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Who Worries About AI at Work? Neuroticism Predicts AI Anxiety, but a Recruitment-Based Occupational Category Does Not

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Karen D. Fox conceived the research question, developed all hypotheses, designed the study, conducted the literature review, analyzed the data, and wrote the manuscript. John E. Deaton served as principal investigator for institutional review board review at the Florida Institute of Technology and reviewed the manuscript, providing comments that shaped the final manuscript. Both authors read and approved the final manuscript.

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Abstract

Little is known about which individual differences predict AI anxiety among employed adults, for whom AI displacement is an occupational reality. We tested whether Big Five traits are associated with AI anxiety and whether occupational type (white-collar cognitive vs. skilled trade, classified by recruitment screening) moderates these associations. Among 491 employed U.S. adults, hierarchical regression showed that Neuroticism was the strongest correlate of AI anxiety. Conscientiousness was negatively associated with AI anxiety and Openness was not significant, but both results were sensitive to careless-responder screening; Extraversion and Agreeableness were not significant. Occupational type neither predicted AI anxiety nor moderated any trait effect, and an equivalence test indicated that the occupational difference was equivalent to zero within $d = \pm 0.30$ but not ± 0.20. However, 28.7% of participants who selected an occupational category chose the one opposite their recruitment group, so the occupational comparison is coarse and does not measure AI exposure directly. Personality and AI anxiety were also reported in the same survey, which may favor personality associations over occupational ones, and the study included no general anxiety control. The findings are therefore associational. Within these limits, AI anxiety in this sample varied with Neuroticism but not with a recruitment-based occupational category.

Keywords: AI anxiety, Big Five personality traits, neuroticism, occupational type, human–AI interaction, job displacement

Who Worries About AI at Work? Neuroticism Predicts AI Anxiety, but a Recruitment-Based Occupational Category Does Not

A decade ago, artificial intelligence (AI) in the workplace was largely theoretical. Today, it is operational: law firms use it to review documents, hospitals deploy it for diagnostics, and banks run algorithmic trading around the clock. This transition is likely to reach most occupations, since most include at least some tasks suited to machine learning (Brynjolfsson et al., 2018). The human cost of this transformation is often overlooked amid discussions of productivity and economic growth. Workers worry whether AI will take their jobs, whether they can adapt, and whether they even understand these systems, concerns that are not irrational but reflect genuine uncertainty about the future of work. Researchers have termed this response "AI anxiety": an affective response of anxiety or fear that inhibits interaction with AI (Wang & Wang, 2022). Because AI anxiety inhibits interaction with AI systems and shapes attitudes toward AI (Kaya et al., 2024), it also bears directly on human–AI interaction at work, including whether workers accept and use the AI tools their organizations introduce.

For organizations rolling out AI tools, understanding what drives employee anxiety is strategically necessary. If the difference between workers who embrace AI and those paralyzed by it maps onto stable psychological characteristics, organizations can intervene more effectively. The Big Five model (Costa & McCrae, 1992; Goldberg, 1990; McCrae & Costa, 2008) offers a well-established framework for studying who is most vulnerable to AI anxiety and why.

Prior studies have often relied on student or convenience samples with limited exposure to the occupational pressures that make AI anxiety consequential (e.g., Kaya et al., 2024) or measured AI attitudes broadly rather than as a distinct outcome. Research on AI anxiety among

employees is still accumulating (Alsudays, 2026), and studies of working adults that include personality have treated occupational role as a control rather than a moderator (e.g., Shalu et al., 2026). To the authors' knowledge, none has asked whether the personality–anxiety relationship differs by occupation. This omission matters, because a neurotic accountant and a neurotic plumber face very different levels of AI displacement risk. The present study addresses these gaps by examining the full Big Five model as a predictor of AI anxiety among employed adults, with particular focus on Neuroticism, Openness, and Conscientiousness. It also introduces occupational type as a moderator, testing whether the personality–anxiety relationship differs between white-collar cognitive workers and skilled trade workers, whom the displacement literature places at opposite ends of the risk spectrum.

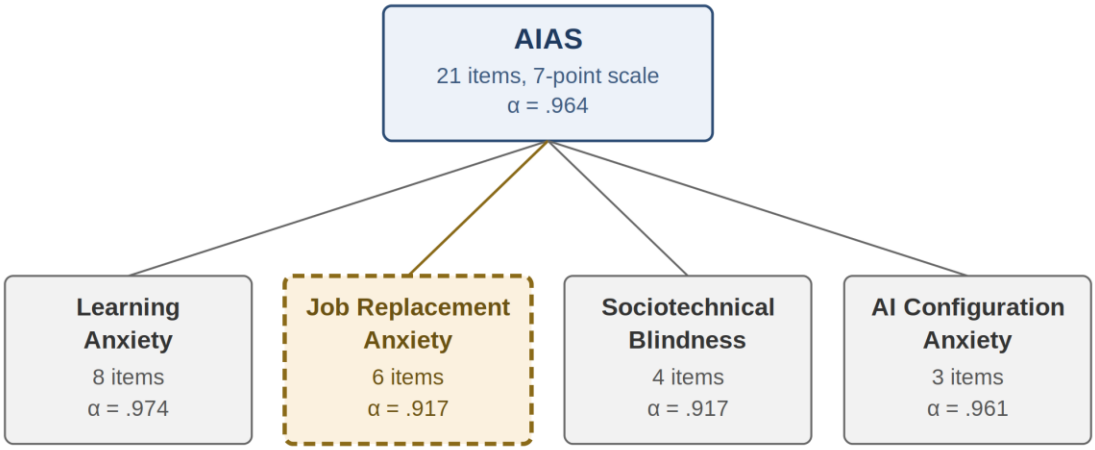
AI Anxiety: Definition and Measurement

AI anxiety developed alongside AI as a psychological response to a technological shift that feels categorically different from earlier waves of automation. Computer and internet anxiety have been studied for decades. However, AI elicits concerns that those constructs were never designed to capture: not simply learning to use a new device, but what the device may ultimately do to one's livelihood, autonomy, and occupational identity. Wang and Wang (2022) defined AI anxiety as an overall affective response of anxiety or fear that inhibits interaction with AI, distinct from earlier technology anxiety constructs. Drawing on prior work, they traced it to three sources: inaccurate perceptions of how AI is developing, confusion about AI autonomy, and sociotechnical blindness, the failure to recognize that AI depends on people and social institutions. To measure this construct, Wang and Wang (2022) developed the Artificial Intelligence Anxiety Scale (AIAS), a 21-item instrument with four subscales, illustrated in Figure 1. These are Learning Anxiety (anxiety about learning to use or understand AI techniques

and products), Job Replacement Anxiety (fear that AI will displace human workers), Sociotechnical Blindness (fear that AI may be misused, malfunction, or otherwise operate beyond human control), and AI Configuration Anxiety (fear evoked by humanoid or anthropomorphic AI). The Job Replacement Anxiety subscale is the most relevant here. Its items concern AI replacing human workers in general rather than the respondent's own job, but it is the dimension closest to displacement concerns, which have grown as research identifies higher-income, white-collar jobs as among the most exposed to AI (Eloundou et al., 2024).

Figure 1

Four-Factor Structure of the Artificial Intelligence Anxiety Scale



Note. Item counts and Cronbach's alpha values are as reported in Wang and Wang (2022). Job Replacement Anxiety, shown with a heavier dashed border, is the subscale closest to the displacement concerns underlying Hypotheses 4a and 4b.

Empirical research has confirmed that AI anxiety carries meaningful consequences for workplace attitudes and behavior. Kaya et al. (2024) found that AI anxiety, particularly its learning and configuration dimensions, significantly predicted attitudes toward AI in a sample of Turkish adults (mean age 24). Feng et al. (2025) found that AI workplace anxiety diminished

employees' life satisfaction, an effect fully mediated by negative emotions. These findings underscore the practical importance of understanding the origins of AI anxiety, a question this study directly addresses. Despite growing interest in the construct, relatively little research has examined the individual-difference predictors of AI anxiety, that is, why some workers experience noticeably more anxiety than others facing identical circumstances.

The Big Five Personality Model

The Five Factor Model, or Big Five, has emerged from decades of research as the most widely validated taxonomy of human personality traits, replicated across cultures, languages, and methods (Costa & McCrae, 1992; Goldberg, 1990; McCrae & Costa, 2008). The Big Five comprises five broad, largely independent trait dimensions (OCEAN): Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, each representing a continuum from low to high. Two alternative trait frameworks merit consideration. The HEXACO model adds an Honesty-Humility dimension (Ashton & Lee, 2007), and the Dark Triad captures socially aversive traits (Paulhus & Williams, 2002). Neither aligns with the process examined here. AI anxiety is a threat response, and threat appraisal is rooted in the negative-emotionality domain, which the Big Five and HEXACO share. Honesty-Humility and the Dark Triad traits concern how people treat others, not how they appraise uncertainty about their own futures. The Big Five also provides continuity with prior work. The studies linking personality to AI attitudes and fear of AI all used it (Kaya et al., 2024; Schepman & Rodway, 2023; Sindermann et al., 2022), so using the same model allows direct comparison with that work.

Appraisal theory explains why traits should matter here. Whether a change is experienced as stressful depends on whether a person appraises it as a threat and judges their coping resources

adequate (Lazarus & Folkman, 1984). Personality shapes both judgments, so the same AI rollout can be appraised differently by different employees. Neuroticism should amplify threat appraisal, consistent with a recent scoping review that described it as a dispositional amplifier in human–AI interaction (Singh & Sharma, 2026), whereas traits linked to curiosity and adaptive confidence should dampen it. Occupation should matter to the extent that it changes what there is to appraise.

Of all five traits, Neuroticism carries the most direct theoretical link to AI anxiety. Defined as the tendency to experience negative emotional states, including anxiety and worry, it predisposes individuals to perceive threat in ambiguous situations (Costa & McCrae, 1992). A neurotic employee confronting AI adoption faces rapid, unpredictable change with potentially permanent consequences for their livelihood. Of the trait's three facets in the BFI-2 model (anxiety, depression, and emotional volatility), anxiety is the most central (Soto & John, 2017), so a tendency to worry is built into Neuroticism itself. Workplace AI gives that tendency a ready target: the timeline is unclear, the eventual scope of automation is uncertain, and the outcome matters.

Where Neuroticism predisposes people toward fear, Openness to Experience points the other way. Characterized by intellectual curiosity and an appetite for novelty, high scorers approach unfamiliar situations with interest rather than dread (Costa & McCrae, 1992), which, in technology contexts, translates into a greater willingness to adopt new tools and more positive attitudes toward innovation. The facet most relevant here is intellectual curiosity (Soto & John, 2017). An employee who wants to understand how things work is more likely to try an AI tool than to avoid it. That firsthand experience may correct one of the sources of AI anxiety that Wang and Wang (2022) describe: inaccurate perceptions of technological development.

Conscientiousness reflects organization, self-discipline, and dependability (Costa & McCrae, 1992), and is the single strongest personality predictor of job performance across occupational domains (Barrick & Mount, 1991). Its relationship with AI anxiety is less clear: conscientious individuals may adapt confidently to new demands, or their high-performance standards and occupational identity may make disruption feel more threatening. Given this ambiguity, the present study treats the direction of this relationship as an open empirical question.

Extraversion reflects sociability, assertiveness, and positive emotionality (Costa & McCrae, 1992). Prior research has linked Extraversion to greater acceptance of technology in general, although AI may offer extraverts fewer social rewards than other technologies (Kaya et al., 2024). However, researchers have not systematically examined the direct relationship between Extraversion and AI anxiety, as opposed to broader AI attitudes, in employed adult samples, and effect sizes have generally been small and inconsistent (Sindermann et al., 2022).

Agreeableness reflects cooperativeness, empathy, and interpersonal trust (Costa & McCrae, 1992). Its relationship with AI anxiety is theoretically complex: agreeable individuals' trust in new systems suggests lower anxiety, but their sensitivity to social disruption and the potential harms of AI could predict the opposite. The available evidence concerns attitudes rather than anxiety: agreeable individuals have tended to view AI more favorably (Kaya et al., 2024; Schepman & Rodway, 2023), but the association has not replicated across cultural contexts (Sindermann et al., 2022). This pattern motivates treating both Extraversion and Agreeableness as research questions rather than hypotheses. The Big Five has well-established links to job performance (Barrick & Mount, 1991) and other workplace outcomes. More recently,

researchers have begun examining these traits as predictors of attitudes toward emerging technologies, including AI, a body of work reviewed in the following section.

Big Five Personality Traits and AI Attitudes: Existing Evidence

Research on personality and AI attitudes is growing, though most of it stops short of examining AI anxiety directly in workplace settings. Much of this work appears in the human–computer interaction literature (Kaya et al., 2024; Schepman & Rodway, 2023), where researchers have examined personality mainly as a predictor of attitudes toward AI rather than AI anxiety. This section reviews the empirical evidence and the gaps the present study addresses. Neuroticism has received consistent empirical attention as a predictor of technology-related anxiety: Sindermann et al. (2022) found significant positive correlations between Neuroticism and fear of AI in both German and Chinese samples, with similar effect sizes. However, in regression models, the association was significant only in the German sample. More recent studies point the same way: Montag et al. (2026) replicated small positive correlations between Neuroticism and fear of AI in German and Singaporean samples, Liebherr et al. (2025) found that Neuroticism predicted more negative views of AI's effect on well-being in British and Arab samples, and a scoping review of 45 studies concluded that Neuroticism consistently predicts heightened AI anxiety and reduced trust (Singh & Sharma, 2026). The pattern is weaker for favorability: using the TIPI, Grassini et al. (2025) found that Neuroticism did not predict positive attitudes toward AI. This evidence supports the hypothesis that Neuroticism will positively predict AI anxiety in workplace settings.

The evidence for Openness to Experience is less consistent. Kaya et al. (2024) found that Openness predicted more positive attitudes toward AI until they added AI anxiety to the model. Sindermann et al. (2022) found it associated with greater acceptance of AI in a Chinese but not a

German sample. In contrast, Schepman and Rodway (2023) found no Openness effect, suggesting contextual factors may moderate the relationship. The relationship between Conscientiousness and AI anxiety has received less direct empirical attention, and the competing mechanisms outlined above (systematic adaptation predicting lower anxiety versus displacement-sensitivity predicting higher anxiety) remain unresolved. In one study, Conscientiousness predicted more tolerant views of AI's drawbacks (Schepman & Rodway, 2023). However, another study found only a weak correlation with such views (Kaya et al., 2024), and neither study measured anxiety, motivating the non-directional hypothesis adopted here.

Among the most comprehensive studies to date examining Big Five traits alongside AI anxiety measures is Kaya et al. (2024), who administered the TIPI, AIAS, and a general AI attitudes scale to 350 Turkish adults, over half of whom were university students. Personality traits, AI anxiety, and demographic factors each contributed unique variance to AI attitudes, with AI anxiety emerging as a strong predictor. However, this study illustrates the gaps identified above. Its young, majority-student sample limits generalizability to the employed adults for whom AI displacement is an immediate reality. It also treated AI anxiety as a predictor of attitudes rather than an outcome, leaving open the question of which individual differences give rise to it. Sindermann et al. (2022) positioned fear of AI as an outcome of personality but used a brief five-item measure of AI acceptance and fear in a general, non-occupational population. The present study directly addresses this question.

For Extraversion and Agreeableness, the evidence is weaker and less consistent. For Extraversion, Schepman and Rodway (2023) found that introverts held more positive attitudes toward AI. Sindermann et al. (2022) found that extraverts reported greater acceptance and less

fear of AI in a Chinese sample but not in a German one. Kaya et al. (2024) found no significant association once other predictors were controlled. For Agreeableness, the direction has been more consistent, but the effects have been small and have not replicated across samples. Agreeable individuals held more tolerant views of AI's drawbacks (Kaya et al., 2024; Schepman & Rodway, 2023) and reported greater acceptance and less fear of AI in Sindermann et al.'s (2022) Chinese sample, but not in their German sample. Because none of these studies examined AI anxiety as an outcome, the present study examines both traits as research questions.

AI Displacement Risk and Occupational Type

For most of the twentieth century, the automation story was simple: machines replaced manual workers such as assembly-line operators and clerical typists. That landscape has since shifted as AI systems have begun performing cognitive tasks (reasoning, synthesizing, generating) long considered the exclusive province of educated professionals. Contemporary research on AI exposure points to a striking finding: white-collar cognitive workers, not blue-collar trade workers, face the greatest near-term exposure to AI. Brynjolfsson et al. (2018) found that machine learning affects different occupations than earlier waves of automation did, and that most occupations include at least some tasks suited to it. Eloundou et al. (2024) analyzed more than 1,000 U.S. occupations against large language model capabilities. They found that approximately 80% of workers could have at least 10% of their job tasks affected, with 19% facing exposure of 50% or more, and that higher-income occupations faced greater exposure.

The legal profession offers a clear example: AI systems can now review contracts, conduct legal research, and draft standard documents, making junior associate roles more vulnerable even as senior partners' complex judgment and client relationships remain difficult to automate. Similar dynamics are unfolding in accounting and financial analysis, and even

medicine, long considered automation-resistant, now faces displacement risk in pattern-recognition-heavy specialties such as radiology and dermatology. Skilled trade workers tell a different story. Plumbers, electricians, and mechanics rely on physical dexterity, spatial reasoning, and real-time improvisation in unpredictable environments, qualities AI cannot reliably replicate. This messiness of physical, contextual work is, paradoxically, its protection, leaving these occupations more secure in the AI era than many white-collar professions that have long outranked them in social prestige (Eloundou et al., 2024).

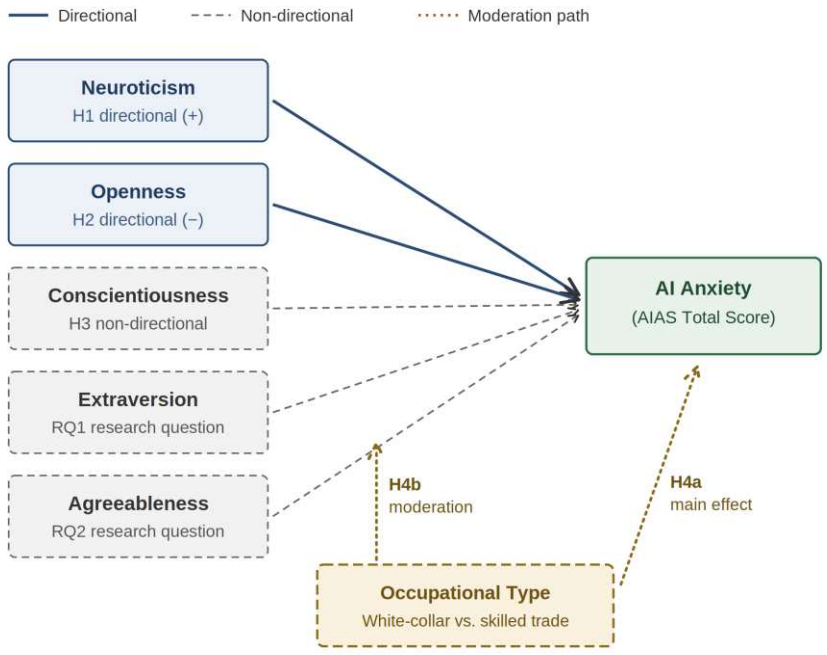
This is not purely speculative: Challenger, Gray & Christmas attributed 54,836 announced job cuts by U.S.-based employers to AI in 2025 (Blumenfeld, 2026), a figure that likely understates the impact, since many workforce reductions anticipate AI's effects rather than respond to them directly. Exposure here refers to technical feasibility, not inevitability; AI may augment cognitive work rather than replace it, and the question of displacement versus complementarity remains open (Eloundou et al., 2024). Workers' perceived exposure to displacement is likely the more proximal driver of AI anxiety; the present study did not measure it directly and instead tests whether occupational category, a proxy for objective exposure, matters. If white-collar cognitive workers face higher objective displacement risk than skilled trade workers, occupational type may meaningfully moderate the personality–anxiety relationship: a highly neurotic lawyer faces a different threat landscape than a highly neurotic electrician, and that difference in objective risk may amplify or attenuate how strongly personality translates into experienced anxiety. To the authors' knowledge, this study is the first to test this proposition, using a recruitment-based occupational classification as a proxy for displacement risk.

Research Questions and Hypotheses

These gaps point to a central research question: do Big Five traits and occupational type predict workplace AI anxiety, and does occupational type moderate those links? Five hypotheses address it; two exploratory research questions cover the remaining traits (Figure 2). Given Neuroticism's well-established link to anxiety and threat perception, reviewed above, a workplace being transformed by AI should be especially anxiety-provoking for employees high in this trait.

Figure 2

Conceptual Model of Big Five Personality Traits as Predictors of AI Anxiety in the Workplace, With Occupational Type as Moderator



Note. H1–H4b address the central question: H1–H2 are directional, H3 is non-directional, H4a tests the main effect of occupational type, and H4b tests moderation. RQ1 and RQ2 explore Extraversion and Agreeableness. AIAS = Artificial Intelligence Anxiety Scale.

Hypothesis 1 (H1): Higher levels of Neuroticism will positively predict AI anxiety in the workplace, such that employees scoring higher on Neuroticism will report significantly greater AI-related anxiety than those scoring lower.

Where a neurotic employee may see AI as a threat, an employee high in Openness is more likely to see an opportunity, suggesting a negative relationship with AI anxiety.

Hypothesis 2 (H2): Higher levels of Openness to Experience will negatively predict AI anxiety in the workplace, such that employees scoring higher on Openness will report significantly lower AI-related anxiety than those scoring lower.

Hypothesis 3 (H3): Conscientiousness will be examined as a non-directional predictor of AI anxiety in the workplace, given mixed findings in the existing literature.

The fourth hypothesis treats occupational type as both a predictor and a moderator. As a main effect, white-collar cognitive workers should report higher overall AI anxiety than skilled trade workers, given their greater objective displacement exposure. As a moderator, occupational type should shape how strongly personality traits translate into AI anxiety. These are distinct claims: the former asks whether one group is more anxious on average, the latter asks whether the same trait carries different weight depending on a worker's objective displacement risk. In the present study, both predictions were tested using a recruitment-based classification as a proxy for these occupational groups (see Method).

Hypothesis 4a (H4a): Employees in white-collar cognitive roles, including professionals such as lawyers, accountants, analysts, and physicians, will report significantly higher levels of AI anxiety than employees in skilled trade roles such as plumbers, electricians, and welders (main effect).

Hypothesis 4b (H4b): Occupational type will moderate the relationship between Big Five personality traits and AI anxiety, such that the personality–anxiety relationship will be stronger among white-collar cognitive workers than among skilled trade workers (moderation effect).

Although the primary hypotheses concern Neuroticism, Openness, and Conscientiousness, all five traits are included in the regression model. Extraversion and Agreeableness are examined as research questions given the mixed evidence reviewed above.

Research Question 1 (RQ1): Is Extraversion associated with AI anxiety in the workplace?

Research Question 2 (RQ2): Is Agreeableness associated with AI anxiety in the workplace?

Method

Participants

The sample consisted of 491 employed adults whose current country of residence was the United States, recruited via Prolific. In a comparison of online research platforms, Prolific was among the platforms providing the highest data quality (Peer et al., 2022). To be eligible, participants had to be U.S. residents currently employed full- or part-time in one of the two target occupational groups. Occupational-group assignment for all analyses was based on Prolific's platform-level prescreening, which routed participants into one of two parallel studies according to their registered industry role (described under Occupational Type, below). Participants also completed a self-report occupation item within the survey, which served as a validity check rather than the basis for group assignment. The sample was evenly divided by occupational group (247 white-collar cognitive workers, 244 skilled trade workers). Table S1 in Online Resource 1 presents sample demographic characteristics.

Participants reported their gender as man (*n* = 280, 57.0%), woman (*n* = 203, 41.3%), or non-binary/gender nonconforming (*n* = 8, 1.6%); no participant selected the available "prefer to self-describe" or "prefer not to say" options. Age was collected in bands, with most participants between 25 and 44 years old (25–34, *n* = 155, 31.6%; 35–44, *n* = 155, 31.6%), followed by 45–54 (*n* = 77, 15.7%), 18–24 (*n* = 55, 11.2%), 55–64 (*n* = 36, 7.3%), and 65 or older (*n* = 13, 2.6%). Educational attainment ranged from less than high school to doctoral or professional degrees, with a bachelor's degree the modal category (*n* = 182, 37.1%). Table S1 shows the full distribution. Reported job tenure was distributed across experience levels, most commonly more than 10 years (*n* = 133, 27.1%) or 4–6 years (*n* = 132, 26.9%). All participants were informed that their responses were anonymous and that the study had been approved by the institutional review board at the authors' institution.

Measures

The study measured two focal constructs, Big Five personality traits and AI anxiety, each assessed with an established self-report instrument, along with the occupational-type and demographic items described above. Table S2 presents descriptive statistics for all study variables, and Tables S3 and S4 present sample characteristics and descriptive statistics by occupational group.

Big Five Personality Traits

We assessed personality traits using the Ten-Item Personality Inventory (TIPI; Gosling et al., 2003), a validated, brief measure of the Big Five personality dimensions. The TIPI measures Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism using two items per trait, rated on a 7-point Likert scale ranging from 1 (*disagree strongly*) to 7 (*agree strongly*); a sample item is "Anxious, easily upset" (Neuroticism; Gosling et al., 2003, p.

525). Despite its brevity, the TIPI has demonstrated adequate reliability and validity across multiple studies and is widely used in large-scale survey research where respondent burden is a practical consideration. Because each TIPI dimension is measured with only two items, we assessed internal consistency using the Spearman–Brown coefficient, the recommended reliability estimate for two-item scales (Eisinga et al., 2013). In the present sample, coefficients were .79 for Neuroticism, .66 for Openness, .71 for Conscientiousness, and .70 for Extraversion, values consistent with those typically reported for the TIPI. Agreeableness showed lower reliability (.43), a limitation of the TIPI's Agreeableness scale that the Limitations section addresses.

AI Anxiety

We measured AI anxiety using the Artificial Intelligence Anxiety Scale (AIAS; Wang & Wang, 2022), a 21-item instrument with a four-factor structure assessing Learning Anxiety, Job Replacement Anxiety, Sociotechnical Blindness, and AI Configuration Anxiety (see Figure 1). Respondents rate items on a 7-point Likert scale from 1 (*strongly disagree*) to 7 (*strongly agree*), with higher scores indicating greater AI anxiety; for example, "I am afraid that AI techniques/products will replace someone's job" (Job Replacement Anxiety; Wang & Wang, 2022, p. 625). In its original validation, the AIAS showed excellent internal consistency (overall $\alpha = .964$; subscale values in Figure 1; Wang & Wang, 2022). Although the AIAS was originally developed and validated on a Taiwanese sample, researchers have since confirmed its four-factor structure in Turkish (Akkaya et al., 2021; Terzi, 2020) and German-language validations. Hajek et al. (2025) confirmed it in a large, quota-based adult sample ($N = 3{,}270$; CFI = .96, RMSEA = .06) and also replicated its excellent internal consistency (overall $\alpha = .97$). A reliability generalization of the original 21-item AIAS reported a pooled alpha of .949 across 15 studies

(Yıldırım et al., 2026). In the present sample, internal consistency was likewise high for the AIAS total score (α = .95) and each subscale: Learning Anxiety (α = .96), Job Replacement Anxiety (α = .92), Sociotechnical Blindness (α = .86), and AI Configuration Anxiety (α = .92). In a confirmatory factor analysis, the four-factor model showed marginal fit (CFI = .93, SRMR = .06, RMSEA = .09). Metric invariance held across occupational groups, and scalar invariance held by the ΔCFI criterion ($|\Delta CFI| \leq .001$; Chen, 2007), although the chi-square difference test was marginally significant ($p = .049$; Table S5). Reliability estimates for all measures are presented in Table S6.

To maintain data quality, the survey included an attention-check item instructing participants to select a specified response, and we excluded participants who failed it. Because experienced online participants may learn to recognize such items, we also screened for careless responding after data collection using three indices recommended by Curran (2016). The longstring index captured identical consecutive responses across the 21 AIAS items. The even-odd consistency index was the within-person correlation between odd- and even-numbered item halves across the four AIAS subscales and five TIPI dimensions. Multivariate outliers were identified with Mahalanobis distance across all 31 TIPI and AIAS items (χ^2 criterion, $p < .001$). Because we did not specify these screens in advance, we retained flagged cases in the primary analyses and, as a sensitivity check, re-estimated the main models without them.

Occupational Type

We operationalized occupational type through Prolific's platform-level recruitment screening rather than a within-survey self-report item, using two parallel Prolific studies, each restricted to a distinct set of registered industry roles. The white-collar cognitive group comprised Upper Management, Middle Management, Junior Management, Trained Professional,

Consultant, and Researcher; the skilled trade group comprised Skilled Laborer. This recruitment-stage classification served as the binary occupational-type variable in all analyses, coded 0 (skilled trade) or 1 (white-collar cognitive). Prolific's role categories describe position level as well as occupation, so the white-collar group includes managers and the skilled trade group includes manual roles beyond the licensed trades; the variable is therefore a coarse proxy for occupational AI exposure rather than a measure of it. As a validity check, participants also self-reported their primary occupational category; the Results report agreement between recruitment-based and self-reported occupational type.

Procedure

We collected data via Prolific, an online research platform widely used in peer-reviewed psychological research, through two parallel studies targeting white-collar cognitive and skilled trade workers, respectively, each using Prolific prescreening filters for full- or part-time employment, U.S. residence, and the relevant occupational role. Eligible participants completed an online survey comprising an informed-consent item, employment and occupation screeners, a brief demographic questionnaire, the TIPI followed by an embedded attention check, the AIAS, and an item requesting the participant's Prolific ID. All participants completed the measures in this fixed order. Prolific IDs were collected only to verify completion and process payment and were removed from the analysis dataset. When a participant submitted the survey more than once (one participant, three submissions), we retained the earliest response. Median completion time was 6 min 41 s (white-collar) and 5 min 15 s (skilled trade), and participants received $6.00 upon completion. Completion time was not used as an exclusion screen. All data collection followed institutional review board guidelines approved through the authors' institution.

Common Method Variance

Because personality traits and AI anxiety were both measured via self-report in a single online survey, the design risks common method variance. Several features reduce, but do not remove, this risk. First, self-report is the most direct way to measure these constructs, because personality traits and anxiety are internal states that others cannot observe directly (Paulhus & Vazire, 2007). Both the TIPI and the AIAS are self-report instruments that have been developed and validated (Gosling et al., 2003; Wang & Wang, 2022). Second, the two measures share no item content. The TIPI uses trait adjectives to assess stable dispositions, whereas the AIAS uses statements about AI to assess a domain-specific anxiety response. Third, the survey included procedural safeguards: an attention-check item separated the two instruments, and participants were told their responses were anonymous, which reduces evaluation apprehension (Podsakoff et al., 2003). As a secondary check, we also conducted Harman's single-factor test (reported in Preliminary Analyses), following the recommendation that such post hoc tests supplement rather than replace procedural safeguards (Podsakoff et al., 2003).

Data Analysis

We targeted a sample of 500 participants to ensure adequate statistical power for all planned analyses. An a priori power analysis (G*Power 3.1) for hierarchical multiple regression with 10 predictors ($\alpha = .05$, power = .80, $f^2 = 0.05$) indicated that 160 participants would suffice to detect a small-to-moderate effect of an individual Big Five trait (Sindermann et al., 2022; Wang & Wang, 2022). However, the moderation hypotheses (H4b) require substantially greater power, as detecting interaction effects typically demands larger samples than detecting main effects (McClelland & Judd, 1993); a separate power analysis for the moderation interaction (11 predictors including the interaction term, $f^2 = 0.02$, $\alpha = .05$, power = .80) indicated a required

sample of 395. We therefore adopted a target of 500 to exceed this threshold, allow for exclusions, and support stratified recruitment of comparable samples from white-collar and skilled trade occupations. The achieved sample of 491 exceeded the 395 required to detect a single interaction of that size, although the study was not powered to detect smaller interactions.

We conducted all analyses in SPSS Statistics version 32. We began with descriptive statistics and bivariate correlations, then evaluated regression assumptions: linearity via partial regression plots, homoscedasticity via residual scatterplots, normality via Q-Q plots and the Shapiro–Wilk test, and multicollinearity via VIF (values exceeding 5 flagged as problematic). We assessed influential cases using Cook's distance. Given the large sample size ($N = 491$), we retained ordinary least squares estimates despite the modest departure from normality detected via the Shapiro–Wilk test, consistent with OLS's established robustness to non-normality at this sample size; we report standard parametric significance tests throughout.

To test H1–H3 and the H4a main effect and address RQ1 and RQ2, we ran a hierarchical multiple regression with total AIAS score as the outcome. Block 1 contained the demographic covariates (age, gender, education), with gender dummy-coded (woman and non-binary/gender nonconforming contrasts, man as reference). Block 2 added the five Big Five traits and occupational type simultaneously. For H4b, we tested moderation in a separate model for each trait, following Hayes's (2018) logic for Model 1. Each model included the demographic covariates, all five Big Five traits, occupational type, and the product of the focal trait and occupational type, so that every interaction was estimated net of the other traits and of both constituent main effects. Because the moderator was a single dichotomous variable, we estimated the interaction directly through ordinary least squares regression, which is mathematically equivalent to the PROCESS macro for this design. We probed significant interactions with

simple-slopes analyses. Age bands and education levels were entered as ordinal covariates; re-estimating the main model with both entered as categorical variables did not change any conclusion (Neuroticism, $p < .001$; Conscientiousness, $p = .016$; occupational type, $p = .357$). Re-estimating it with HC3 heteroscedasticity-consistent standard errors (Hayes & Cai, 2007) gave the same pattern (Neuroticism, $p < .001$; occupational type, $p = .470$), except that Conscientiousness fell just above the threshold ($p = .051$). We set the alpha threshold at .05 throughout and reported effect sizes as R^2. The study was not preregistered. The occupational-type analyses (H4a and H4b) and the Job Replacement Anxiety secondary analysis were specified in a dated analysis protocol recorded before data collection; the careless-responding screens and the robustness checks reported below were not. We used Claude (Anthropic), a large language model, to support manuscript drafting and editing and to write Python code for the supplementary analyses (careless-responding sensitivity checks, robustness checks using self-reported occupation, equivalence tests, HC3 robust standard errors, reliability-corrected correlations, and confirmatory factor analyses); we specified all analyses and verified every reported value in SPSS, or in JASP for the factor analyses.

Results

Preliminary Analyses

The survey received 497 submissions from 495 unique participants. We retained $N = 491$ participants for analysis after excluding two who failed the embedded attention check and two who did not meet the employment eligibility criterion despite passing Prolific's prescreening. The final sample comprised 247 white-collar cognitive workers and 244 skilled trade workers, closely matching the intended balanced allocation. During revision, we found that one participant's Neuroticism score was miscoded (2.0 rather than the 1.0 implied by the two TIPI

items); we corrected it, and all tables and analyses reported here were generated from the corrected data. No responses were missing on any analytic variable.

Table 1 reports zero-order correlations among all study variables. As expected, Neuroticism was positively correlated with total AI anxiety ($r = .35$, $p < .001$), and Openness to Experience was negatively correlated with AI anxiety ($r = -.20$, $p < .001$). Conscientiousness ($r = -.26$, $p < .001$), Extraversion ($r = -.11$, $p = .017$), and Agreeableness ($r = -.14$, $p = .001$) were also significantly and negatively correlated with AI anxiety at the bivariate level. Occupational type was not significantly correlated with AI anxiety ($r = -.05$, $p = .317$). All variance inflation factors fell below 1.7 (range = 1.04–1.69), indicating that multicollinearity was not a concern. Correlations between the predictors and the four AIAS subscales, also shown in Table 1, followed the same pattern: Neuroticism correlated positively with every subscale (rs = .25 to .32, all ps < .001), and Openness, Conscientiousness, and Agreeableness correlated negatively with every subscale. Extraversion, by contrast, correlated with Job Replacement Anxiety ($r = -.14$) and Sociotechnical Blindness ($r = -.11$) but not with Learning Anxiety or AI Configuration Anxiety.

As a supplementary check for common method variance, an exploratory (unrotated) factor analysis of all TIPI and AIAS items yielded five factors with eigenvalues greater than 1. The first factor (eigenvalue = 11.04) accounted for 35.6% of the variance, well below the 50% threshold conventionally used to indicate a single dominant factor (Podsakoff et al., 2003). Only the AIAS items loaded strongly and consistently on this factor (loadings of .55 to .75), whereas TIPI items showed weak, inconsistent loadings (−.37 to .45), suggesting this factor reflects the AIAS construct rather than a method artifact spanning both instruments. Because Harman's test

is an insensitive check (Podsakoff et al., 2003), this result does not rule out common method variance, a limitation addressed in the Discussion.

The careless-responding screens flagged 9 participants on the longstring index (identical responses to all 21 AIAS items), 16 with negative even-odd consistency, and 30 multivariate outliers. Seven of the 9 longstring cases selected the lowest response option throughout, a pattern consistent with genuinely low AI anxiety. Two or more indices flagged five participants. We re-estimated the primary models five times, excluding, in turn, the longstring cases, cases with negative even-odd consistency, multivariate outliers, cases flagged by either of the last two screens, and cases flagged by two or more indices (*N*s = 449 to 486). Across these analyses, Neuroticism remained a significant positive predictor of AI anxiety (all *p*s < .001), and occupational type remained unrelated to it (all *p*s > .48). Two effects were less stable: Conscientiousness ranged from $p = .032$ to $p = .076$, and Openness from $p = .020$ to $p = .104$. The Extraversion × Occupational Type interaction on Job Replacement Anxiety ranged from $p = .043$ to $p = .061$. These effects are therefore interpreted cautiously.

Regression Assumptions

Before hypothesis testing, we evaluated regression assumptions. Partial regression plots supported linearity, and residual scatterplots indicated no marked departure from homoscedasticity. Residuals departed modestly from normality per the Shapiro–Wilk test ($W = .990$, $p = .002$), though OLS estimates are considered robust to this given the large sample ($N = 491$). The maximum Cook's distance (.083) fell well below 1.0, and excluding the 25 cases above 4/N did not change any conclusion.

Big Five Traits Predicting AI Anxiety (H1–H3, RQ1–RQ2)

We conducted a hierarchical multiple regression to test the Big Five traits as predictors of total AI anxiety. We entered demographic covariates (age, gender, and education) in Block 1, with gender dummy-coded (woman and non-binary/gender nonconforming contrasts; man as reference), and entered the five personality traits and occupational type simultaneously in Block 2. Table 2 presents the full results. Block 1 was not statistically significant, $F(4, 486) = 1.26$, $p = .284$, $R^2 = .010$. In Block 2, adding the Big Five traits and occupational type accounted for a significant increase in explained variance, $\Delta R^2 = .134$, $\Delta F(6, 480) = 12.49$, $p < .001$, with the full model explaining 14.4% of the variance in AI anxiety ($R^2 = .144$).

Turning to the individual predictors, Neuroticism significantly and positively predicted AI anxiety ($\beta = .26$, $b = .22$, $p < .001$), supporting H1. Contrary to expectations, Openness to Experience did not significantly predict AI anxiety once the full set of predictors was included in the model ($\beta = -.09$, $b = -.09$, $p = .063$); although the association trended in the predicted negative direction, H2 was not supported at conventional significance thresholds. Conscientiousness was negatively associated with AI anxiety ($\beta = -.11$, $b = -.12$, $p = .029$), answering the non-directional question posed in H3. Regarding the research questions, neither Extraversion ($\beta = .02$, $p = .679$; RQ1) nor Agreeableness ($\beta = .00$, $p = .985$; RQ2) was associated with AI anxiety after controlling for the other traits.

Occupational Type as Main Effect and Moderator (H4a and H4b)

Before testing H4, we compared recruitment-based occupational type with participants' self-reported occupation. Of the 491 participants, 76 (15.5%) typed a specific occupation rather than selecting one of the two categories, and 119 of the remaining 415 (28.7%) selected the category opposite their recruited group. Disagreement was concentrated among skilled-trade

recruits: of the 177 who selected a category, 101 chose white-collar, compared with 18 of the 238 white-collar recruits who chose skilled trade. The groups also differed in education: 38.1% of skilled-trade recruits and 75.7% of white-collar recruits held a bachelor's degree or higher (Table S3). The occupational comparison should therefore be read as a contrast between recruitment categories rather than between clearly defined occupations. To test whether misclassification affected the results, we re-estimated the main models with self-reported occupation in place of the recruitment variable (n = 415) and in the subsample whose two classifications agreed (n = 296; 220 white-collar, 76 skilled trade). These results are reported below alongside the primary tests.

Hypothesis 4 comprised a main-effect prediction (H4a) and a moderation prediction (H4b). To test H4a, we entered occupational type as a predictor of total AI anxiety, along with personality traits and covariates. Unadjusted, skilled trade workers reported slightly higher AI anxiety (M = 3.45, SD = 1.30) than white-collar workers (M = 3.33, SD = 1.20). After adjustment, the sign reversed but the effect remained nonsignificant, b = 0.09, SE = 0.12, 95% CI [−0.15, 0.32], t = 0.72, p = .470, not supporting H4a. The reversal reflects the groups' difference in Neuroticism: skilled trade workers scored higher on Neuroticism (M = 3.17 vs. 2.51; r = −.23 with occupational type), which largely accounts for their slightly higher unadjusted anxiety. To evaluate whether this null result reflects the absence of a meaningful effect, we conducted an equivalence test on the covariate-adjusted estimate using two one-sided tests (Lakens, 2017). Because no smallest effect size of interest was specified in advance, we report two conventional bounds. The occupational difference was statistically equivalent to zero within d = ±0.30 (90% CI for d [−0.09, 0.23], p = .008) but not within d = ±0.20 (p = .083). A Bayes factor approximated from the BIC (Wagenmakers, 2007) indicated that the data were about 17 times

more likely under a model without occupational type (BF_{01} = 17.0). The null held with self-reported occupation (p = .708) and in the agreement subsample (p = .210).

To test H4b, a separate model was estimated for each trait containing the demographic covariates, all five traits, occupational type (coded 0 = skilled trade, 1 = white-collar cognitive), and the product of the focal trait and occupational type. Table 3 presents the results. None of the five trait-by-occupation interactions reached significance (all ps ≥ .33), and each added less than 0.2% of explained variance ($\Delta R^2 \leq .002$). With the trait and outcome standardized, the 90% confidence intervals for all five interaction coefficients fell within ±0.23 (90% intervals correspond to the two one-sided tests used for equivalence), so interactions larger than about 0.23 SD are unlikely, but moderation of practically relevant size cannot be ruled out. The same conclusion held when the other traits were omitted from each model (all ps > .29). With self-reported occupation, only the Openness interaction reached significance (p = .043), which does not survive Bonferroni correction; in the agreement subsample, no interaction was significant (all ps ≥ .15). Occupational type therefore showed no detectable moderation of the personality–anxiety relationships for total AI anxiety; H4b was not supported.

Planned Secondary Analysis: Job Replacement Anxiety

As a secondary analysis specified in the pre-data-collection protocol, the personality-by-occupation interactions were also tested using the Job Replacement Anxiety subscale, the AIAS dimension closest to displacement concerns, although its items refer to AI replacing human workers in general rather than to the respondent's own job. Table 4 presents the full results. Occupational type did not significantly predict Job Replacement Anxiety, whether as a group comparison or as a regression main effect. Using the same model specification as for H4b, four of the five trait-by-occupation interactions were also non-significant (all ps > .23).

However, the Extraversion × Occupational Type interaction was significant, $b = -0.19$, $SE = 0.09$, 95% CI [−0.37, −0.01], $t = -2.10$, $p = .036$ (Table 4). Simple-slopes analysis indicated that Extraversion was negatively associated with Job Replacement Anxiety among white-collar workers ($b = -0.15$, $SE = 0.07$, $p = .034$) but not among skilled trade workers ($b = 0.04$, $SE = 0.06$, $p = .510$). Although H4b predicted stronger personality–anxiety relationships among white-collar workers, all interactions were tested two-tailed, and Extraversion was examined as a research question rather than a hypothesis, so the direction of this effect should not be taken as confirmatory.

However, this effect must be interpreted with substantial caution. Because H4b was tested as five separate trait-by-occupation interactions, the familywise probability of at least one spurious result at $\alpha = .05$ is approximately .23, and the Extraversion interaction ($p = .036$) does not survive Bonferroni correction ($\alpha = .010$). It was also sensitive to careless-responder screening ($p = .043$ to .061) and to how occupation was classified ($p = .679$ with self-reported occupation; $p = .288$ in the agreement subsample). Moreover, the H4b prediction concerned the personality–anxiety pattern across the traits in general rather than Extraversion specifically, which was not singled out a priori. This isolated result is therefore best regarded as hypothesis-generating, requiring direct, preregistered replication before any strong conclusion is drawn.

Discussion

This study examined whether Big Five personality traits predict AI anxiety among employed adults and whether occupational type moderates that relationship. Neuroticism emerged as the strongest predictor of AI anxiety, supporting H1, and Conscientiousness was a significant negative predictor (H3), though this effect was sensitive to careless-responder screening. Openness to Experience trended in the hypothesized negative direction but did not

reach conventional significance once other predictors were included, leaving H2 unsupported at the .05 threshold. Extraversion and Agreeableness, examined as research questions, were not associated with total AI anxiety once the other traits were controlled (RQ1, RQ2). Occupational type did not predict AI anxiety as a main effect, and it did not moderate the relationship between any of the five personality traits and total AI anxiety, leaving both H4a and H4b unsupported. A single exception emerged in the secondary analysis of the Job Replacement Anxiety subscale, where occupational type moderated the Extraversion–anxiety relationship; because this effect was one of several interactions tested and did not hold under alternative occupational classifications, it should be treated as tentative. Taken together, the findings extend research on individual-difference predictors of workplace AI anxiety by showing that AI anxiety varied with Neuroticism in an employed sample, while a recruitment-based occupational category carried no detectable signal; same-survey measurement may favor the personality associations.

The Neuroticism finding (Table 2) matches the mechanism proposed at the outset. Individuals high in Neuroticism are disposed to perceive threat and ruminate on negative outcomes (Costa & McCrae, 1992), and workplace AI adoption is ambiguous by design: timelines are unclear, the eventual scope of automation is uncertain, and communication often lags the technology itself. This uncertainty creates fertile ground for the threat-appraisal tendencies characteristic of Neuroticism, consistent with Sindermann et al. (2022) and Montag et al. (2026). A one-standard-deviation difference in Neuroticism corresponded to roughly a quarter-standard-deviation difference in AI anxiety ($\beta = .26$), the largest personality effect in the model. In appraisal terms (Lazarus & Folkman, 1984), this pattern is consistent with Neuroticism amplifying threat appraisal of AI, although exposure itself was not measured.

The negative Conscientiousness relationship aligns better with the adaptive-confidence account than with the threatened-identity account. Conscientious individuals may approach AI as another domain to be managed with the same disciplined, systematic effort that characterizes their broader work style, rather than as a threat to their professional identity. This finding also converges with evidence that Conscientiousness relates to more tolerant views of AI's drawbacks (Kaya et al., 2024; Schepman & Rodway, 2023) and extends it to a workplace-anxiety outcome. This effect is tentative: it was the model's smallest significant effect and lost significance with robust standard errors and in two of five careless-responding sensitivity analyses.

Openness trended in the hypothesized direction, consistent with the expectation that curiosity buffers against AI-related fear (Costa & McCrae, 1992), but did not reach statistical significance after accounting for the other predictors ($p = .063$). This near-threshold result should not be read as evidence that Openness is irrelevant to AI anxiety; rather, its unique contribution appears to shrink once variance shared with other traits, particularly Neuroticism, is partitioned out. The bivariate correlation between Openness and AI anxiety was significant and in the predicted direction (Table 1), but it did not hold net of the other traits. Neither Extraversion nor Agreeableness significantly predicted total AI anxiety, consistent with the mixed and inconsistent effects reported for both traits in the broader AI-attitudes literature (Kaya et al., 2024; Sindermann et al., 2022) and with the non-directional, exploratory status assigned to them as research questions at the outset.

The occupational-type findings depart from prediction in a way that, in retrospect, is more informative than a confirmatory result would have been. H4a and H4b were motivated by labor-economics research indicating that white-collar cognitive occupations face substantially greater near-term exposure to AI-driven task automation than skilled trade occupations

(Eloundou et al., 2024). Given that objective exposure gradient, it seemed reasonable to expect that white-collar workers would report more AI anxiety on average, and that personality traits linked to threat sensitivity would predict anxiety more strongly within that higher-risk group. Neither prediction was borne out. White-collar and skilled trade workers reported similar levels of AI anxiety, and any difference was at most small; its direction depended on whether Neuroticism was controlled. No trait showed detectable moderation by occupational type (Table 3), although the study could not rule out small interactions. Because the occupational comparison rested on recruitment categories that many participants did not endorse, these nulls show that a broad occupational classification carried little signal, not that occupational exposure is irrelevant.

One interpretation is that objective task-level exposure to AI, as estimated by economists analyzing occupational codes against model capabilities, does not translate directly or proportionately into the subjective, felt anxiety employees report in their day-to-day work lives. If that is correct, AI anxiety may function less as a rational appraisal of one's own job's automatability and more as a dispositional response, an anxiety that certain personality profiles are prone to regardless of the objective risk landscape they happen to occupy. Large-sample survey data point the same way: in Gallup panel data on U.S. workers, fear of AI-driven job displacement differed only slightly by occupational exposure to AI (Makridis, 2026). This account fits naturally with the strength of the Neuroticism finding relative to the null occupational effects: personality explained meaningful variance in AI anxiety, while the occupational classification explained essentially none, a comparison that same-survey measurement may tilt toward personality. The full model accounted for 14.4% of the variance in AI anxiety, an effect size consistent with prior work linking personality to domain-specific technology attitudes, where individual traits typically account for small-to-moderate portions of

variance (Kaya et al., 2024; Sindermann et al., 2022). This also aligns with a broader pattern in the risk-perception literature, where subjective risk appraisal is well known to diverge from objective hazard exposure across many domains, not just AI (Slovic, 1987).

A second, non-competing possibility concerns measurement. In the present study, we operationalized occupational type as a binary contrast based on Prolific's platform-level recruitment channel, not as a validated, continuous measure of an individual's perceived exposure to AI-driven task automation. A worker's recruitment-channel label may correlate imperfectly with how exposed that worker actually perceives their own role to be. If awareness of displacement risk is unevenly distributed within occupational categories, a binary channel-based variable could mask a true relationship that a more fine-grained self-report measure of perceived exposure would detect. The mismatch between recruitment and self-reported occupation reported in the Results makes this possibility more plausible. Continuous exposure measures can reveal effects that a binary category hides: industry-level AI exposure has been found to amplify the behavioral consequences of occupation insecurity (Probst et al., 2026). The present design cannot adjudicate between the dispositional-response account and this measurement account, and the two are not mutually exclusive; disentangling them is a natural next step for future research.

The one occupational-type effect that emerged, the Extraversion × Occupational Type interaction on Job Replacement Anxiety, aligns with a narrower version of the original moderation logic: more extraverted white-collar workers reported lower job-replacement anxiety, whereas extraversion showed no such association among skilled trade workers. As detailed in the Results, however, this secondary analysis produced only one significant interaction among five tested; that interaction does not survive correction for multiple comparisons, Extraversion was

not singled out a priori, and the interaction did not replicate when occupation was classified by self-report. It is therefore best treated as a candidate for preregistered replication rather than an established finding.

Practical Implications

These findings have implications for how organizations approach AI anxiety, but they should be read in light of the correlational design. First, the findings bear on how AI tools are introduced to the people expected to use them. Technology acceptance models explain adoption chiefly through perceived usefulness and ease of use (Davis, 1989) or, in the unified model, through performance and effort expectancy (Venkatesh et al., 2003), and organizational rollouts accordingly tend to emphasize training and usability. In the present sample, however, AI anxiety was lowest for Learning Anxiety ($M = 2.48$ on a 7-point scale) and highest for Sociotechnical Blindness ($M = 4.35$) and Job Replacement Anxiety ($M = 4.18$; Table S2). Although this is a descriptive comparison across subscales with different item content, workers' concerns centered less on whether they could learn to use AI than on whether AI could be controlled and what it would mean for their jobs. If that pattern holds, interfaces and rollout practices that make AI behavior transparent and keep human oversight visible may address employees' concerns more directly than additional training in how to use the tools. Because AI anxiety varied with Neuroticism but not with recruitment category, job type alone is unlikely to target these efforts well. These implications are correlational and untested.

Second, recruitment category was a poor guide to which employees were anxious. White-collar and skilled trade workers reported similar AI anxiety, so organizations that focus support only on roles labeled as highly exposed may miss anxious employees elsewhere. Where AI anxiety matters for a rollout, a better approach is to assess it directly, for example through brief,

voluntary surveys during implementation, rather than to infer it from occupation or personality. The personality associations observed here are modest. With correlations of this size, many employees high in Neuroticism or low in Conscientiousness will report low AI anxiety, so using personality as a proxy would misdirect support.

Third, if AI anxiety tracks disposition more than objective exposure, communication focused only on the technical security of particular roles may not reach the employees most anxious. This is a hypothesis for intervention research rather than a demonstrated effect, since the present study did not test any strategy for reducing AI anxiety. Fourth, these findings do not support using personality in selection decisions for AI-intensive roles. AI anxiety is an emotional response that may change with experience and support, and screening on traits associated with it would be neither ethically defensible nor justified by effects of this size.

Limitations and Future Directions

Several limitations suggest directions for future research. The first set concerns the study's design. Because the data are cross-sectional, the reported associations cannot establish temporal order or causal relationships. All measures were self-reported in a single survey. An attention-check item separated the two instruments, but this brief separation falls well short of the psychological separation of at least 7.5 minutes that Rubenstein et al. (2025) found necessary to reduce method variance to levels comparable to temporal separation. A time-lagged design would provide a stronger safeguard against common method variance. The measures were also completed in a fixed order, with the TIPI before the AIAS, so order effects cannot be ruled out. This concern bears directly on the study's central comparison. Personality and AI anxiety were both reported in the same session, whereas occupational group came from a registration category set before the study. Common method variance could therefore inflate the personality

associations relative to the occupational ones, and the comparison between them should be interpreted with that asymmetry in mind.

A related concern is specificity. The study did not include a measure of general anxiety, so it cannot show whether the personality associations are specific to AI anxiety or reflect a broader tendency to feel anxious. Neuroticism is partly defined by that broader tendency. In addition, one of the two TIPI Neuroticism items asks directly about being "anxious, easily upset" (Gosling et al., 2003, p. 525). The Neuroticism association may therefore partly reflect overlap between the predictor and the outcome rather than a relationship specific to AI. As a check, we re-estimated the main model using only the other Neuroticism item ("calm, emotionally stable," reverse-scored; Gosling et al., 2003, p. 525). Neuroticism remained a significant predictor (β = .15, p = .004), though the estimate was smaller than for the two-item score (β = .26). Some of the association may therefore reflect item overlap, although a single item is also less reliable, which would itself shrink the estimate. Future studies should control for general anxiety and test whether personality predicts AI anxiety beyond it.

A second set concerns the sample. Participants were recruited through Prolific, whose users may be more familiar with online technologies than the general working population, potentially attenuating observed anxiety levels and limiting generalizability to less technologically engaged workers. We also did not measure how often participants used AI at work, which may shape AI anxiety independently of occupation (Makridis, 2026). The sample was also drawn from a single national context (the United States), so the findings may not generalize to other national or cultural settings. Replication in other labor markets, and with workers in industries undergoing especially rapid AI-driven change, would clarify the boundaries of these findings.

A third set concerns measurement. Personality was the focal predictor, yet we assessed it with the Ten-Item Personality Inventory, which measures each broad Big Five domain with two items. That choice limits construct coverage, yields modest reliability, and cannot capture facets. The facet limitation matters theoretically: the mechanisms proposed here operate at the facet level, through the anxiety facet of Neuroticism and the intellectual-curiosity facet of Openness, and broad domain scores dilute those facets with content less relevant to AI anxiety. The present estimates may therefore understate the true relationships, which could partly explain the nonsignificant Openness, Extraversion, and Agreeableness results. Correcting the bivariate correlations for unreliability (Spearman, 1904) illustrates the scale of this attenuation: the corrected correlation with AI anxiety was .40 for Neuroticism (observed .35), −.32 for Conscientiousness (−.26), −.26 for Openness (−.20), −.23 for Agreeableness (−.14), and −.13 for Extraversion (−.11). This concern is most acute for Agreeableness, whose Spearman–Brown coefficient (.43) fell well below the other four traits (Table S6); the null Agreeableness findings reported here (RQ2) should accordingly be interpreted with particular caution, as low reliability attenuates observable effects and may have obscured a true relationship with AI anxiety. A facet-level instrument such as the BFI-2 (Soto & John, 2017) would enable finer-grained analysis of which facets drive AI anxiety.

Another consideration concerns the AIAS itself, originally validated on a Taiwanese sample, though its four-factor structure has since been confirmed in Turkish (Akkaya et al., 2021; Terzi, 2020) and German validations, the latter drawing on a large, quota-based adult sample (Hajek et al., 2025). Because the present study's moderation hypothesis (H4b) concerns the relative pattern of personality–anxiety relationships across occupational groups rather than absolute anxiety levels, it is less sensitive to the mean-level cross-cultural variability documented

by the same evidence, and the AIAS showed metric invariance across the two groups, with scalar invariance supported by ΔCFI (Table S5). Cross-national invariance remains to be established before anxiety levels are compared across countries.

An additional consideration concerns how occupational type was determined. As reported in the Results, many participants' self-reported occupation did not match their recruitment category, particularly among skilled-trade recruits, and Prolific's role categories describe position level as well as occupation. The occupational variable therefore indexes recruitment category rather than occupation or AI exposure. The robustness checks, while reassuring, cannot fully correct for this: the agreement subsample was unbalanced (220 vs. 76), and occupation could not be coded to a standard occupational classification for most participants, because only the write-in responses named a specific job. Future studies could reduce this ambiguity by administering a more granular occupational classification before the main survey and by attaching task-based exposure scores to each participant's occupation.

Finally, occupational type was a binary contrast between white-collar cognitive and skilled trade workers. Although theoretically motivated by the AI displacement literature, this dichotomy treats each category as internally uniform: a junior associate and a senior partner share a label despite facing markedly different displacement trajectories. This coarseness limits how null occupational effects can be read; future research would be better served by a continuous, task-based measure of AI exposure that models displacement risk as a matter of degree rather than category.

Two directions follow most directly from the present findings. First, because AI anxiety varied with Neuroticism but not with recruitment category, a valuable next step would be to model workers' perceived exposure to AI (how threatened they believe their own roles to be)

alongside objective, task-based exposure estimates, using validated measures of personal displacement threat such as the Occupation Insecurity Scale (Roll et al., 2025). If perceived risk predicts anxiety where occupational category did not, this would clarify whether AI anxiety reflects a felt appraisal of one's situation or a broader dispositional tendency, helping adjudicate between the dispositional-response and measurement accounts discussed above. Second, the Extraversion × occupational-type interaction for Job Replacement Anxiety needs a direct, adequately powered, preregistered replication before it can be regarded as established.

Among the employed adults in this sample, AI anxiety varied with Neuroticism but not detectably with recruitment-based occupational group. Given the design limitations noted above, this pattern is best treated as a question for better-controlled research rather than a settled conclusion. Does AI anxiety reflect a disposition largely independent of objective risk, or does a coarse occupational category fail to capture the exposure individual workers perceive? Answering this question will require continuous, task-based exposure measures, facet-level personality assessment, a general anxiety control, and temporal separation of measures.

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Statements and Declarations

Competing interests. The authors have no competing interests to declare.

Ethics approval and consent. This study was reviewed by the Institutional Review Board of the Florida Institute of Technology (IRB-CY2026-90) and determined to be exempt under 45 CFR 46.104, Category 2. The study was performed in accordance with the ethical principles of the Declaration of Helsinki. Informed consent was obtained electronically from all individual participants before their participation.

Consent to publish. Participants gave informed consent electronically before taking part. The consent page described the study's purpose, stated that responses were completely anonymous, and noted approval by the Florida Institute of Technology Institutional Review Board. The manuscript reports only aggregated, anonymized data and contains no information that could identify any individual participant.

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Declaration of generative AI use. In preparing this manuscript, the authors used Claude (Anthropic), a large language model, to support drafting, editing, and structural organization of the text, and to write Python code for the supplementary analyses (careless-responding sensitivity checks, robustness checks using self-reported occupation, equivalence tests, HC3 robust standard errors, reliability-corrected correlations, and confirmatory factor analyses); all reported values were verified in SPSS or, for the factor analyses, JASP. The authors developed the research concepts, hypotheses, theoretical arguments, and interpretation of results. The authors specified all analyses, verified all reported values against the data, and take full responsibility for the content.

Data availability statement. The data are not publicly available because participants were informed that their responses would not be shared with third parties. The SPSS analysis syntax, Python code for the factor analyses, and the dated pre-data-collection analysis protocol are available on the Open Science Framework at https://osf.io/k3j8z/overview?view_only=69067f0805c54ceab105b984467a5df8 (anonymized link for peer review; a DOI will be added on acceptance).

Table 1

Zero-Order Correlations Among Study Variables

Variable	1	2	3	4	5	6	7	8	9	10
1. Age										
2. Education	.07									
3. Gender (W)	.06	.09*								
4. Gender (NB)	−.05	−.09*	−.11*							
5. Occ. Type	.04	.38***	−.06	.00						
6. Neuroticism	−.09	−.07	.06	.07	−.23***					
7. Openness	.02	.08	.05	.04	.21***	−.39***				
8. Conscient.	.13**	.11*	.10*	−.09	.15***	−.54***	.30***			
9. Extraversion	.07	.09	.03	−.08	.16***	−.30***	.39***	.21***		
10. Agreeable.	.13**	.08	.10*	.02	.15***	−.39***	.36***	.32***	.26***	
11. AI Anxiety	−.01	.02	.08	.05	−.05	.35***	−.20***	−.26***	−.11*	−.14**
12. Learning	.05	.04	.09*	.01	.01	.27***	−.21***	−.21***	−.06	−.12**
13. Job Replacement	−.05	.01	.03	.07	−.05	.30***	−.15***	−.23***	−.14**	−.11*
14. Sociotech.	−.02	.01	.02	.07	−.08	.25***	−.11*	−.17***	−.11*	−.13**
15. Config.	−.04	.01	.11*	.03	−.08	.32***	−.15***	−.23***	−.02	−.12**

Note. $N = 491$. 1. Age; 2. Education; 3. Gender (Woman); 4. Gender (Nonbinary); 5. Occupational Type; 6. Neuroticism; 7. Openness; 8. Conscientiousness; 9. Extraversion; 10. Agreeableness; 11. AI Anxiety (Total); 12–15. AIAS subscales: Learning Anxiety, Job Replacement Anxiety, Sociotechnical Blindness, and AI Configuration Anxiety. Subscales correlated with the total score ranged from .78 to .85, and intercorrelations among the subscales ranged from .36 to .78 (all ps < .001). Gender variables are dummy-coded (man as reference); occupational type is coded 0 = skilled trade, 1 = white-collar cognitive. Correlations involving occupational type, a dichotomous variable, are point-biserial correlations, which are mathematically equivalent to the Pearson coefficient and computed with the same formula. Correlations are rounded to two decimals; p values were computed from unrounded values. *p < .05. **p < .01. ***p < .001.

Table 2

Hierarchical Regression Results Predicting AI Anxiety (H1–H3, H4a, RQ1–RQ2; N = 491)

Predictor	*b*	*SE*	95% CI	β	*t*	*p*
Block 1						
Age	−0.01	0.05	[−0.11, 0.08]	−.01	−0.31	.753
Gender (Woman)	0.21	0.12	[−0.02, 0.44]	.08	1.80	.073
Gender (Nonbinary)	0.62	0.45	[−0.26, 1.50]	.06	1.38	.169
Education	0.02	0.04	[−0.06, 0.10]	.02	0.50	.614
Block 2						
Age	0.02	0.04	[−0.07, 0.11]	.02	0.45	.656
Gender (Woman)	0.20	0.11	[−0.02, 0.41]	.08	1.76	.079
Gender (Nonbinary)	0.43	0.43	[−0.41, 1.27]	.04	1.01	.313
Education	0.04	0.04	[−0.04, 0.12]	.04	0.93	.352
Neuroticism	0.22	0.05	[0.13, 0.32]	.26	4.74	< .001
Openness	−0.09	0.05	[−0.19, 0.01]	−.09	−1.86	.063
Conscientiousness	−0.12	0.06	[−0.23, −0.01]	−.11	−2.19	.029
Extraversion	0.02	0.04	[−0.06, 0.09]	.02	0.41	.679
Agreeableness	0.00	0.05	[−0.10, 0.10]	.00	0.02	.985
Occupational Type	0.09	0.12	[−0.15, 0.32]	.03	0.72	.470

Note. Block 1 $R^2 = .010$, $F(4, 486) = 1.26$, $p = .284$. Block 2 $R^2 = .144$, $\Delta R^2 = .134$, $\Delta F(6, 480) = 12.49$, $p < .001$. CI = confidence interval for *b*. Coefficients and standard errors are rounded to two decimals; *t* and *p* were computed from unrounded values. Gender dummy-coded with man as the reference category; occupational type coded 0 = skilled trade, 1 = white-collar cognitive. With HC3 robust standard errors, Conscientiousness $p = .051$.

Table 3

Trait × Occupational Type Interactions Predicting Total AI Anxiety (H4b, N = 491)

Interaction	*b*	*SE*	95% CI	*t*	*p*
Neuroticism × Occupational Type	0.06	0.08	[−0.09, 0.21]	0.75	.454
Openness × Occupational Type	0.01	0.09	[−0.16, 0.18]	0.13	.900
Conscientiousness × Occupational Type	−0.09	0.09	[−0.27, 0.09]	−0.97	.330
Extraversion × Occupational Type	−0.07	0.07	[−0.20, 0.07]	−0.97	.330
Agreeableness × Occupational Type	0.09	0.10	[−0.10, 0.28]	0.93	.353

Note. CI = confidence interval for *b*. None of the five interactions was statistically significant; each added $\Delta R^2 \leq .002$ to a base model with $R^2 = .144$. Occupational type coded 0 = skilled trade, 1 = white-collar cognitive. Each row is a separate model that included the demographic covariates (age, gender, education), all five Big Five traits, occupational type, and the product of the focal trait and occupational type.

Table 4

Occupational Type and Trait × Occupational Type Interactions Predicting Job Replacement Anxiety (Planned Secondary Analysis, N = 491)

Predictor	*b*	*SE*	95% CI	*t*	*p*
Group comparison (*M* white-collar = 4.10, *SD* = 1.53; *M* skilled trade = 4.26, *SD* = 1.70)	—	—	—	1.06	.288
Occupational Type (main effect)	0.05	0.16	[−0.26, 0.36]	0.33	.740
Neuroticism × Occupational Type	0.12	0.10	[−0.08, 0.32]	1.18	.239
Openness × Occupational Type	−0.10	0.12	[−0.33, 0.13]	−0.87	.383
Conscientiousness × Occupational Type	−0.09	0.12	[−0.33, 0.15]	−0.74	.461
Extraversion × Occupational Type	−0.19	0.09	[−0.37, −0.01]	−2.10	.036
White-collar simple slope	−0.15	0.07	[−0.28, −0.01]	−2.13	.034
Skilled trade simple slope	0.04	0.06	[−0.08, 0.17]	0.66	.510
Agreeableness × Occupational Type	0.11	0.13	[−0.14, 0.36]	0.89	.375

Note. The group comparison row reports an independent-samples *t* test, *df* = 489; all other rows report regression coefficients. The main-effect row is from a model including the demographic covariates and all five traits. Each interaction row is a separate model that included the demographic covariates, all five Big Five traits, occupational type, and the product of the focal trait and occupational type, so each interaction is estimated with both constituent main effects in the model. CI = confidence interval for *b*. Each interaction added ΔR^2 = .001 to .008 to a base model with R^2 = .103. Only the Extraversion interaction reached significance; it does not survive Bonferroni correction (α = .010) and should be treated as hypothesis-generating pending replication. White-collar and skilled trade rows show simple slopes for the Extraversion interaction. Occupational type is coded 0 = skilled trade, 1 = white-collar cognitive.

Supplementary Files

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- ESM1.pdf