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#2026-014

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Published 9 November 2026

DOI: https://www.doi.org/10.53330/GGJN5216

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UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology
UNU-MERIT

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Age, Education, and Occupational Gradients in Artificial Intelligence Anxiety*

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Abstract

Higher levels of anxiety about artificial intelligence (AI) among older and less-educated adults have now been documented in large population-based samples from high-income countries. Much less is known about how these differences arise, whether age and education interact, and whether occupational position helps understand them, particularly in middle-income economies. It evaluates the measurement structure of the scale, tests flexible functional forms and age–education interactions, and decomposes both gradients by occupational skill level, task class, and routine-task intensity. AI anxiety increases approximately linearly with age, whereas its association with education is strongly negative and nonlinear, with the largest gap between the lowest and highest education categories. Age and education largely show additive associations with AI anxiety. The age gradient is weaker among university graduates, although evidence for an interaction is limited for the total score and more evident for several subdimensions. Among the 409 employed respondents, occupational skill level and task class substantially reduce the education gradient but leave the age gradient unchanged: labor-market position helps explain educational but not age differences. Routine-task intensity contributes little beyond broad occupational categories, while professionals and managers report relatively high anxiety conditional on education and task class. Because the cross-sectional design precludes causal and age-period-cohort interpretations, the estimates are conditional associations. Even so, the results show that AI anxiety is not randomly distributed: it is systematically structured by human capital, age, and occupational position in a large middle-income economy.

Keywords: artificial intelligence anxiety; human adaptation to AI; AI adoption; age and education gradients; occupational exposure; task content; human capital; technological change; automation; Turkey

JEL codes: J24, O33, D91, J14, I21

* Data collection for this study was supported by the Scientific and Technological Research Council of Türkiye (TÜBİTAK) under the 1002-A Short-Term Support Module [grant number 125K265].
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1. Introduction

Artificial intelligence (AI) is spreading rapidly through labor markets, creating adjustment challenges for workers and institutions. Alongside the expected productivity gains, a substantial share of the population reports anxiety about AI, a domain-specific apprehension that spans fear of job displacement, skill obsolescence, dependence, and the growing opacity of algorithmic systems (J. Li & Huang, 2020; Wang & Wang, 2022). Representative European survey data show that public attitudes toward workplace automation have grown more negative over time, most sharply among women and lower-educated blue-collar workers (Gnambs & Appel, 2019). These concerns may also have consequences for technology adoption and labor-market behavior. Research on technology acceptance and computer self-efficacy indicates that anxiety and perceived ease of use are among the stronger correlates of whether people take up new tools (Davis, 1989; Compeau & Higgins, 1995; Venkatesh et al., 2003). Evidence specific to AI points the same way: in a structural model of AI acceptance, AI literacy raises acceptance both directly and indirectly by lowering anxiety, and anxiety itself carries a small but significant negative effect on acceptance (Schiavo et al., 2024). Recent studies of generative AI reach similar conclusions: anxiety has a small negative association with the intention to adopt generative AI (Pham et al., 2026), it weakens the link between positive attitudes toward AI and motivation among university students (Girgin, 2026), and trust in AI, itself rooted in trust in governments, technology companies, and the scientific community, predicts the intention to use AI-based technologies (Amir et al., 2025). How people adapt to AI therefore depends not only on what the technology can do but also on how they appraise it. Automation risk has also been linked to redistribution preferences and policy attitudes (Thewissen & Rueda, 2019; Kurer & Gallego, 2019). AI anxiety may influence whether people adopt new technologies, which occupations they choose, and whether they support automation-related policy.

This study does not directly examine these outcomes but identifies which groups experience greater AI anxiety and the magnitude of these differences. The analysis focuses on age and education, two theoretically relevant dimensions of how individuals experience and adapt to technological change, with education serving as a standard empirical proxy for human capital. Task-based models of automation imply that the burden of technological change falls unevenly on workers. Routine, codifiable tasks are the most automatable and are concentrated among older and less educated workers (Autor et al., 2003; Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2022). Human-capital theory adds a life-cycle dimension: because the horizon over which retraining can be amortized shortens with age, older workers rationally invest less in new skills and face a higher perceived risk of obsolescence (Becker, 1964; Ben-Porath, 1967). Education raises general adaptive capacity and the likelihood that one's tasks complement rather than compete with new technology. These mechanisms generate testable predictions about the demographic profile of AI anxiety.

A key limitation concerns the interpretation of age. Because the study uses a single cross-section, we refer throughout to an age gradient rather than an aging effect. In cross-sectional data, older

respondents differ from younger ones not only in age but also in schooling systems, technology exposure during formative years, and occupational history. Whether the same individuals would grow more anxious as they age is a question that design cannot answer, and the issue is revisited when interpreting the results.

The existing evidence is uneven rather than absent. A long tradition in the psychology of technology finds that computer and technology anxiety rise with age (Czaja et al., 2006; Charness & Boot, 2009), and a recent German validation study of the AIAS in a quota-based sample of 3,270 adults records the highest mean anxiety among older respondents and among those with low education (Hajek et al., 2025). That the age and education gradients exist is therefore not in question. The existence of age and education differences is therefore reasonably well established. What remains unclear is how these differences are related to one another and to occupational position. The German study, like most of this literature, compares unadjusted group means across broad age bands and three education levels, without adjusting the two for each other or for income and family background, testing the functional form of the age gradient, asking whether education moderates it, and the occupational information that would indicate where the gradients originate. Nor is the picture uniform. A recent multidimensional study of AI anxiety reports null age-group differences, attributing this to the normalization of AI across cohorts (Uğur & Dursun, 2025), and comparative work on automation fear finds it concentrated among lower-educated and lower-income workers, in line with expectations for education, but higher among younger rather than older respondents (Włoch et al., 2025). Finally, the bulk of the evidence comes from high-income Western settings or from student and worker convenience samples, leaving the general adult populations of middle-income economies understudied, even though these economies face high occupational exposure to generative AI (Gmyrek et al., 2025). Since most attitudinal scale validation and determinant studies are conducted on Western, educated, industrialized, rich, and democratic (WEIRD) samples, effects estimated elsewhere need not transfer (Muthukrishna et al., 2020). Evidence from other middle-income settings is only beginning to accumulate; across sixteen Latin American countries, education is among the most consistent predictors of fear of job loss to AI and robotics (Cremaschi et al., 2025). The literature on human adaptation to AI faces a related constraint. Much of the recent evidence on AI anxiety and adoption comes from university students (Al-Maroof et al., 2026; Girgin, 2026), from academic and research users of generative AI (Pham et al., 2026), or from digital natives (Kuhail et al., 2025). Such samples are informative about the psychological mechanisms of adoption, but they offer little variation in age, education, and occupation, which are precisely the dimensions along which the capacity to adapt to AI is likely to differ.

This study characterizes the age and education gradients of AI anxiety in an online survey of working-age adults in Turkey, and its contribution lies in what is done with those gradients rather than in establishing that they exist. First, the functional form of the age gradient is tested rather than assumed, using flexible polynomial specifications and nonparametric smoothing. Second, the age slope is estimated within each education group, with marginal slopes and confidence intervals

reported rather than moderation inferred from a single interaction coefficient; this allows the substitutes and additive views of human capital and the work horizon to be distinguished. Third, occupational skill level, task class, and routine-task intensity are added for the employed subsample, which decomposes how far each gradient reflects labor-market position and provides a first pass at the task-exposure channel that the literature usually only invokes. Fourth, the setting is a large middle-income economy with high projected exposure to generative AI, a class of country for which this evidence remains scarce. Of these, the occupational decomposition is the least common in work on AI anxiety, which normally stops at demographic correlates: it is what allows the analysis to ask not only who is anxious, but how much of that anxiety travels with the jobs people hold. In doing so, the study extends the literature on AI anxiety and human adaptation to AI beyond student and specialized-user samples to a broad working-age population in which age, education, and occupation vary jointly. The Artificial Intelligence Anxiety Scale (AIAS) is measured in full, and the results are probed across its subdimensions, across related outcomes, and against general anxiety symptoms.

The results can be summarized as follows: AI anxiety increases with age by approximately two points per decade on the 16-80 AIAS scale, with no evidence of curvature. Education shows the largest gap among the demographic variables included: holding age, gender, income, and parental education constant, respondents with a bachelor's degree or more score about ten points lower than those with at most middle school. However, the two gradients are not simply additive. The age slope is steep and precisely estimated in the two lowest education groups and is statistically indistinguishable from zero among university graduates. The joint interaction test does not reach significance at the 5 percent level, so this is presented as suggestive buffering rather than established moderation; however, the pattern recurs and reaches joint significance for job-replacement anxiety, sociotechnical-blindness anxiety, and a separate automation-anxiety index. Among employed respondents, the occupational gradient is steep in its own right: relative to workers in abstract tasks, those in routine tasks score about six points higher and those in manual tasks about twelve. Occupational skill level and task class absorb much of the education gradient while leaving the age gradient untouched, and a finer routine-task-intensity index adds nothing once the broad task class is controlled for. All gradients survived the adjustment for general anxiety symptoms and reappeared with opposite signs for AI attitudes, where higher scores indicate more positive attitudes toward AI.

The remainder of this paper is organized as follows: Section 2 develops the conceptual background and presents the hypotheses. Section 3 describes the data and the empirical strategy. Section 4 reports the results, and Section 5 concludes.

2. Conceptual Background and Hypotheses

Three strands of literature bear on the demographic patterning of AI anxiety: The first comes from the economics of technological change, where the central question is not simply whether new

technologies matter, but who is exposed to them, through which tasks, and with what capacity to adapt. Task-based accounts of technological change show that new technologies substitute most directly for routine and codifiable work while complementing analytical, problem-solving, and interpersonal tasks, thereby generating uneven exposure across workers and occupations rather than uniform effects across the labor market (Autor et al., 2003; Acemoglu & Autor, 2011; Autor & Dorn, 2013). This literature links technological vulnerability to human capital, occupational position, and the transferability of skills. It also emphasizes that technological anxiety is historically recurrent: fears of displacement regularly accompany major technological advances, even when aggregate long-run employment effects prove more mixed than contemporary observers first expect (Mokyr et al., 2015; Autor, 2015; Graetz & Michaels, 2018; Bessen, 2019; Hötte et al., 2023). Worker-level and political-economy research further suggests that the distributional consequences of technological change are socially salient, shaping insecurity and preferences for protection and redistribution (Kurer & Gallego, 2019; Thewissen & Rueda, 2019). However, the classic automation literature is no longer sufficient for AI anxiety research. Recent AI-specific exposure measures show that contemporary AI, especially generative AI, reaches not only routine production or clerical tasks but also a broad range of cognitive, professional, and technical activities that earlier frameworks often treated as relatively sheltered (Brynjolfsson et al., 2018; Webb, 2019; Felten et al., 2021; Eloundou et al., 2024). Therefore, the economics literature provides a crucial starting point for this study: anxiety about AI may be structured by human capital, occupational task content, and perceived exposure to technological substitution or complementarity.

The second strand comes from psychological and behavioral research on how individuals appraise and approach new technologies. This literature shows that responses to technological change depend not only on objective exposure or formal skills, but also on perceived competence, confidence, and readiness to engage with unfamiliar systems. Research on computer self-efficacy demonstrates that beliefs about one's own ability to use digital tools affect both the willingness to adopt them and the anxiety experienced when doing so (Compeau & Higgins, 1995). Related work on technology readiness conceptualizes technology-related optimism, innovativeness, discomfort, and insecurity as stable orientations that shape whether people are predisposed to embrace or resist new tools (Parasuraman, 2000).

Technology-acceptance models develop a complementary perspective by showing that perceived usefulness and perceived ease of use are central predictors of acceptance, while broader unified models incorporate performance expectations, effort expectations, and facilitating conditions into the study of adoption behavior (Davis, 1989; Venkatesh et al., 2003). Within this strand, anxiety is not merely a generalized negative effect; it is part of a cognitive appraisal of complexity, controllability, and anticipated demands of learning. This matters for demographic analysis because age differences in technology engagement are often mediated by technology-specific psychological variables. Older adults tend to report higher computer anxiety and lower technology self-efficacy, which help explain the variation in technology use more directly than age alone

(Czaja et al., 2006; Charness & Boot, 2009). From this perspective, AI anxiety may reflect not only labor market fears such as displacement or deskilling, but also concerns about whether one can understand, learn, supervise, and safely use AI systems in everyday and work contexts.

The third strand is a younger AI-specific literature on attitudes toward algorithms and artificial intelligence. Experimental studies on algorithm aversion show that people may avoid algorithmic judgment after observing errors, even when algorithmic performance is objectively strong. Parallel work on algorithm appreciation demonstrates that people in other contexts prefer algorithmic recommendations to human ones (Dietvorst et al., 2015; Logg et al., 2019). Beyond judgment and advice tasks, experimental evidence shows that merely attributing identical output to AI rather than to a human causally lowers the meaning people derive from a task and their willingness to contribute effort (Nikolova et al., 2026), indicating that reactions to AI extend to the perceived value of human contribution itself. These findings establish that reactions to AI are not reducible to a simple continuum from technophilia to technophobia; instead, they depend on perceptions of accuracy, transparency, accountability, trustworthiness, and the appropriate boundaries of machine decision-making. More recent work has strengthened this literature by developing validated scales that distinguish between broad evaluative attitudes toward AI and more specific forms of anxiety related to using, learning, depending on, or being displaced by AI systems (Schepman & Rodway, 2020; Wang & Wang, 2022). This measurement advance is important because it allows researchers to move beyond generic acceptance questions and isolate AI as a distinct object of concern.

The theoretical case for treating AI anxiety as multidimensional is made most explicitly by J. Li and Huang (2020), who derive eight sources of AI anxiety (privacy violation, bias behavior, job replacement, learning, existential risk, ethics violation, artificial consciousness, and lack of transparency) from integrated fear acquisition theory, and group them in pairs into the four pathways by which such fears are acquired: conditioning, vicarious exposure, transmission of information and instruction, and the absence of any pertinent prior experience. Two implications bear on the present analysis. First, AI anxiety need not rest on direct experience with AI, which is one reason it can be widespread in populations where actual exposure remains uneven. Second, the two dimensions most closely tied to human capital, job replacement and learning, fall under vicarious exposure, the pathway in which fear is acquired by observing others; occupational position and schooling shape whom one observes and against whom one compares, which is a further reason to expect anxiety to be structured along precisely these lines. The distribution of anxiety also matters for what follows from it. In a structural model of AI acceptance estimated on 313 respondents, AI literacy raises acceptance both directly and indirectly through lower anxiety, with anxiety exerting a small but significant negative direct effect and partially mediating the effect of literacy (Schiavo et al., 2024). Anxiety is therefore not only an outcome worth measuring but also a channel through which unequal preparation for AI may translate into unequal use of it. If anxiety is concentrated among older and less-educated adults, the groups already least equipped to adapt, then its distribution bears directly on who ends up benefiting from the technology and who does not.

Simultaneously, the AI-specific literature has advanced faster on measurement than on explanation. Validated instruments now exist in several languages, and the population studies accompanying them report higher anxiety among older and less-educated adults (Hajek et al., 2025). Much of the remaining evidence comes from experimental settings, convenience samples, or studies focused on trust, aversion, or acceptance in specific decision domains. The open questions are therefore no longer whether AI anxiety varies with age and education, but how: how large the gradients are once each is adjusted for the other and for income and family background, what shape the age gradient takes, whether education attenuates it or leaves it intact, and how much of either gradient is attributable to the occupational positions that people of different ages and levels of schooling occupy.

These three strands suggest that AI anxiety should not be understood as a purely psychological reaction or a simple reflection of objective labor market exposure. It is more plausibly a domain-specific appraisal shaped by the intersection of economic position, task content, human capital**,** and beliefs about one's ability to cope with technological change. This framing is especially useful here because age and education sit at the intersection of all three literatures. Both help structure exposure to technological change, influence the costs and expected returns of adaptation, and are associated with differences in technology-related confidence and evaluative attitudes. Against this broader literature, the analysis now turns to hypotheses about age, educational attainment, and their possible interplay in shaping AI anxiety. More targeted literature directly related to each hypothesis is reviewed in the following subsections.

2.1 Age, Work Horizons, and Exposure

Several theoretical mechanisms may underlie the positive association between age and AI anxiety. The first operates through the life-cycle logic of human capital investment. In Ben-Porath's (1967) framework, individuals invest in skills until the discounted return equals the marginal cost. Because the remaining horizon over which any new investment can be amortized shrinks with age, the optimal level of retraining declines over the life cycle (Becker, 1964). When a general-purpose technology raises the rate at which existing skills depreciate, the same logic implies that older workers face a higher perceived risk of obsolescence and a lower expected payoff for adaptation. The mechanism has an empirical counterpart in the training literature: participation in work-related training declines with age, and the prospect of (early) retirement further depresses it, indicating that the remaining horizon, rather than age itself, drives the decline (Fouarge & Schils, 2009; Picchio, 2021).

The second mechanism is task-based learning. The routine-biased technological change literature shows that automation substitutes most directly for routine codifiable tasks, which are disproportionately performed by older and less-educated workers (Autor et al., 2003; Autor & Dorn, 2013; Acemoglu & Autor, 2011). Acemoglu and Restrepo (2022) attribute a large share of the rise in U.S. wage inequality to the displacement of workers from automatable tasks. Occupation-level estimates of computerization risk find that exposure is concentrated in routine,

lower-wage, lower-education jobs (Frey & Osborne, 2017). Workers who perceive their own task exposure have a corresponding basis for their anxiety. Two qualifications are important: Estimates of aggregate employment effects are mixed (Graetz & Michaels, 2018; Bessen, 2019; Hötte et al., 2023), so perceived and actual displacement risks need not coincide. Moreover, the exposure geometry of generative AI differs from that of earlier automation: large language models reach clerical, professional, and other cognitive occupations that the routine-biased framework classifies as sheltered (Brynjolfsson et al., 2018; Webb, 2019; Felten et al., 2021; Eloundou et al., 2024; Gmyrek et al., 2025). Routine-task exposure is therefore treated as one candidate channel rather than the whole story.

The third channel is psychological. Older adults report higher computer anxiety and lower technology self-efficacy, and the association between age and technology use runs through these variables rather than age (Czaja et al., 2006). Qualitative work identifies unfamiliarity, low confidence, and fear of error as central barriers for older adults encountering new devices (Vaportzis et al., 2017), and reviews emphasize normative age-related changes in cognitive and perceptual abilities (Charness & Boot, 2009).

These channels all predict a positive age gradient in the cross-section, but they are observationally similar in this design, and none can be distinguished from cohort explanations: older cohorts were schooled before digital technology and may report more anxiety at any age. The shape of the gradient is also open to further research. A pure horizon mechanism implies a roughly monotonic increase, whereas cohort-specific digital familiarity could accelerate at older ages. The functional form should be treated as an empirical issue.

Hypothesis 1 (age). AI anxiety increases with age; whether the relationship is linear or exhibits curvature is tested empirically.

2.2 Human Capital and the Education Gradient

Human capital theory predicts that education is protective. General education raises the capacity to acquire new skills, lowering the cost and raising the expected return of adapting to AI. It shifts workers toward non-routine analytic tasks that AI has historically complemented, in line with the long-documented complementarity between technology and skills (Katz & Autor, 1999). It also improves the information with which individuals can appraise technological risks. Risk-perception research holds that hazards perceived as poorly understood and uncontrollable evoke stronger dread (Slovic, 1987); insofar as education demystifies AI and increases perceived control, it should reduce anxiety. Comparative evidence finds that fear of automation is concentrated among lower-educated, lower-income, and lower-control workers (Włoch et al., 2025), and AI is perceived as a greater workforce threat in more unequal societies (Shoss & Ciarlante, 2022). A large German population study of the AIAS likewise records the highest mean anxiety among respondents with low education, although without conditioning on age, income, or occupation (Hajek et al., 2025). Gender may intersect with these gradients: repeated U.S. survey data show that fear of AI is concentrated among older adults, mitigated by education, and most pronounced among older

women (W. Li et al., 2025). Gender was used as a control variable in this study, leaving this intersection for future research. Objective exposure runs in the same direction: the risk of automation falls steeply with educational attainment (Nedelkoska & Quintini, 2018; Frey & Osborne, 2017), although the generative-AI exposure literature cited above cautions that this alignment may weaken as AI reaches educated cognitive workers. Because credential thresholds may matter more than years of schooling, education is considered as a categorical indicator.

Hypothesis 2 (education). Higher educational attainment is associated with lower AI anxiety, net of age, income, gender, and parental education.

2.3 Do Age and Education Interact?

Whether education buffers the age gradient is both theoretically interesting and policy relevant. One view treats human capital and the work horizon as substitutes: highly educated older workers hold more transferable skills; therefore, their age gradient should be flatter, implying a negative age by education interaction. A competing view treats the two as independent inputs, with age capturing the remaining horizon and cohort-specific familiarity and education capturing the stock of adaptable skills, so the gradients are additive. Direct evidence on the interaction is scarce: studies documenting both gradients typically report them one at a time, as in the German AIAS validation, which compares age bands and education levels separately and does not test whether they interact (Hajek et al., 2025). The finding that education mitigates fear of AI specifically at older ages (W. Li et al., 2025) is closer to the substitutes view. The distinction is important for policy-making. If education flattens the age gradient, expanding access to education and reskilling could address the age dimension of AI anxiety as well as its level. If the gradients are additive, reskilling would shift the levels but leave the age slope intact. The interaction is tested using a joint Wald test of all age by education terms. Because the interaction coefficients alone can be misleading, the implied marginal age slope is reported with a confidence interval for each education group (Brambor et al., 2006).

Hypothesis 3 (interaction). The age gradient in AI anxiety differs across education levels, tested against the null of parallel gradients.

2.4 General Anxiety Symptoms

A natural concern is that AI anxiety merely reflects an anxious disposition. To probe this, general anxiety symptoms are controlled for, measured by the anxiety subscale of the Depression Anxiety Stress Scales (DASS-21). The DASS-21 is a symptom inventory rather than a pure trait-anxiety instrument; therefore, it is used here as a proxy for the baseline anxious affect, and the resulting model is presented as a robustness check rather than as a clean separation of domain-specific anxiety from general affect: shared response styles and negative affectivity cannot be ruled out with survey measures alone, given the pervasive imprint of negative affectivity on self-reported distress (Watson & Clark, 1984). If the age and education gradients reflect appraisals of AI rather than disposition, they should nonetheless persist under this adjustment.

Hypothesis 4 (robustness to general anxiety symptoms). The age and education gradients persist after controlling for general anxiety symptoms, which are themselves positively associated with AI anxiety.

3. Data and Methods

3.1 Sample and Procedure

The target population for our survey comprised working-age adults (18–64 years) residing in Turkey. As a large middle-income economy with high projected occupational exposure to generative AI (Gmyrek et al., 2025), Turkey is a substantively informative and understudied setting for a research literature on root causes that has so far been dominated by samples following WEIRD criteria (Western, Educated, Industrialized, Rich, and Democratic; Muthukrishna et al., 2020).

The survey was administered online by the professional survey firm between February and May 2025, using the firm's existing participant panels. Although the survey was administered via an online interface, a trained interviewer was present throughout each session to provide technical and procedural assistance, as needed. To minimize interviewer effects and avoid influencing participants' responses, all interviewers received standardized training in neutral communication, non-directive assistance, and uniform survey administration. Panel members received the survey link by e-mail; those who chose to respond first completed screening questions, and participants were admitted until the gender, age, and income quotas were filled. Respondents provided informed consent, were assured that participation was voluntary and responses confidential, and completed the questionnaire in approximately 35 minutes. Ethical approval was obtained from the Istanbul University Social Sciences Ethics Committee (Approval No. 3063522) before data collection, and the study was conducted in accordance with the Declaration of Helsinki.

The sample size was determined a priori. Comparable AI anxiety survey studies in the literature typically draw samples in the low hundreds to under a thousand: cross-sectional AI anxiety surveys of healthcare professionals report samples of 898 (Zhong et al., 2026) and 155 (Ongun et al., 2025), and a meta-analytic reliability generalization of the AIAS across its primary studies reports average sample sizes of roughly 330 -340 respondents per study (Yıldırım et al., 2026). No directly comparable effect size estimate existed in the AI anxiety literature at the design stage; therefore, the target sample size followed Cohen's (1977) convention for a small effect ($f^2 = .02$) in the core demographic specification (age, education, gender, income; six predictors). A power analysis (G*Power 3.1; F tests, linear multiple regression, fixed model, R^2 deviation from zero) indicated that this effect size required a minimum of 688 respondents to achieve 80 percent power at $\alpha = .05$; recruitment continued until the gender, age, and income quotas were filled.

The survey yielded 757 complete responses. One observation with missing personal income data was excluded, yielding an analytic sample of 756. The constructed scales contained no item-level missing data. Therefore, all models used the same complete-case sample. Although quota controls

improved demographic coverage, the sample remains non-probabilistic and is not claimed to reproduce the national population distributions. The implications of this limitation are discussed in Section 5 below.

The analytic sample is balanced by gender (49.6% women) and spans the full working-age range, with respondents in the 18-24 (24.2%), 25-34 (21.7%), 35-44 (22.8%), 45-54 (18.9%), and 55-64 (12.4%) age bands. Educational attainment is recorded in four categories: middle school or below (25.9%), high school (36.4%), associate degree (9.1%), and bachelor's degree or higher (28.6%). Table 1 reports descriptive statistics.

Table 1. Descriptive Statistics

Variable	Mean / n	SD / %	Min	Max
AI anxiety (AIAS total, 16–80)	46.56	17.00	16	80
Learning subscale (5–25)	11.70	6.67	5	25
Job replacement subscale (4–20)	12.92	4.66	4	20
Sociotechnical blindness (4–20)	13.02	4.64	4	20
AI configuration subscale (3–15)	8.92	4.05	3	15
AI attitudes (AIAS-4, 4–40)	24.74	11.04	4	40
Automation anxiety (0–15)	7.61	4.44	0	15
General anxiety symptoms (DASS-21, 0–42)	7.71	9.74	0	40
Age (years)	36.73	13.35	18	64
Personal income (₺1,000/month)	33.52	40.56	0	500
Categorical variables				
Gender: Women	375	49.6		
Gender: Men	381	50.4		
Education: middle school or below	196	25.9		
Education: high school	275	36.4		
Education: associate degree	69	9.1		
Education: bachelor's or higher	216	28.6		

Notes. N=756. AIAS = Artificial Intelligence Anxiety Scale; AIAS-4 = Artificial Intelligence Attitude Scale; DASS-21 = Depression Anxiety Stress Scales-21 anxiety subscale. Subscale rows are components of the AIAS total. For scale scores and other numeric variables, the Mean / n and SD / % columns report the mean and standard deviation; for categorical variables (gender and education), they report n and column percentages.

3.2 Measures

Artificial intelligence anxiety scale (AIAS). AI anxiety was measured using the 16-item Artificial Intelligence Anxiety Scale (Wang & Wang, 2022) in its validated Turkish adaptation (Akkaya et al., 2021). Items were rated on a five-point agreement scale. The scale yields a total score (range

16-80) and four subscales: learning (five items; apprehension about acquiring AI-related skills), job replacement (four items; fear of employment loss), sociotechnical blindness (four items; concern about loss of control and misuse), and AI configuration (three items; unease about humanoid AI). Cronbach's α in the analytic sample is .950 for the total score, .964 for learning, .849 for job replacement, .882 for sociotechnical blindness, and .943 for AI configuration.

Age, human capital, and demographics. Age is measured in years. Educational attainment, an empirical proxy for human capital, is coded in four ordered categories, with middle school or below as the reference. Respondents with graduate degrees are combined with bachelor's-degree holders because the graduate cell is very small (n = 16, 2.1% of the sample), and separate coefficients for it would be too imprecise to interpret. Personal income is self-reported as the average monthly after-tax income in Turkish lira. Gender is coded as male = 1 and female = 0; it was recorded as a single self-reported binary item and is therefore used here as a self-identified social category rather than as a measure of sex assigned at birth, and the binary response format does not allow gender-diverse respondents to be identified. Maternal and paternal education, originally six categories each, are collapsed into three groups (middle school or below, high school, and higher) because several upper categories had very small cell counts.

General anxiety symptoms. General anxiety symptoms were assessed using the seven-item anxiety subscale of the Depression Anxiety Stress Scales-21 (DASS-21; Lovibond & Lovibond, 1995) in its Turkish validation (Sarıçam, 2018), reported in the standard 0–42 metric. In the analytic sample, Cronbach's α for the seven-item anxiety subscale is .908. As noted in Section 2.4, the DASS-21 measures recent symptoms and serves as a proxy for general anxious affect.

Related outcomes. Two further outcomes enter the analysis with distinct roles; they are convergent with the AIAS but not interchangeable. Automation anxiety, a five-item index of worry that automation will reduce control over one's work, underuse one's skills, lower income, lead to less interesting work, and disrupt working hours (each item rated 0–3; total score from 0–15; wording in Appendix B; cf. Brougham & Haar, 2018), captures a narrower, employment-specific construct and serves as a labor-market-focused convergent outcome; its Cronbach's α in the analytic sample is .919. Attitudes toward AI were measured using the Artificial Intelligence Attitude Scale (AIAS-4; Grassini, 2023), which was adapted into Turkish by Köse, Şimşek, and Demir (2025). The scale consists of four items rated on a 10-point Likert scale (1 = strongly disagree, 10 = strongly agree), yielding a unidimensional composite score, with higher values indicating more positive attitudes toward AI. The Turkish adaptation demonstrated good internal consistency, with Cronbach's alpha of .86. In the current sample, the internal consistency was α = .91. In the analytic sample, the AIAS total correlates .70 with automation anxiety and −.51 with the AIAS-4; automation anxiety correlates most weakly with the learning subscale (.49), consistent with its narrower, employment-specific content. Permission to use the Turkish versions of the AIAS, the DASS-21, and the AIAS-4 was obtained before data collection.

Occupational variables. Occupational skill level, based on ISCO-08 major groups, is available for 414 respondents, comprising all 409 respondents currently in paid employment and five respondents who reported sufficient information about their most recent occupations. The task class, based on the PIAAC abstract, routine, and manual taxonomy, is defined for the 409 currently employed respondents. Routine task intensity scores, ranging from 1 to 9, are available for 408 of these respondents. Appendix B, Table B.1, reports the composition. These variables are included in the employed subsample models in Section 4.5.

3.3 Empirical Strategy

The AIAS total is an additive score ranging from 16 to 80, with higher values indicating greater anxiety. We use ordinary least squares because its coefficients are directly interpretable as conditional mean differences in AIAS points and facilitate comparisons across specifications. Following the broader applied-econometric discussion of linear and nonlinear limited-dependent-variable models, all regressions are estimated with heteroskedasticity-robust (HC1) standard errors (Angrist & Pischke, 2009; Roman et al., 2022). (As a robustness check, the main specifications were also estimated using ordered probit models, treating each observed AIAS total as an ordered outcome. The signs, statistical significance, and substantive conclusions for the age and education gradients remained unchanged. Given this similarity and the more direct interpretation of OLS coefficients in AIAS points, the paper reports the OLS estimates; see Roman et al., 2022, p. 13, note 6, for a related discussion of the practical similarity between linear and nonlinear limited-dependent-variable models.)

Age is centered on its sample mean (36.73 years). In the interaction models, the age coefficient represents the age slope for the reference education group, whereas the education coefficients represent group differences at the mean age. Statistical significance is denoted with asterisks at the 5 percent (*), 1 percent (**), and 0.1 percent (***) levels; joint (Wald) tests are reported with their exact p-values rather than significance stars.

The analysis was conducted in five steps. First, the functional form of the age gradient is characterized by adding quadratic and cubic age terms to a common control set and testing the higher order terms jointly (Table 3). Second, the main model is built hierarchically: demographics only; adding education; adding parental education; adding the age by education interaction; and adding general anxiety symptoms (Table 4). Education and parental education enter as indicator sets with joint Wald tests. Third, because the interaction coefficients by themselves do not show how the age slope varies, the marginal age slope and 95 percent confidence interval are reported for each education group (Table 5 and Figure 3). Fourth, three nested models are estimated for the employed subsample that add occupational skill level and task class, then routine-task intensity, to the baseline specification (Table 6). Fifth, the full model is re-estimated for each AIAS subscale (Table 7) and for the two related outcomes (Table 8), and robustness is examined for the functional form of income, a broader battery of affect controls, and employment status (Section 4.7 and Appendix B).

All estimates are interpreted as conditional associations. The key coefficients are stable as successive blocks of controls are added, which is reassuring. However, with cross-sectional survey data, unobserved confounding cannot be ruled out, and no causal language is attached to these results. Multicollinearity is not a concern: the maximum variance inflation factor is 2.1 in the additive specification and 4.3 in the interaction specification, the latter attached to the age main effect, which is mechanically correlated with its interaction terms (Appendix A).

4. Results

4.1 Correlations

The pairwise correlations in Table 2 preview the regression results. AI anxiety is positively correlated with age (r = .22) and general anxiety symptoms (r = .35) and negatively correlated with education (r = −.30), male gender (r = −.23), and personal income (r = −.25). Age and general anxiety symptoms are essentially uncorrelated (r = −.001); therefore, the age gradient in AI anxiety is not a reflection of older respondents being more anxious in general. Education is positively correlated with income (r = .28) and negatively correlated with age (r = −.24), motivating a multivariate analysis.

Table 2. Pearson Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)
(1) AI anxiety (AIAS)	1.000					
(2) Age	0.222	1.000				
(3) Education	−0.298	−0.242	1.000			
(4) Gender (Male)	−0.227	−0.019	0.051	1.000		
(5) Personal income	−0.246	0.051	0.279	0.372	1.000	
(6) General anxiety symptoms	0.349	−0.001	−0.148	−0.134	−0.155	1.000

Notes. N= 756. Male = 1 for men, 0 for women. Personal income in ₹1,000/month. Education coded 0 (middle school or below) to 3 (bachelor's or higher). Correlations with $|r| \geq .07$ are significant at $p < .05$.

4.2 The Functional Form of the Age Gradient

Table 3 examines whether the age effect on AI anxiety (AIAS) is linear. In the linear specification, age enters positively and precisely (b = 0.21, p < .001), implying an increase of about two AIAS points per additional decade. The quadratic term is small and not significant (b = −0.006, p = .12), the cubic term is essentially zero, and the joint test of the two higher-order terms cannot reject linearity (p = .29). The Akaike Information Criterion is effectively flat across the three specifications, with the explained variance changing only in the third decimal. The conclusion is unchanged when the higher-order age terms are added to the full specification of Table 4 (joint p

= .26 with the Model 3 control set; p = .16 with general anxiety symptoms added). The linear form is therefore retained. Figure 1 shows why: a locally weighted regression of AI anxiety on age tracks the OLS line closely across the 18–64 range, and binned means rise steadily as age increases. In this sample, the age gradient is monotonic and not hump-shaped.

Table 3. Functional Form Tests for the Age Gradient of AI Anxiety

Term	(1) Linear	(2) Quadratic	(3) Cubic
Age (centered)	0.211*** (0.050)	0.231*** (0.051)	0.215* (0.106)
Age² (centered)		−0.006 (0.004)	−0.006 (0.005)
Age³ (centered)			0.000 (0.000)
Test of higher-order age terms (p-value)	n/a	0.115	0.288
R^2	0.176	0.179	0.179
AIC	6296.7	6295.9	6297.9

Notes. N=756. OLS with HC1 robust standard errors in parentheses. All models control for education (categorical), gender, and personal income. For the quadratic model, the reported p tests the quadratic term; for the cubic model, it is the joint test of the quadratic and cubic terms. * p < .05, ** p < .01, *** p < .001.

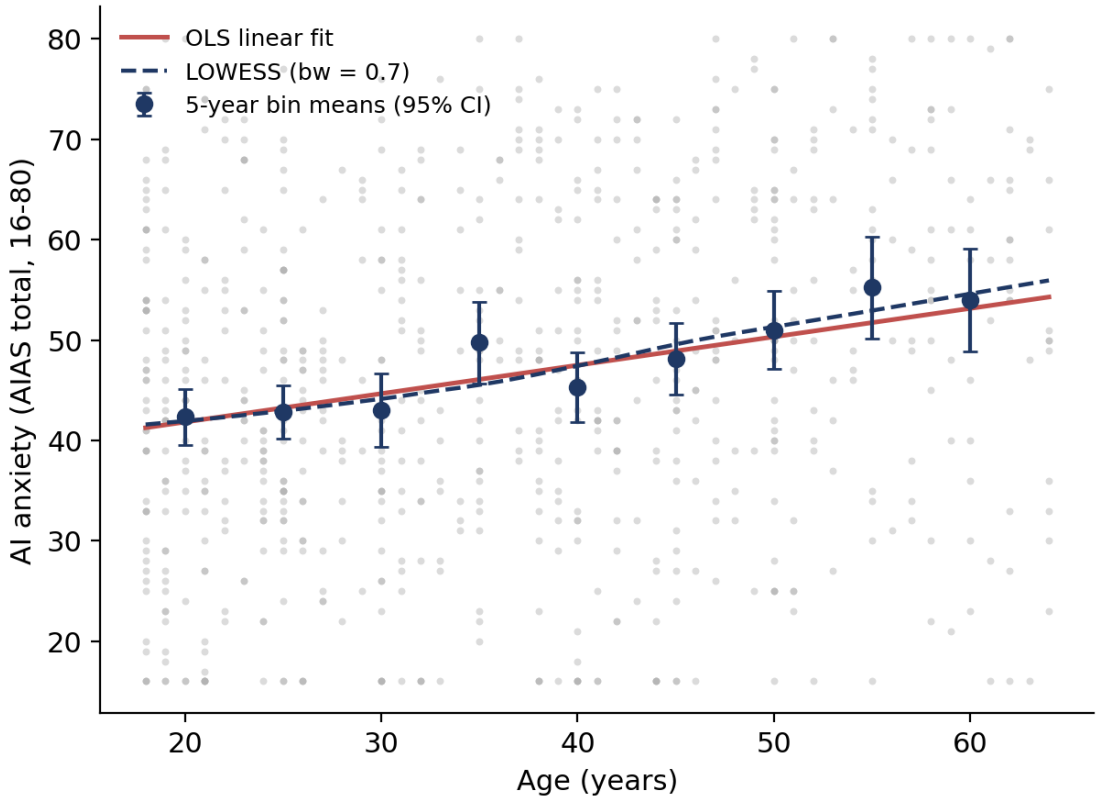


Figure 1. AI anxiety rises approximately linearly with age.

Note. Grey points are individual observations; navy markers are mean AIAS within five-year age bins with 95% confidence intervals. The solid line is the OLS linear fit; the dashed line is a LOWESS smoother (bandwidth 0.7).

4.3 Main Results: Age, Education, and AI Anxiety

Table 4 presents the hierarchical models. Model 1 includes demographics only: age is positive ($b = 0.29$, $p < .001$), men score about five points lower than women, and higher personal income is associated with lower anxiety. Model 2 adds education, which is jointly significant ($p < .001$) and produces the largest gaps among the demographic variables in the model. Relative to respondents with at most middle school, those with a bachelor's degree or higher score about ten points lower on the AIAS ($b = -10.16$, $p < .001$), more than half a standard deviation; high-school ($b = -4.68$, $p < .01$) and associate-degree ($b = -4.15$, $p < .05$) respondents also report lower anxiety. Adding education leaves the age, gender, and income coefficients essentially unchanged. The age coefficient remains positive and significant throughout, ranging from 0.21 to 0.29 in the additive specifications; in the interaction specifications, the corresponding age slope for the reference education group is 0.32–0.33.

Figure 2 shows the adjusted education gradient from Model 3. With the other covariates held at their means or reference values, predicted AIAS falls from 54.3 (95% CI 51.4 to 57.2) among respondents with middle school or below to 49.8 among high-school graduates and 50.4 among associate-degree holders, and to 43.9 (95% CI 40.9 to 46.9) among those with a bachelor's degree

Table 4. Hierarchical OLS Models of AI Anxiety (dependent variable: AIAS total)

Variable	(1)	(2)	(3)	(4)	(5)
	Demographics	*+ Education*	*+ Parental*	*+ Interaction*	*+ Gen. anxiety*
Age (centered)	0.293***(0.04)	0.211***(0.05)	0.221***(0.05)	0.316** (0.10)	0.331** (0.10)
Education: High school		−4.684**(1.64)	−4.509**(1.67)	−3.318 (1.81)	−2.603 (1.77)
Education: Associate		−4.146* (2.10)	−3.904 (2.19)	−3.491 (2.30)	−2.465 (2.21)
Education: Bachelor's or higher		−10.159***(1.84)	−10.441***(1.99)	−9.904**(2.11)	−7.505***(2.04)
Gender (Male)	−4.993***(1.29)	−5.530***(1.23)	−5.796***(1.25)	−5.656***(1.25)	−4.727***(1.20)
Personal income (per ₺10,000)	−0.851** (0.20)	−0.553** (0.18)	−0.534**(0.18)	−0.556** (0.18)	−0.451** (0.15)
Mother edu.: intermediate			−1.426 (1.88)	−1.637 (1.89)	−2.181 (1.75)
Mother edu.: higher			4.600 (3.36)	3.351 (3.36)	1.354 (3.10)
Father edu.: intermediate			0.196 (1.61)	0.375 (1.60)	−0.345 (1.52)
Father edu.: higher			1.552 (2.70)	2.562 (2.78)	2.139 (2.52)
Age × High school				−0.016 (0.123)	−0.059 (0.119)
Age × Associate				−0.206 (0.158)	−0.194 (0.155)
Age × Bachelor's or higher				−0.318* (0.146)	−0.302* (0.141)
General anxiety symptoms					0.491***(0.05)
Constant	51.93***(0.90)	56.188***(1.31)	56.09***(1.32)	55.19***(1.57)	49.86***(1.64)
N	756	756	756	756	756
R^2	0.134	0.175	0.182	0.190	0.264
F	32.49	27.18	17.01	13.34	22.48
Joint test: education (p)	n/a	<0.001	<0.001	<0.001	0.001
Joint test: age × education (p)	n/a	n/a	n/a	0.070	0.122

Notes. OLS with HC1 robust standard errors in parentheses. Reference categories: education = middle school or below; gender = female; parental education = middle school or below. Age is mean-centered. Personal income is scaled per ₺10,000/month. "Joint test" rows report p-values from Wald tests of the indicated coefficient sets. Maximum variance inflation factor is 2.1 in Models 1–3 and 4.3 in Models 4–5 (on the age main effect). * p < .05, ** p < .01, *** p < .001.

or higher; the confidence intervals of the two end categories do not overlap, and the ten-point spread between them corresponds to about six-tenths of a standard deviation of the AIAS. Model 3 adds the maternal and paternal education variables. Neither set is jointly significant, and the own-education and age gradients are unaffected by their inclusion. This result should be read cautiously: parental education is measured coarsely here, so the result shows that the own-education gradient is robust to controlling for coarse parental education categories, not that family background is irrelevant.

4.4 Is the Age Gradient Uniform Across Education Levels?

Model 4 adds the age by education interaction terms, and Table 5 translates them into what matters substantively: the implied age slope within each education group. Two pieces of evidence need to be read together here: the joint test of the interaction terms and the implied age slope within each education group. The joint test of the three interaction terms does not reach significance at the 5 percent level ($p = .070$; $p = .122$ once general anxiety symptoms are added); therefore, the data do not provide strong joint evidence against parallel gradients. However, the marginal slopes are far from uniform. The age slope is 0.32 (95% CI 0.13 to 0.51) among respondents with middle school or below and 0.30 (0.15 to 0.45) among high school graduates, while it is small and imprecise among associate-degree holders (0.11; −0.14 to 0.36) and essentially zero among respondents with a bachelor's degree or higher (−0.00; −0.21 to 0.21). The bachelor's interaction term is individually significant ($b = −0.32$, $p = .029$). Figure 3 shows the corresponding profiles: rising anxiety with age in the two lower education groups, a shallower, less precise profile for associate degree holders, and a flat line for university graduates.

In summary, the age gradient in AI anxiety is concentrated among the less educated, and the evidence for buffering by higher education is suggestive rather than conclusive in the total score. The pattern confirms the theoretical expectations. As Sections 4.6 and 4.7 show, the age by education interaction is jointly significant for the job replacement, sociotechnical blindness, and automation anxiety index, in each case with the age slope attenuated among university graduates.

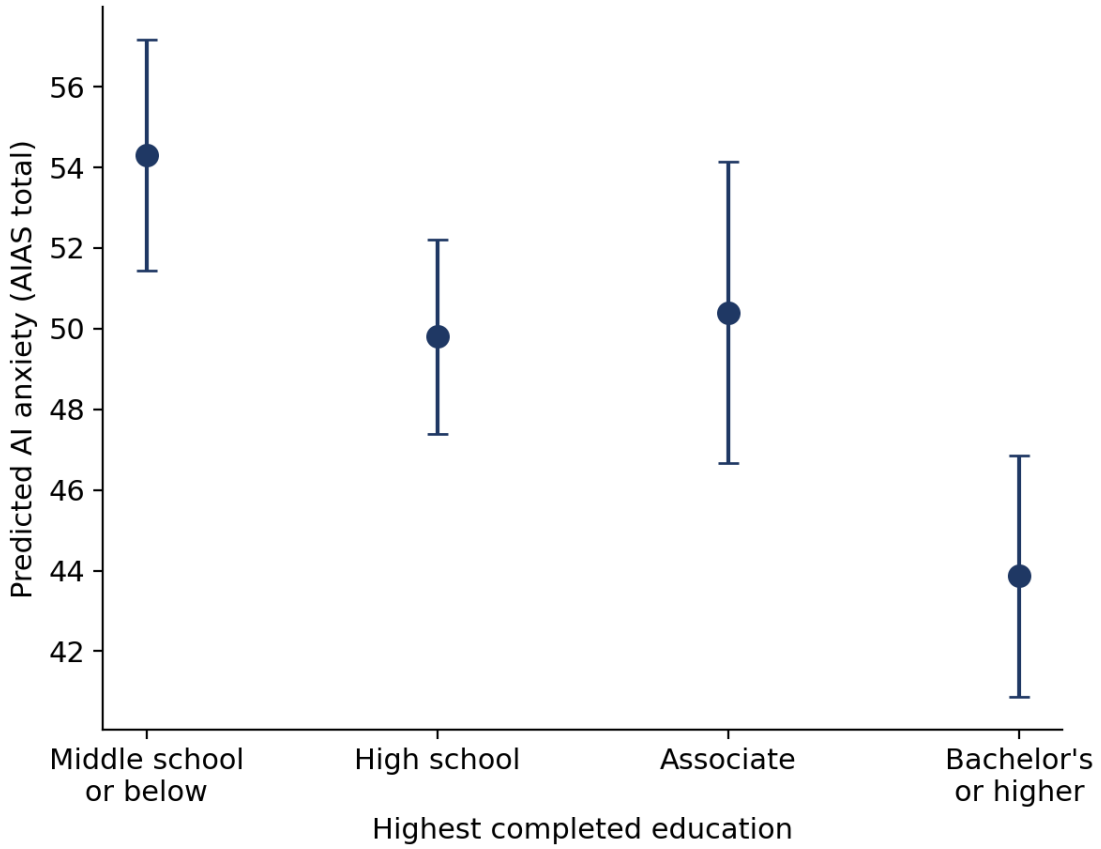


Figure 2. Adjusted AI anxiety declines with education.

Note. Predicted AIAS total by highest completed education from the additive model (Model 3, Table 4), holding age at its mean, income at its mean, gender at female, and parental education at the reference category. Whiskers are 95% confidence intervals based on robust standard errors.

Table 5. Marginal Age Slopes by Education Group (dependent variable: AIAS total)

Education group	Model 4 slope	95% CI	p	Model 5 slope	95% CI	p
Middle school or below	0.317	[0.129, 0.505]	.001	0.331	[0.143, 0.518]	<.001
High school	0.301	[0.149, 0.453]	<.001	0.272	[0.130, 0.414]	<.001
Associate	0.111	[−0.136, 0.358]	.379	0.137	[−0.103, 0.376]	.263
Bachelor's or higher	−0.001	[−0.214, 0.211]	.991	0.028	[−0.172, 0.229]	.782

Notes. Implied age slopes (AIAS points per year of age) computed from the interaction models in Table 4, with delta-method standard errors based on the HC1 covariance matrix. Model 5 adds general anxiety symptoms. Joint test of all age × education terms: p = .070 (Model 4), p = .122 (Model 5).

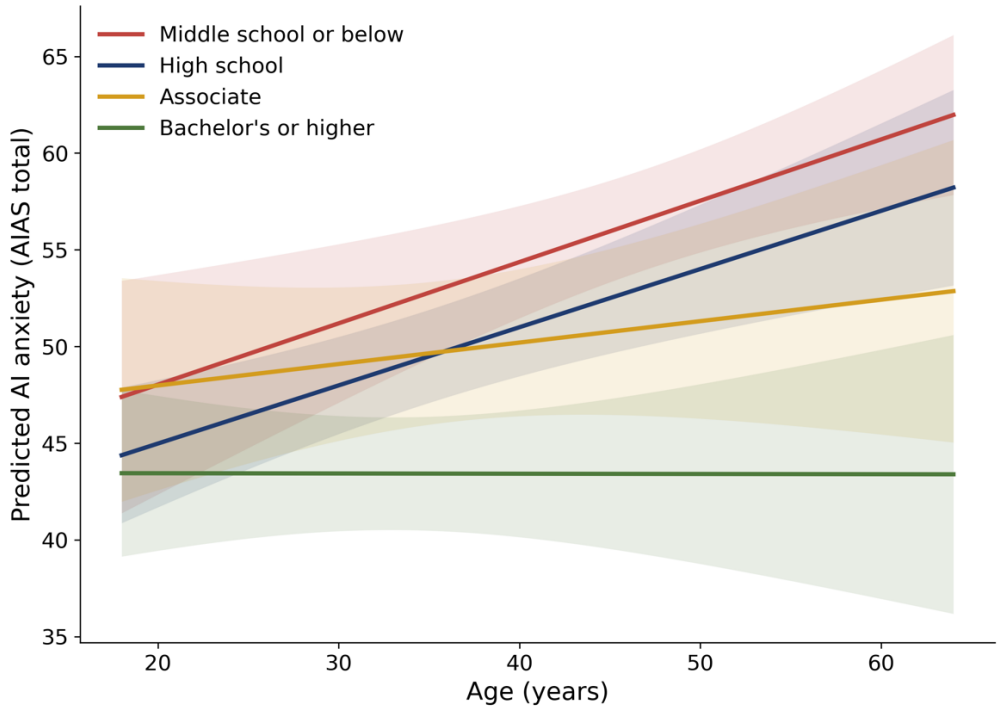


Figure 3. Predicted AI anxiety by age and education level.

Note. Predicted AIAS total as a function of age for the four education groups, from the interaction model (Model 4, Table 4), holding other covariates at reference or mean values; shaded bands are 95% confidence intervals. The joint test of all age × education interaction terms is not significant at the 5 percent level (p = .070); Table 5 reports the marginal slopes.

4.5 Occupational Gradients: Skill Level and Task Content

Occupational position enters the analysis with two roles. It is a gradient in its own right, since exposure to AI differs across skill levels and task types, and it is a candidate explanation for the education gradient, which should attenuate once occupational characteristics are introduced if task exposure contributes to it. Table 6 examines this possibility among the 409 respondents currently in paid employment, for whom occupational skill level (ISCO-08) and task class (abstract, routine, or manual) are observed. Routine task intensity information is available for 408 respondents.

Model A first re-estimates the additive baseline specification for the employed subsample. The age gradient closely matches the full-sample estimate ($b = 0.22$, $p < .01$), while the education gradient is smaller but remains evident: respondents with a bachelor's degree or higher score 6.68 points lower than those with middle school education or below ($p = .018$), and the education indicators are jointly significant ($p = .039$).

Model B adds occupational skill level and task class. Both sets are jointly significant ($p < .001$), and their inclusion absorbs most of the remaining education gradient: the bachelor's coefficient falls to −3.00, and the education set is no longer jointly significant ($p = .19$). The occupational gradient is itself substantial: relative to abstract task holders, respondents in routine tasks score 6.1 points higher and those in manual tasks 11.9 points higher, a spread of the same order as the ten-point education gap in the full sample. In contrast, the age gradient does not move at all ($b = 0.22$, $p < .01$).

Model C adds the routine-task-intensity index, which contributes nothing once the broad task class is controlled ($b = −0.30$, $p = .38$); the index is also unrelated to AI anxiety unconditionally ($r = .015$). Anxiety appears to track the broad type of work people do rather than fine gradations of task routineness, which is what one would expect if it rested on coarse appraisals of occupational position rather than task-level calculations of automability.

The occupational gradient is also not monotonic in skill. Conditional on education and task class, respondents at the highest occupational skill level (ISCO skill level 4; professionals and managers) score about 12 points higher than those in elementary occupations. Under the older routine-biased view, this group should feel sheltered; their elevated anxiety is easier to reconcile with the exposure geometry of generative AI, which reaches professional and clerical work (Eloundou et al., 2024; Felten et al., 2021; Gmyrek et al., 2025).

The same pattern is observed for the employment-specific outcomes. In the employed subsample with task controls, automation anxiety increases with age ($b = 0.045$, $p = .043$) and manual task class ($b = 2.13$, $p < .01$), while education is not significant.

Results are consistent with, but do not identify, a possible task-exposure channel underlying the education gradient. For the age gradient, the reading is different: the occupational indicators included in the analysis do not account for it. Digital familiarity, cohort socialization, and the psychological channels of Section 2.1 remain the more plausible candidates for age, and the cross-section cannot separate them from the age effect.

Table 6. Occupation and Task Content, Employed Respondents (dependent variable: AIAS total)

Variable	(A) Baseline	(B) + ISCO and task class	(C) + Routine intensity
Age (centered)	0.216** (0.078)	0.224** (0.075)	0.217** (0.075)
Education: High school	−2.297 (2.52)	0.114 (2.49)	0.088 (2.49)
Education: Associate	−1.330 (3.09)	2.261 (3.17)	2.516 (3.23)
Education: Bachelor's or higher	−6.679* (2.81)	−2.995 (2.97)	−2.804 (2.98)
Gender (Male)	−4.008* (1.69)	−5.411** (1.68)	−5.442** (1.70)
Personal income (per ₺10,000)	−0.432* (0.18)	−0.355 (0.20)	−0.379 (0.21)
ISCO skill level 2		3.667 (2.59)	3.792 (2.58)
ISCO skill level 3		−0.585 (3.49)	−0.802 (3.50)
ISCO skill level 4		12.547*** (3.50)	11.771** (3.63)
Task class: Routine		6.076** (2.18)	6.099** (2.20)
Task class: Manual		11.900*** (2.36)	12.101*** (2.38)
Routine-task intensity (1–9)			−0.297 (0.34)
N	409	409	408
R^2	0.082	0.153	0.154
Joint test: education (p)	0.039	0.193	0.198
Joint test: ISCO (p)	n/a	<0.001	0.001
Joint test: task class (p)	n/a	<0.001	<0.001

Notes. OLS with HC1 robust standard errors in parentheses. All models include parental education. Reference categories: education = middle school or below; ISCO = skill level 1 (elementary); task class = abstract. One employed respondent lacks the routine-task-intensity index. * p < .05, ** p < .01, *** p < .001.

4.6 Adjusting for General Anxiety Symptoms

Model 5 in Table 4 adds general anxiety symptoms. The DASS-21 anxiety score is a strong predictor: each additional point is associated with about half a point more AI anxiety (b = 0.49, p < .001), and the explained variance rises from .19 to .26. The age and education gradients persist. The bachelor's-or-higher gap remains large (b = −7.50, p < .001; education jointly p = .001), and the age slope for the lower education groups is unchanged (Table 5). Because age and general anxiety symptoms are uncorrelated (r = −.001, Table 2), the age gradient cannot be a disguised disposition gradient. A more demanding specification that adds the DASS-21 depression and stress subscales alongside anxiety, three highly intercorrelated symptom scales, leaves the conclusions intact (age b = 0.23, p < .001; bachelor's or higher, b = −7.40, p < .001). Hypothesis 4 is taken as supported in the sense that the design allows the gradients to be robust to adjustments for measured symptoms of general anxiety, which is not the same as proof that AI anxiety and general affect are cleanly separable.

4.7 Robustness

Subscales. Table 7 re-estimates the full specification for each AIAS subdimension, and Figure 4 plots the standardized effects from the additive versions. The age gradient is positive and significant for all four subscales, and the bachelor's-or-higher coefficient is negative and significant in all four, the largest for learning. The age-by-education interaction is jointly significant for job replacement ($p = .031$) and sociotechnical blindness ($p = .034$), with the age slope attenuated among university graduates in both cases; it is absent for learning ($p = .71$). Heterogeneity is evident for job-replacement anxiety, where human capital reasoning predicts it most directly, but also appears for sociotechnical-blindness anxiety.

Table 7. OLS Models of AIAS Subscales (full specification; N = 756)

Variable	Learning	Job repl.	Sociotech.	AI config.
Age (centered)	0.13*** (0.04)	0.07* (0.03)	0.09** (0.03)	0.05* (0.02)
Education: High school	−1.55* (0.68)	−0.30 (0.50)	−0.40 (0.48)	−0.36 (0.41)
Education: Associate	−2.39** (0.92)	−0.09 (0.66)	−0.13 (0.65)	0.15 (0.57)
Education: Bachelor's or higher	−3.14*** (0.74)	−1.34* (0.60)	−1.71** (0.57)	−1.30** (0.47)
Gender (Male)	−1.15* (0.49)	−0.83* (0.35)	−1.28*** (0.34)	−1.47*** (0.30)
Personal income (per ₺10,000)	−0.10 (0.07)	−0.11* (0.04)	−0.13** (0.04)	−0.11** (0.03)
General anxiety symptoms	0.19*** (0.02)	0.10*** (0.02)	0.11*** (0.01)	0.09*** (0.01)
Age × Bachelor's or higher	−0.042 (0.051)	−0.099* (0.040)	−0.104** (0.039)	−0.058 (0.033)
N	756	756	756	756
R^2	0.233	0.149	0.206	0.202
Joint: age × education (p)	0.706	0.031	0.034	0.216

Notes. OLS with HC1 robust standard errors in parentheses. Each model includes the full control set (age, education, gender, personal income, parental education, general anxiety symptoms) and the age × education interaction; selected coefficients are shown. Subscale ranges: learning 5–25, job replacement 4–20, sociotechnical blindness 4–20, AI configuration 3–15. * $p < .05$, ** $p < .01$, *** $p < .001$.

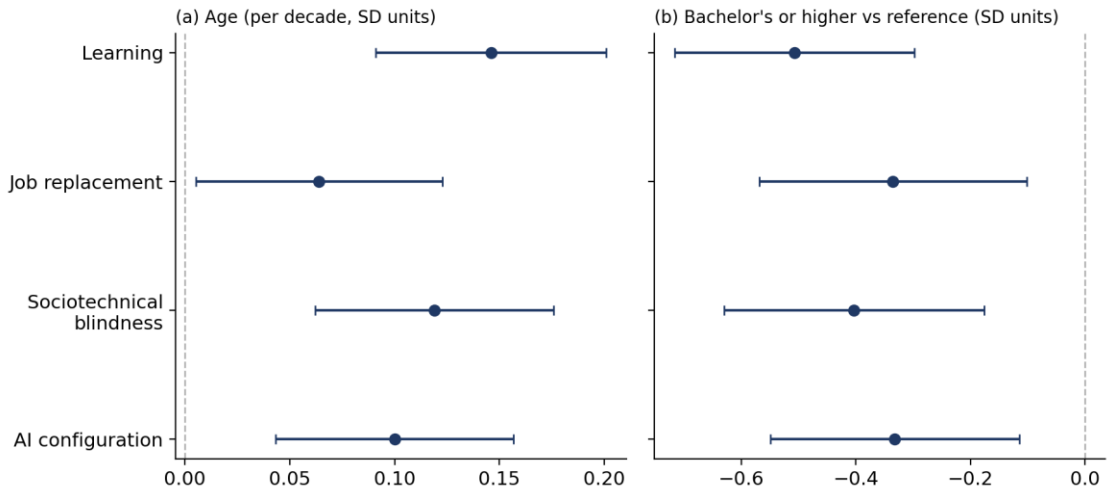


Figure 4. Age and education gradients hold across all AIAS subscales.

Note. Standardized coefficients (each subscale z-scored) from additive versions of the models in Table 7. Panel (a): change in standard-deviation units per decade of age. Panel (b): difference for respondents with a bachelor's degree or higher relative to middle school or below. Horizontal bars are 95% confidence intervals based on robust standard errors; the dashed line marks zero.

Alternative outcomes. Table 8 presents the two related outcomes. For automation anxiety, the pattern mirrors the main results: anxiety rises with age ($b = 0.06$, $p = .023$), respondents with a bachelor's degree or higher are less anxious ($b = -1.10$, $p = .034$), and the age by education interaction is jointly significant ($p = .004$), again with the slope attenuated among university graduates. For AI attitudes, the gradients reverse, as they should if they capture a coherent underlying appraisal: education is strongly associated with more positive views (bachelor's or higher, $b = +7.98$, $p < .001$), men are more positive, and older respondents are less positive ($b = -0.21$, $p < .01$). The same variables predict less anxiety and more favorable attitudes with opposite signs, which contradicts a measurement artifact.

Table 8. Related Outcomes (N = 756)

Variable	Automation anxiety	AI attitudes (AIAS-4)
Age (centered)	0.059* (0.026)	−0.206** (0.063)
Education: High school	−0.26 (0.46)	5.00*** (1.21)
Education: Associate	0.46 (0.66)	6.79*** (1.72)
Education: Bachelor's or higher	−1.10* (0.52)	7.98*** (1.25)
Gender (Male)	−0.56 (0.34)	2.93*** (0.75)
Personal income (per ₺10,000)	−0.10 (0.06)	0.19 (0.10)
General anxiety symptoms	0.12*** (0.02)	−0.10** (0.04)
Age × Bachelor's or higher	−0.097** (0.038)	0.143 (0.081)
N	756	756
R^2	0.173	0.284
Joint: age × education (p)	0.004	0.074

Notes. OLS with HC1 robust standard errors in parentheses. Both models include the full control set and the age × education interaction; selected coefficients are shown. Automation anxiety ranges 0–15 (higher = more anxious); AI attitudes (AIAS-4) are scored so that higher = more positive. * p < .05, ** p < .01, *** p < .001.

Functional form of income. Personal income is highly skewed (Table 1), so a linear term may be sensitive to outliers. Re-estimating the additive model with log income, inverse hyperbolic sine income, income winsorized at the 99th or 95th percentile, or income quartiles moves the age coefficient only between 0.22 and 0.23 and the bachelor's-or-higher coefficient between −9.8 and −10.9, all significant at the 1 percent level (Appendix B, Table B.2). The gradients do not depend on how income is included in the model.

Employment status and the non-employed. Adding an employment indicator to the full-sample additive model changes nothing (employed b = −2.15, p = .145; age and education coefficients are unchanged). Estimating the additive model separately for the 347 respondents not currently in paid work shows that the gradients are not specific to workers: among the non-employed, the bachelor's-or-higher gap is large (b = −13.7, p < .001), and the age slope is similar (b = 0.20, p < .01). The subscale decomposition in Appendix B, Table B.3, shows that this education gradient is present in all four dimensions but is strongest by a clear margin for learning, which is consistent with education operating through broader appraisal channels rather than only through the automation risk of one's job. It should also be noted that the non-employed group includes students and unemployed respondents who anticipate entering the labor market, for whom job-related AI anxiety is forward-looking rather than irrelevant.

Measurement invariance. Because the analysis compares AIAS scores across gender, age, and education groups, the analysis tested whether the scale measures the same construct in the same metric across these groups. Multigroup confirmatory factor analyses (Appendix B, Table B.4)

support metric invariance across all three groupings and scalar invariance by the conventional ΔCFI criterion, indicating that the group differences documented above are not artifacts of differential scale interpretations.

5. Conclusion

Using data from an online survey of a general adult sample in Turkey, a large middle-income country, this paper documents several systematic patterns in the distribution of AI anxiety. AI anxiety increases approximately linearly with age and decreases steeply with education. The age gradient is concentrated among respondents with lower education and is statistically indistinguishable from zero among university graduates, with the joint moderation test falling short of conventional significance in the total score but significant for job-replacement anxiety, sociotechnical-blindness anxiety, and automation anxiety. Among employed respondents, the occupational gradient is steep: workers in manual and routine tasks report substantially more anxiety than those in abstract tasks. Differences in occupational skill level and task class account for most of the observed education gradient, but they do not explain any part of the age gradient. When education and task class are held constant, respondents in the highest occupational skill category, comprising professionals and managers, score substantially higher than those employed in elementary occupations. The patterns are robust to general anxiety symptoms, family background, functional form of income, and employment status; they recur across all subdimensions of the used Artificial Intelligence Anxiety Scale and reverse in sign for AI attitudes.

The age gradient findings presented in this study contribute to a debated area in the literature. The classic technology-anxiety tradition concludes that computer anxiety rises with age (Czaja et al., 2006; Charness & Boot, 2009), whereas Uğur and Dursun (2025) report null age-group differences in AI anxiety and interpret them as normalization across cohorts. Descriptive evidence from a large German quota sample is closer to the former, with the highest mean AI anxiety among the oldest and least-educated respondents (Hajek et al., 2025). These results side with the former in this population and add a qualification the earlier literature rarely makes: once age and education are considered jointly, the age gradient belongs mostly to the less educated. The same qualification bears on recent studies of AI anxiety and adoption that are confined to narrow age bands, such as university students aged 18 to 24 (Girgin, 2026) or digital natives (Kuhail et al., 2025): in such samples, the age gradient documented here cannot emerge, and the education gradient is compressed by design. On the education side, Włoch et al. (2025) provide convergent evidence that the fear of automation declines with education and income. Their finding that fear is higher among younger workers, however, contrasts with the positive age gradient found in this study. This divergence may reflect differences in the outcomes measured, automation fear versus AI anxiety, as well as differences in sample composition or institutional context. However, the available evidence does not allow these possibilities to be distinguished.

What generates these gradients? The task-content analysis provides one piece of discriminating evidence. For education, the gradient among the employed shrinks substantially once the occupational skill level and task class are controlled. The attenuation of the education coefficient after occupational controls is consistent with the possibility that occupational sorting and task content contribute to the observed education gradient. For age, the same controls move nothing; the occupational indicators included in the analysis do not account for the observed age gradient. This leaves shorter retraining horizons (Ben-Porath, 1967), lower technology self-efficacy and digital familiarity acquired before the digital era (Czaja et al., 2006; Vaportzis et al., 2017), and cohort effects as plausible sources. The present design cannot separate them. Two further observations fit this division of labor between the channels. The age gradient is more pronounced in the learning and sociotechnical-blindness dimensions than in job replacement anxiety, a pattern that is more consistent with familiarity-based accounts. And the education gradient is, if anything, larger among the non-employed, where own-job task exposure cannot be the mechanism, pointing to education operating also through general appraisal capacity and information.

The buffering pattern deserves further discussion. The hypothesis that the age gradient in AI anxiety differs across education levels contrasts a substitute view, in which education flattens the age gradient, with an additive view. The evidence leans toward the substitutes view, most clearly for the employment-related dimensions of anxiety: among university graduates, the age slope is flat, and the attenuation is jointly significant for job replacement and automation anxiety. This is also where the task-based account expects heterogeneity, since older workers with little schooling are the group, whose tasks are most exposed. This paper avoids a strong claim for the total score, where the joint test does not reach the 5 percent level.

This paper resists the temptation to draw direct policy conclusions from a cross-section, and instead states them conditionally, since the appropriate response depends on which mechanism generates the age gradient. If the age gradient reflects shorter adaptation horizons, then age-inclusive training design and credible employment protection during transitions are natural instruments (Acemoglu & Restrepo, 2019). If it reflects digital unfamiliarity, hands-on AI literacy programs are more important. If it reflects occupational exposure, support targeted at exposed occupations would be indicated, and the task-content results suggest that this last channel is more relevant for the education gradient than for age. Regardless of the combination, the descriptive finding that anxiety is most concentrated among older respondents with little schooling identifies where such measures would reach the most anxious groups.

The societal stakes extend beyond the discomfort the scale records. Anxiety is not only an outcome but also an input into behavior: it lowers acceptance of AI and partly carries the effect of AI literacy on acceptance (Schiavo et al., 2024). Recent evidence on generative AI points in the same direction: anxiety is negatively associated with the intention to adopt generative AI (Pham et al., 2026), and fear of using AI is examined alongside self-efficacy, perceived usefulness, and ease of use as a factor in students' continued use of AI in learning systems (Al-Maroof et al., 2026). If anxiety is concentrated among older and less-educated adults, then the characteristics that limit the

capacity to adapt to AI also discourage engagement with it, so diffusion may widen rather than narrow existing disparities in skills and labor-market position. The same gradients appear with the opposite sign for attitudes toward AI, which means that the most anxious groups are also the least favorable, a pattern that bears on public support for AI deployment and on whose concerns are voiced when its governance is debated. The setting sharpens the concern: middle-income economies face occupational exposure to generative AI on a scale comparable to that of high-income countries (Gmyrek et al., 2025), while the institutions that cushion technological transitions, from adult training systems to income support during job changes, are often less extensive, so a given distribution of anxiety may carry larger unmanaged adjustment costs. The elevated anxiety found among professionals once the task class is held constant is a reminder that generative AI may be redrawing the exposure map faster than public perceptions of who is safe. If public debate continues to locate technological risk in routine and manual work, the groups now most exposed to generative AI may also be the least prepared for it, since neither training provision nor political attention has yet been organized around professional and managerial exposure.

Some limitations qualify these conclusions. The design is cross-sectional, so the gradients are conditional associations; the coefficients are stable across nested specifications, but unobserved confounding cannot be excluded, and age, cohort, and period effects cannot be separated without longitudinal or repeated cross-sectional data. The sample was recruited between February and May 2025 from the existing online participant panels of a professional survey firm using predefined gender, age, and income quotas. Because participation was voluntary and individual selection probabilities were unknown, the sample is non-probabilistic. Therefore, the estimates characterize AI anxiety in Turkey during the survey period. As attitudes toward a rapidly evolving technology may change over time, the gradients documented here should be understood as period specific. Occupational analysis is confined to the current jobs of employed respondents and rests on coarse task classifications. The AIAS also captures four dimensions of AI anxiety and therefore leaves aside sources of concern that other frameworks treat as distinct, including privacy violation, ethical breach, opacity, and existential risk (J. Li & Huang, 2020). Whether the gradients documented here extend to those dimensions, which are less obviously tied to labor-market position, remains an open question. Online administration may under-represent adults with limited internet access, a group with plausibly higher AI anxiety. Future work should link individual occupations to AI exposure indices (Felten et al., 2021; Eloundou et al., 2024; Gmyrek et al., 2025) to test the exposure channel directly, exploit panel data to distinguish horizons from cohort effects, compare countries that differ in labor market institutions, and use survey experiments that vary how AI's economic effects are framed to test whether these appraisals are malleable. Finally, the outcome studied here is an appraisal rather than observed behavior; linking the anxiety gradients to subsequent AI adoption and use would show how far they translate into unequal adaptation to AI.

The broad conclusion stands regardless. In this middle-income general-population sample, anxiety about artificial intelligence is patterned by exactly the variables that economic accounts of adaptation to technological change point to, education above all, and it accumulates where short

horizons and low adaptive capacity meet. This is not only a fact about sentiment. The groups in which anxiety is highest are also those with the least capacity to adapt and, on the available evidence, the least inclined to engage with the technology; whether AI narrows or widens existing inequalities will therefore depend in part on whether policy reaches these groups before the technology does.

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Appendix A. Estimation Diagnostics

All estimates were produced from the survey dataset; the analytic sample is N = 756 after excluding one observation with missing personal income. Estimates use OLS with HC1 heteroskedasticity-robust standard errors. Age is centered at the sample mean (36.73 years). Education is coded in four categories, with graduate degrees combined with bachelor's degrees. Maternal and paternal education were recoded from six categories to three before estimation.

In the additive specification (Model 3, Table 4), the maximum variance inflation factor is 2.1; in the interaction specification (Model 4), it is 4.3, attached to the mean-centered age main effect, which is mechanically correlated with its own interaction terms. All values are far below the conventional threshold of 10.

Appendix B. Measurement, Sample Composition, and Additional Robustness

B.1 Sample Composition by Employment and Occupation

Table B.1 summarizes the employment and occupational composition of the analytical sample. Occupational skill level is available for 414 respondents, including all 409 respondents currently in paid employment and five respondents with information on their most recent occupations. The task class is defined for the 409 currently employed respondents, and routine task intensity is available for 408 of them.

Table B.1. Sample Composition by Employment and Occupation

Category	n	%
Employment status (N = 756)		
Currently in paid employment	409	54.1
Not currently in paid employment	347	45.9
ISCO skill level (n = 414)		
Skill level 1 (elementary)	46	11.1
Skill level 2 (clerical/services/trades)	261	63.0
Skill level 3 (technicians/associate professionals)	52	12.6
Skill level 4 (professionals/managers)	55	13.3
Task class (employed, n = 409)		
Abstract (analytic/interactive)	101	24.7
Routine (cognitive/manual)	130	31.8
Manual (physical)	178	43.5
Routine-task intensity (employed, n = 408): M = 4.25, SD = 2.45, range = 1–9		

Notes. Employment-status percentages are calculated using the full sample (N = 756). Occupational skill level is coded according to ISCO-08 major-group skill levels for the 414 respondents who provided sufficient occupational information. This group includes all 409 respondents currently in paid employment and five respondents not currently in paid employment who provided sufficient information about their most recent occupation; employment-status and ISCO distributions therefore overlap. Task class follows the PIAAC abstract/routine/manual taxonomy and was assigned only to respondents currently in paid employment (n = 409). One employed respondent lacked routine-task-intensity information, yielding n = 408 for this measure and for Model C of Table 6. Routine-task intensity ranges from 1 to 9, with higher values indicating greater task routineness.

B.2 Automation-Anxiety Index: Item Wording and Scoring

Respondents indicated how worried they were that future automation and technological change might affect their job along five facets, each rated 0 = not at all worried, 1 = not very worried, 2 = somewhat worried, 3 = very worried (total range 0–15): (1) reduced control over how the work is done; (2) difficulty in using one's skills and abilities; (3) a reduction in income; (4) being transferred to a less interesting job; and (5) unexpected changes in working hours.

B.3 Functional Form of Income

Table B.2. Age and Education Coefficients under Alternative Income Specifications (DV: AIAS total; N = 756)

Income specification	Age	Bachelor's or higher	R^2
Linear (baseline)	0.221*** (0.050)	−10.44*** (1.99)	0.182
Log(income + 1)	0.223*** (0.050)	−10.89*** (2.00)	0.180
Inverse hyperbolic sine	0.223*** (0.050)	−10.91*** (2.00)	0.180
Winsorized at 99th pct.	0.234*** (0.050)	−9.82*** (1.99)	0.186
Winsorized at 95th pct.	0.231*** (0.050)	−9.83*** (1.99)	0.184
Income quartiles	0.224*** (0.050)	−10.21*** (2.01)	0.181

Notes. Each row is the additive specification of Model 3, Table 4, with income entered as indicated. OLS with HC1 robust standard errors in parentheses. * p < .05, ** p < .01, *** p < .001.

B.4 Education Gradient among Non-Employed Respondents

Table B.3. Bachelor's-or-Higher Coefficient by AIAS Subscale, Non-Employed Respondents (n = 347)

Outcome	b	SE	p	Effect size (SD)
AIAS total	−13.72	3.07	<.001	−0.81
Learning	−5.79	1.14	<.001	−0.87
Job replacement	−2.67	0.87	.002	−0.57
Sociotechnical blindness	−3.14	0.83	<.001	−0.68
AI configuration	−2.11	0.70	.003	−0.52

Notes. Additive specification (age, education, gender, personal income, parental education) estimated on respondents not currently in paid work; OLS with HC1 robust standard errors. Effect sizes divide the coefficient by the full-sample standard

deviation of the outcome. The gradients are present in all four dimensions and are strongest for learning; this group includes students and unemployed respondents who anticipate entering the labor market.

B.5 Measurement Invariance of the AIAS

Multigroup confirmatory factor analyses of the 16-item, four-factor AIAS model were estimated by maximum likelihood with marker-variable identification, comparing configural (all parameters free), metric (equal loadings), and scalar (equal loadings and intercepts) models across gender, age bands (18–34, 35–49, 50–64), and the four education groups.

Table B.4. Measurement Invariance Tests (ML estimator)

Grouping	Model	χ^2	df	CFI	RMSEA	$\Delta\chi^2$ (df), p	ΔCFI
Gender	Configural	747.8	196	.953	.086		
	Metric	756.2	208	.953	.084	8.4 (12), .75	+.000
	Scalar	779.8	220	.952	.082	23.6 (12), .02	−.001
Age bands	Configural	916.5	294	.947	.092		
	Metric	942.3	318	.947	.088	25.8 (24), .36	−.000
	Scalar	982.7	342	.945	.086	40.4 (24), .02	−.001
Education	Configural	1037.1	392	.944	.093		
	Metric	1078.4	428	.943	.090	41.3 (36), .25	−.001
	Scalar	1126.8	464	.942	.087	48.4 (36), .08	−.001

Notes. Metric invariance is supported for all three groupings by the χ^2 difference test. The χ^2 difference tests for scalar invariance are sensitive to the sample size; by the conventional $\Delta CFI \leq .01$ criterion (Cheung & Rensvold, 2002; Chen, 2007), scalar invariance is supported throughout, and RMSEA improves at each step. The primary invariance models used a continuous-indicator estimator. Re-estimation with categorical-data estimators yielded the same substantive conclusions.

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