich,” “exploitation,” “profits over people,” “economic collapse.”
  - “Corporations are evil, and robots are just tools. As a country, we all need to acknowledge that our society is not structured to ensure that all, or even a majority of Americans have access to safe jobs that pay a living wage.”

Example of themes that were mainly optimistic

- **Increased Efficiency and Productivity**: People appreciate AI tools for their ability to streamline workflows and reduce time spent on repetitive tasks.
  - Key Words: “makes my life easier”, “time-saving”, “streamlines”, “enhanced productivity”, “better decisions”, “efficiency.”
  - Example Sentence: “AI tools and machines have the potential to streamline processes, automate repetitive tasks, and enhance productivity.”
  - Example Sentence: “As a general manager, my experience with technology at work has been transformative. The integration of machines and AI tools has greatly enhanced productivity, efficiency, and decision-making processes within the organization..”
- **AI as a Supplementary Tool**: Many individuals see AI as a complementary tool that augments human capabilities rather than replacing jobs.
  - Key Words: “augment”, “support”, “complementary.”
  - Example Sentence: “I work in higher education as a professor. We see AI tools currently used as supplementary/supportive technologies, not replacements for work done through humans.”
  - Example Sentence: “AI has been able to take some of the work I usually do on contract, but always expanding my skills is part of my job. I see it as growth instead of replacement.”
- **Satisfied with Using Technology**: AI helps improve accuracy and reduce errors in various tasks, which is widely appreciated.
  - Key Words: “reduces errors”, “accuracy”, “reliable.”
  - Example Sentence: “Artificial intelligence system provide accurate results and very reliable source. “
- **Access to New Opportunities**: AI opens doors to innovative solutions, creative approaches, and unexplored areas for growth.
  - Key Words: “new opportunities”, “creative solutions”, “growth.”
  - Example Sentence: “They help create new opportunities. They create a better future.”

- **Relieving Tedious Work**: AI and automation reduce the burden of mundane or repetitive tasks, allowing humans to focus on more meaningful work.
  - Key Words: "reduces burden", "focus on meaningful tasks", "eliminates tedious parts" "reduces workload", "physical burden", "help humans."
  - Example Sentence: "In my next job, I worked at a law firm. I did not see much technology taking over here, other than computers made it easier to share and submit paperwork instead of having to print everything and physically hand things to people or courts. And now with zoom, you don't even always have to be in person.."
- **Technology in Healthcare**: In fields like healthcare, AI is appreciated for improving patient care and treatment processes.
  - Key Words: "healthcare", "improved treatment", "coexist with humans."
  - Example Sentence: "Being in healthcare for the past 35 years, I can attest that innovation via technology has made my work more efficient and has contributed to better patient care."
- **Future Adaptability**: Many recognize AI as an inevitable advancement, preparing to adapt to its integration in the workplace.
  - Key Words: "adapt", "inevitable", "future."
  - Example Sentence: "Change in technology is usually inevitable and it is for the good benefit of the organisation and working conditions at large."

A.5.2 Validation of OpenAI-Assigned Topics

To assess the accuracy of topic classification assigned by OpenAI, we conducted a validation study on a random sample of 300 cases, manually coding the topics and comparing them with the machine-generated classifications. The confusion matrix in Figure A11 illustrates the performance of the classification model.
The performance metrics of the classification model are as follows:

- **Accuracy**: 89.38% – proportion of correctly classified topics.
- **Precision**: 93.35% – proportion of correctly predicted topic labels among all assigned labels.
- **Recall**: 91.44% – proportion of correctly identified topics among all true topic labels.
- **F1-score**: 92.01% – harmonic mean of precision and recall, reflecting overall classification performance.

The confusion matrix shows that the model performs well overall, with most classifications aligning with the manually validated topics. However, some misclassifications are observed, particularly in lower-frequency topics.

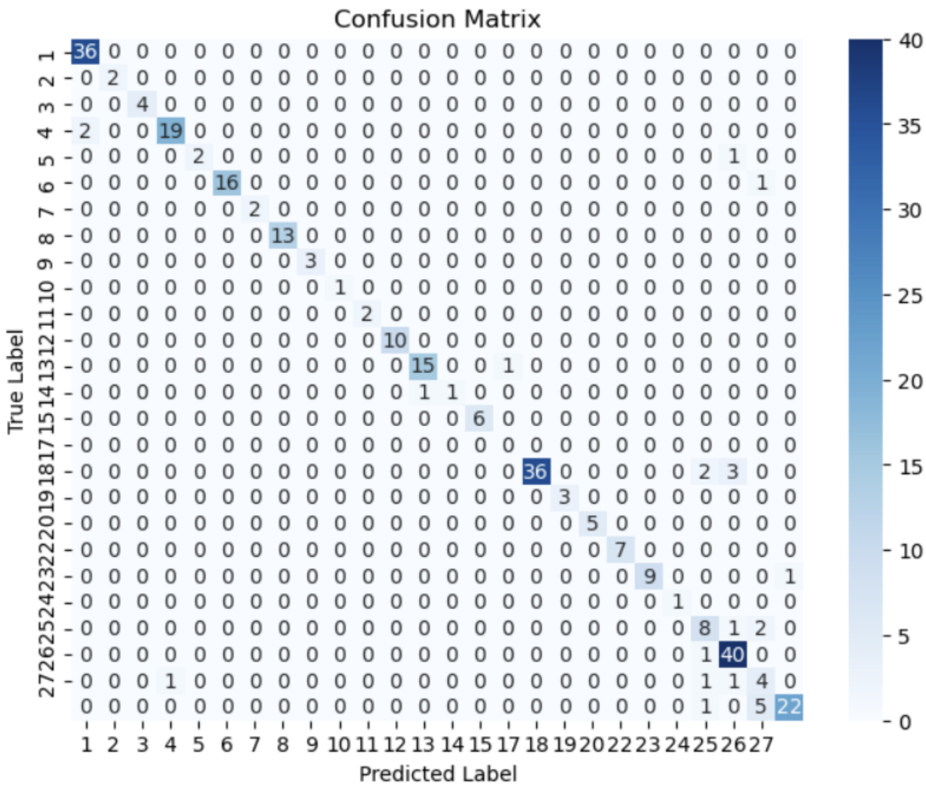


Figure A11: Confusion matrix for OpenAI-assigned topics based on a manually validated sample.

The high precision score (93.35%) indicates that when the model assigns a topic, it is usually correct. The recall score (91.44%) suggests that while most true topics are identified, some instances remain misclassified. The F1-score (92.01%) confirms a strong balance between precision and recall, demonstrating the reliability of the classification system.

Overall, the automated topic classification system shows robust performance, with minor limitations that could be improved through additional training or fine-tuning of the classification model.

A.5.3 Additional Validation of OpenAI-Assigned Topics via Word Clouds

As an additional validation step, we analyze the textual content of each predicted topic using word clouds (see Figure A12). The figure below presents word clouds generated from the responses, displaying the most frequently used words for the top 15 most common topics.

The word clouds help visually assess the coherence of topic assignments. Since each word cloud contains terms related to its assigned topic, it further suggests that the classification model correctly captured meaningful distinctions between topics.

Overall, this validation step provides qualitative insights into the effectiveness of OpenAI's topic classification and supports the quantitative evaluation presented earlier.

Figure A12: Word cloud representation of OpenAI-assigned topics. Each cloud represents the most frequent words within a given topic.