AI Use in the Workplace: Correlational Evidence on Motivation, Autonomy, Job Security, and AI-Related Threat

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***Abstract*—In our study, we investigate how artificial intelligence (AI) use relates to key psychological factors at work: motivation and job satisfaction, perceived autonomy, and job security. In a cross-sectional survey, 185 employees from multiple industries completed a combination of validated, adapted, and self-developed measures on AI use frequency, perceived autonomy, perceived AI-related threat, intrinsic and extrinsic motivation, and Big Five personality traits. AI use was positively associated with autonomy and intrinsic motivation, while effects on extrinsic motivation were smaller. However, as the autonomy indicator and the extrinsic motivation subscale showed low internal consistency in this sample, findings involving these constructs should be interpreted cautiously. Openness to experience predicted higher AI use. Neuroticism and extraversion were linked to more serious perceived AI-related threats, whereas conscientiousness positively predicted perceived autonomy in AI-supported work. Overall, the findings highlight the role of personality in shaping workplace AI use and AI-related perceptions and its psychological and job-security–related consequences.**

Keywords-AI in the workplace; employee motivation; job satisfaction; AI use and personality

I. INTRODUCTION

The growing integration of AI into organizational processes is reshaping workflows, redistributing tasks, and transforming employees' psychological experiences at work [1]. While organizations increasingly rely on AI to enhance efficiency and productivity, employees frequently express uncertainty regarding loss of control, job security, and shifts in role expectations. Recent industry cases suggest AI is already restructuring administrative work (e.g., [2][3]).

Despite this rapid transformation, the psychological consequences of AI use—particularly its effects on motivation, autonomy, and perceived threat—remain insufficiently explored [4][5]. Existing research has primarily focused on economic and technical indicators, whereas employees' subjective experiences and motivational processes have received comparatively little empirical attention.

In our study, we address this research gap by examining how AI use is associated with central psychological constructs in the workplace and how individual personality traits shape these perceptions. Our objective is to analyze the associations between workplace AI use and employees' motivation, autonomy, and job security. The investigation builds on Self-Determination Theory (SDT) by Ryan and Deci [5], as well as technology-acceptance frameworks [6]. Additionally, the predicting role of personality traits, operationalized via the Big Five model [7], is considered.

The study addresses four central research questions:

- RQ1: How is AI use associated with employees' perceptions of job security and autonomy?
- RQ2: To what extent is AI use associated with intrinsic and extrinsic motivation as well as overall job satisfaction?
- RQ3: Do the effects of workplace AI use on employees' intrinsic and extrinsic motivation differ across industries or occupational groups?
- RQ4: How do individual personality traits (Big Five) shape employees' perceived AI-related threat, perceived autonomy, and actual AI use in the workplace?

All four research questions were specified prior to data analysis and treated as exploratory-correlational, without formal confirmatory hypotheses.

Existing studies on AI in the workplace have mostly focused on productivity, technology acceptance, or single psychological variables in isolation. Autonomy, intrinsic and extrinsic motivation, job security, and Big Five personality traits have rarely been addressed within one coherent model. Our contributions are as follows:

1) We jointly analyze how AI use relates to these psychological outcomes,
2) We integrate personality traits as predictors of AI use and perceived AI-related threat, and
3) We derive practical implications for AI-based work design that explicitly consider individual differences.

The remainder of this paper is structured as follows. In Section II, we review the theoretical background In Section III, we describe the study overview and design, including the research approach, sample, instruments, quality criteria, and statistical analyses. In Section IV, we present the empirical results, covering descriptive findings, exploratory analyses of AI use, associations with job security, autonomy, motivation, and job satisfaction, as well as differences across occupational groups and personality-based predictors. In Section V, we discuss the findings in relation to existing research, derive implications for organizations and work design, and outline the study's limitations. Finally, Section VI concludes the paper and highlights directions for future research.

II. BACKGROUND

This section outlines the theoretical foundations of the study by reviewing prior research on AI in the workplace, employee motivation and job satisfaction, job security and autonomy, and the role of personality traits in shaping employees' responses to technological change.

A. Artificial Intelligence in the Workplace

In organizational contexts, AI increasingly takes over tasks previously performed by human experts, reshaping work processes, skill requirements, and professional roles [8]. Current research points to ambivalent effects: AI can accelerate workflows and reduce errors, yet employees often report uncertainty, especially when systems are used for performance monitoring or automated decision-making [9]. Lack of transparency or insufficient employee involvement can reduce trust and negatively affect job satisfaction and technology acceptance [10]. Recent studies also show that employees sometimes perceive AI as a social interaction partner, which can foster emotional attachments but also psychological strain, such as feelings of surveillance, comparison with algorithmic standards, or unclear boundaries between human and machine agency [11]. Overall, these findings suggest that the effects of AI depend less on the technology itself and more on employees' subjective interpretations and the organizational conditions surrounding implementation.

B. Employee Motivation and Job Satisfaction

Work psychology offers several frameworks for understanding how AI influences employees' motivation. SDT [5], the Unified Theory of Acceptance and Use of Technology (UTAUT) [6], and Herzberg's Two-Factor Theory [12] all emphasize that motivational outcomes depend on whether AI supports or undermines autonomy, competence, meaningfulness, and perceived support. AI can enhance motivation when it increases control, task variety, and competence, but may reduce motivation and satisfaction when used primarily for monitoring or opaque algorithmic decision-making [13]–[15]. Although the literature acknowledges these benefits and risks, systematic empirical studies on the underlying psychological mechanisms remain scarce, with prior work focusing largely on economic or efficiency outcomes [16].

C. Job Security and Autonomy

Job security and autonomy are central psychological constructs shaping responses to technological change. In the context of AI, perceived job security depends less on objective job-loss risks than on subjective interpretations of control, competence, and expected change [16]; AI applications that automate decisions or monitor performance are particularly associated with declines in perceived job security [9]. Autonomy is a key predictor of motivation and job satisfaction and is highly sensitive to technological interventions. Algorithmic systems can reduce perceived autonomy even when efficiency improves, but may enhance it when they remove routine tasks and free cognitive and temporal resources [13]. A decisive factor is whether AI is perceived as supportive or controlling, which directly shapes motivation, satisfaction, and acceptance [5]. Organizational context further influences experiences of uncertainty and control: employees in smaller or less digitally mature organizations often report higher overload and insufficient communication, intensifying perceived threat [15]. Thus, job security and autonomy are jointly shaped by individual perceptions and organizational implementation and communication practices.

D. Personality Traits and the Big Five Model

Personality psychology assumes that stable interindividual differences shape how people evaluate and respond to their environment. The Big Five model, one of the most established frameworks, describes personality along openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism [7]. In the work context, these traits correlate with attitudes, satisfaction, and behavior; Judge et al. identified the Big Five—particularly neuroticism and conscientiousness—as strong predictors of job satisfaction [17]. Technology-acceptance models similarly suggest that individual dispositions influence whether new technologies are perceived as helpful or threatening [6]. Research on digital technologies supports these associations: openness is linked to greater willingness to adopt new technologies, whereas individuals high in neuroticism react more strongly to uncertainty and evaluate technological change more critically [18]. However, there is also work showing no association between extraversion and technology acceptance, while neuroticism had a negative direct effect [19]. Despite this relevance, personality differences in the context of workplace AI have received limited empirical attention, making the Big Five a valuable framework for explaining why employees differ in their perceptions, attitudes, and reactions toward AI-based systems.

III. Study Overview and Design

This section presents the methodological foundation of the study, including the overall research approach, sample and data collection, operationalization of key constructs, quality criteria of the measures, and the statistical analyses used to address the research questions.

A. Research Approach and Objectives

In our study, we examine associations between workplace AI use and employees' motivation, perceived autonomy, perceived job security, and perceived AI-related threat, and the predictive role of Big Five personality traits [7]. Using a quantitative cross-sectional survey grounded in SDT and UTAUT [6], we capture employee perceptions at a single point in time.

B. Sample and Data Collection

Data were collected via a standardized online survey distributed through social networks, professional networks, and email distribution lists. The final sample included 185 employed adults ($\geq$ 18 years) from diverse industries and occupational groups. Data quality was ensured by screening for completeness, identifying outliers, and excluding inattentive respondents. No occupational groups were excluded, ensuring broad representation of professional backgrounds, levels of experience, and work contexts. Validated and widely used psychological scales were adapted for this study. Key variables included frequency of AI use, perceived autonomy, perceived AI-related threat, intrinsic and extrinsic motivation, and personality traits

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according to the Big Five. Data collection via an online platform ensured a standardized administration procedure and efficient participation. The survey structure was designed to capture self-reported indicators of AI use and subjective psychological responses.

C. Instruments and Operationalization

A combination of validated psychological scales and self-developed items was used to assess the key constructs, with adaptations made where necessary to fit the context of AI-supported work. AI use was assessed with a self-developed scale capturing both frequency and type of AI-supported activities (e.g., administrative tasks, decision support). Motivation was measured through established scales of intrinsic and extrinsic motivation as well as job satisfaction [5]. Job satisfaction was assessed using a validated single-item measure on a 5-point Likert scale (1 = very dissatisfied, 5 = very satisfied) and analyzed as an outcome distinct from motivation . Autonomy and perceived job security were assessed using self-developed items created for the original study.

Personality traits were measured using an established Big Five inventory, capturing the five broad personality dimensions: extraversion, neuroticism, openness to experience, conscientiousness, and agreeableness [7][17]. Additional demographic variables, including age, years of professional experience, and sector, were collected to support contextual interpretation and further exploratory analyses.

D. Quality Criteria

To ensure the methodological rigor of the study, the measurement instruments were evaluated according to classical test quality criteria: objectivity, reliability, and validity.

Objectivity was considered high due to the standardized online administration via Microsoft Forms. All participants received identical instructions and responded to the same items in the same order. Automated answer coding, predefined recording rules, and the use of statistical software ensured scoring and evaluation objectivity, consistent with the procedures outlined in the original study [20].

Reliability was assessed using Cronbach's alpha as an indicator of internal consistency. The job security scale demonstrated acceptable reliability ($\alpha = .73$, $\omega = .76$). However, the autonomy scale showed weaker internal consistency ($\alpha = .32$, $\omega = .49$), suggesting potential limitations in item quality or construct coverage [21]. This limitation should be addressed in future studies, as it may reduce precision in measuring autonomy. Intrinsic motivation showed high internal consistency ($\alpha = .89$, $\omega = .81$), while extrinsic motivation demonstrated low reliability ($\alpha = .39$, $\omega = .46$), consistent with known limitations of short Work Extrinsic and Intrinsic Motivation subscales (WEIMS) [22]. No reliability was calculated for job satisfaction, as it was measured using a single-item measure.

Construct validity was supported through theoretical grounding and pretesting of newly adapted items. Nevertheless, shortened scales, particularly those with few items, may suffer from reduced content validity, indicating the need for refinement in future research [22][23].

E. Statistical Analyses

To address our research questions, we applied a set of complementary statistical procedures.

First, we used an independent samples t-test to analyze whether the AI use differs by gender. We additionally conducted exploratory group comparisons of AI use across age categories and work-experience categories using one-way ANOVA.

To investigate differences across multiple occupational groups and industries, we conducted a one-way analysis of variance (ANOVA). This analysis assessed whether intrinsic and extrinsic motivation varied depending on participants' professional context (e.g., IT vs. healthcare vs. education) while accounting for work-related AI use. When the omnibus test indicated significant variance across groups, post hoc comparisons were carried out to determine which specific groups differed from one another. This step was essential for revealing patterns that may not be visible in pairwise or aggregated comparisons.

Next, we performed a Pearson correlation analysis to examine the strength and direction of linear associations between key constructs. This included relationships between frequency of AI use and autonomy, between AI use and motivation, and between personality traits (e.g., openness to experience) and perceived job security. Additionally, correlations examined the association between AI use and overall job satisfaction, in line with RQ2. Correlations provided a foundational understanding of how variables co-vary, supporting the identification of potential mediators and predictors relevant to AI acceptance and workplace experiences.

To model the combined influence of multiple predictors, we conducted multiple linear regression analyses. This technique allowed for the simultaneous estimation of the effects of personality traits on AI use, perceived AI-related threat, and perceived autonomy. Regression analyses are especially valuable for isolating unique predictor contributions while controlling for potential confounding variables such as age, experience, or occupational background. Furthermore, the analyses offered insight into whether traits such as openness or neuroticism amplified or attenuated the psychological effects of AI use in the workplace.

Across all statistical analyses, we set significance at $\alpha = .05$. Effect sizes were calculated using Cohen's d for t-tests and η^2 for ANOVA models, interpreted according to Cohen's conventions for small, medium, and large effects to provide meaningful evaluations of practical relevance beyond statistical significance alone [24]. Standard diagnostic tests were conducted to verify model assumptions: Shapiro–Wilk tests were used to assess normality of residuals in regression models, while the Levene test examined homogeneity of variances in ANOVA. These assumptions were largely met, supporting the robustness and validity of the analyses performed.

IV. Results

This section reports the empirical findings of the study, beginning with descriptive results and exploratory analyses of AI use, followed by inferential results concerning autonomy, job security, motivation, occupational differences, and personality-based predictors of AI use and AI-related perceptions.

A. Descriptive Results

The final sample consisted of 185 participants, of whom 52.4% identified as female and 47.6% as male. The average age was 38.4 years ($SD = 14.2$). Regarding professional experience, 39% reported having more than 20 years of work experience, indicating substantial heterogeneity in career stages.

The distribution across industries showed that the public sector and education were strongly represented with 32.4% ($n = 60$), followed by healthcare and the pharmaceutical industry with 15.7% ($n = 29$). In terms of occupational roles, the largest group consisted of employees (60%, $n = 111$), alongside civil servants (11.4%) and managerial staff (9.7%). This diverse composition enabled differentiated analyses across work contexts.

AI use showed a moderate mean level ($M = 2.75$, $SD = 1.25$), suggesting that AI has been adopted by many employees but is not yet used intensively across all roles. Perceived autonomy ($M = 3.40$, $SD = 0.85$) and perceived job security ($M = 3.15$, $SD = 1.05$) were both rated as moderately high, indicating that employees generally perceived their work environment as stable and supportive despite ongoing technological changes.

B. Exploratory Analysis of AI Use

The exploratory analysis examined the frequency with which employees used AI and whether this usage differed across various demographic factors. Overall usage levels were moderate ($M = 2.75$, $SD = 1.25$), indicating that AI is present in many workplaces but has not yet become ubiquitous or deeply integrated across all job roles.

Employees with less than two years of work experience reported the highest AI use ($M = 3.89$), while those with 11 to 15 years of experience reported substantially lower levels ($M = 2.45$). Descriptively, early-career participants reported higher levels of AI use; this trend may reflect greater openness to experimenting with new technologies and should be examined in future research.

No significant gender differences emerged in AI use ($t = 0.99$, $p = .323$). Similarly, AI use did not differ significantly across age categories ($F(5, 179) = 1.20$, $p = .313$), suggesting that experience and organizational exposure may be more critical than demographic characteristics.

C. Associations between AI Use and Perceived Job Security and Autonomy

To address RQ1, we conducted a bivariate Pearson correlation analysis. Results revealed that AI use showed a significant positive association with perceived autonomy ($r = .24$, $p = .001$) with a small-to-medium effect size. Employees who reported more frequent AI use also reported higher perceived autonomy. However, because the autonomy indicator showed low internal consistency in this sample, this association should be interpreted as preliminary rather than as strong evidence for autonomy-enhancing effects of AI.

In contrast, AI use was not significantly associated with perceived job security ($r = .11$, $p = .153$), indicating a negligible effect size. This indicates that employees did not perceive AI as directly threatening their employment stability. Job security perceptions may be more strongly shaped by organizational communication, economic conditions, or leadership practices than by personal AI use alone.

D. Changes in Motivation and Job Satisfaction

For RQ2, Pearson correlations demonstrated a significant positive relationship between AI use and intrinsic motivation ($r = .23$, $p = .001$), representing a small-to-medium effect size. Employees who interacted more frequently with AI reported greater enjoyment, engagement, and perceived meaningfulness in their work tasks.

AI use showed a positive and statistically significant association with extrinsic motivation ($r = .15$, $p = .042$), indicating a small effect size, although the effect was weaker than for intrinsic motivation. Given the low internal consistency of the extrinsic motivation subscale ($\alpha = .39$), this finding should be treated as tentative. This pattern indicates a small association between AI use and extrinsic motivation, although the estimate should be interpreted cautiously due to measurement limitations.

No significant association emerged between AI use and overall job satisfaction ($r = .08$, $p = .285$), corresponding to a negligible effect size. This indicates that AI use alone does not substantially influence employees' general satisfaction, which may be more strongly tied to broader contextual factors such as leadership, workload, and career opportunities.

E. Differences Across Occupational Groups and Industries

To examine whether motivational effects of AI differed across industries or occupational groups (RQ3), we conducted a one-way ANOVA. No significant differences were found for either intrinsic or extrinsic motivation between industries ($F(7, 177) = 1.378$, $p = .217$) or occupational groups ($F(7, 177) = 0.799$, $p = .589$), and all effect sizes were small ($\eta^2 < .05$).

These results indicate that intrinsic and extrinsic motivation did not significantly differ across work contexts. This aligns with core assumptions of SDT and UTAUT, which posit that perceived autonomy and competence are universal needs that transcend occupational boundaries.

F. Personality Traits as Predictors of AI Use and Perception

To address RQ4, we conducted multiple regression analyses to determine whether personality traits influenced AI use and AI-related perceptions. The results are summarized in Table I

Openness to experience emerged as a significant predictor of AI use ($b = .048$, $p < .001$). Employees high in openness were more likely to adopt AI tools, consistent with research linking openness to curiosity, creativity, and willingness to experiment with new technologies.

Perceived AI-related threat was significantly predicted by neuroticism ($b = .176$, $p = .035$) and extraversion ($b = .166$,

$p = .034$). Individuals high in neuroticism may be more sensitive to uncertainty and risk, while extraverted employees may feel more challenged by changes affecting interpersonal dynamics or work identity.

Perceived autonomy in the context of AI-supported work was significantly predicted by conscientiousness ($b = .017$, $p = .010$). Conscientious employees may perceive AI as a helpful tool for structuring tasks, enhancing efficiency, and supporting goal achievement.

TABLE I. PERSONALITY TRAITS AS PREDICTORS OF AI USE, AI-RELATED THREAT AND AUTONOMY

Predictor (Trait)	AI Use	AI-Related Threat	Autonomy
Openness	$b = 0.048^{***}$	$b = -0.100$	$b = 0.080$
Neuroticism	$b = 0.180$	$b = 0.176^{*}$	$b = 0.070$
Extraversion	$b = -0.160$	$b = 0.166^{*}$	$b = -0.008$
Conscientiousness	$b = 0.003$	$b = 0.015$	$b = 0.017^{*}$
Agreeableness	$b = 0.220$	$b = 0.014$	$b = -0.001$

Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.

Overall, these findings highlight the importance of personality traits in shaping employees' perceptions of AI as either a resource or a potential threat.

G. Summary of Key Findings

Across our analyses, AI use was positively associated with perceived autonomy, intrinsic motivation, and, to a lesser extent, extrinsic motivation, while no significant associations emerged for job security or job satisfaction. In addition, openness to experience predicted higher AI use, neuroticism and extraversion predicted greater perceived AI-related threat, and conscientiousness predicted higher perceived autonomy in AI-supported work. Figure 1 provides an integrated overview of the significant associations and predictors identified in Sections

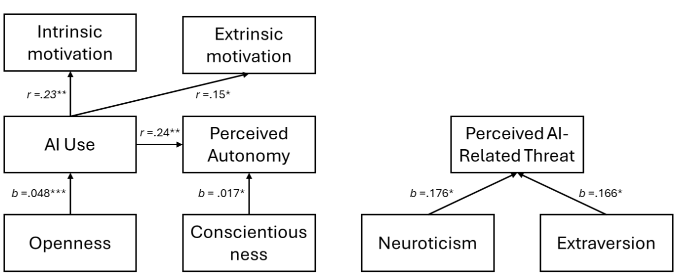

Figure 1. Overview of Significant Associations and Predictors

V. DISCUSSION

This section interprets the results in light of prior research, discusses their implications for organizations and work design, and reflects on the main limitations of the present study.

A. Positioning the Findings Within Existing Research

Our study adds to research on the psychological implications of AI use in the workplace. The positive association between AI use and perceived autonomy aligns with findings that supportive technologies can enhance employees' sense of control [13] and with SDT, which conceptualizes autonomy as a basic psychological need supported when technologies expand individuals' scope of action [5]. Likewise, the link between AI use and intrinsic motivation is consistent with work showing that technology can foster intrinsic motivation by enabling learning opportunities, competence experiences, or creative problem-solving [5][14].

By contrast, AI use was unrelated to perceived job security and overall job satisfaction, deviating from studies that emphasize threat perceptions in the context of automation and digital transformation [8][9]. A plausible explanation is that employees in this sample primarily perceived AI as a complementary tool rather than a substitute for human labour, or that organizational communication and prior digital experience buffered concerns about displacement. These mechanisms were not measured and should be examined in future research; the null finding for job satisfaction also suggests that global satisfaction is more strongly shaped by stable organizational factors than by specific technologies.

The personality findings further highlight individual differences: openness to experience predicted higher AI use [7][18], neuroticism and extraversion predicted higher perceived AI-related threat, and conscientiousness predicted higher autonomy in AI-supported work. Overall, the results support models that integrate technological and psychological dimensions and indicate that AI's impact is contingent on individual dispositions and contextual factors rather than being uniformly positive or negative.

B. Implications for Organizations and Work Design

Our findings suggest that AI can enrich rather than diminish work experiences when it is implemented to support autonomy and intrinsic motivation. AI systems that automate routine tasks or provide decision support can expand employees' decision latitude and foster a stronger sense of control and engagement.

The lack of a negative link between AI use and job security indicates that employees do not automatically view AI as a threat. This offers organizations an opportunity: by emphasizing the augmentative role of AI, communicating transparently about expected changes, and providing training, they can foster trust, acceptance, and psychological safety.

Personality differences further imply that reactions to AI are not uniform. Openness, neuroticism, extraversion, and conscientiousness shape responses to AI, so communication and support should be tailored—for example, by involving more open employees as early adopters and offering additional guidance to those with greater concerns.

Finally, the consistent motivational effects across industries and occupational groups suggest that organizations do not need highly sector-specific strategies. General principles such as autonomy support, transparency, explainability, and employee involvement appear broadly useful and can promote both employee well-being and effective AI implementation.

C. Limitations

This study has several limitations. First, the sample size of 185 participants, although adequate for the analyses, limits generalizability, especially given the uneven distribution across industries. Public sector and education were overrepresented, whereas technology-intensive and industrial sectors were underrepresented, which may restrict applicability to contexts where AI is used differently or plays a more central operational role.

Second, the cross-sectional design does not allow causal inferences. Although associations between AI use, autonomy, and motivation were found, it remains unclear whether AI use promotes autonomy and intrinsic motivation or whether already autonomous and motivated individuals are more likely to use AI. Longitudinal or experimental designs are needed to clarify directionality and the stability of effects over time.

Third, measurement quality is limited, particularly for the autonomy scale, which showed low internal consistency. In addition, the extrinsic motivation subscale showed low internal consistency, further limiting confidence in the corresponding association with AI use. This suggests that autonomy was not captured with sufficient breadth or precision and that future work should employ more comprehensive or multidimensional measures. The exclusive reliance on self-report also introduces potential response biases (e.g., social desirability, common-method variance) that may have influenced responses and inflated correlations.

Finally, contextual factors that likely shape employees' perceptions of AI were not considered. Variables such as organizational culture, leadership, digital maturity, and communication strategies may be decisive for whether AI is seen as a resource or a threat [16]. Without these influences, the explanatory power of the models is limited, and the interaction between technological and organizational conditions cannot be fully understood. Moreover, the sample was recruited via online networks and mailing lists, which may introduce self-selection bias and limit representativeness

These limitations call for cautious interpretation of the findings and highlight the need for more comprehensive, multi-method, and contextually sensitive research in the future.

VI. Conclusion and Future Work

In our study, we examined the psychological effects of AI use in the workplace, focusing on perceived autonomy, motivation, and job security. We further explored the predictive role of personality traits. The results indicate that higher levels of AI use are associated with stronger perceptions of autonomy and increased intrinsic motivation. These findings support theoretical assumptions from SDT, which argues that technologies enhancing autonomy can foster more meaningful and self-directed work experiences [5]. In this context, more frequent AI use was associated with higher intrinsic motivation and higher scores on an autonomy indicator. However, the autonomy measure's low internal consistency and the cross-sectional design preclude strong conclusions about autonomy-enhancing effects.

In contrast, AI use showed no significant association with perceived job security. This diverges from prior research, which has frequently highlighted automation-related job concerns [8]. The present findings suggest that employees in this sample did not predominantly interpret AI as a threat to employment but rather viewed it as a complementary tool. This divergence underscores the importance of contextual and organizational factors—such as communication, leadership, and prior exposure to digital technologies—that may buffer insecurity and shape how AI is interpreted in practice.

The results concerning personality traits provide additional explanatory insight. Openness to experience emerged as a strong predictor of AI use, supporting the view that open and curious individuals engage more readily with novel technologies. Conversely, neuroticism and extraversion were associated with heightened perceived AI-related threat, indicating that emotional sensitivity and social orientation may amplify concerns in the face of technological change. Conscientiousness was linked to higher perceived autonomy when using AI, suggesting that structured and goal-oriented individuals may integrate AI into their workflow more effectively and view it as a means of improving task management.

Overall, the study demonstrates that the impact of AI on employees is nuanced and shaped by both technological features and individual differences. AI is neither inherently motivating nor inherently threatening; rather, its psychological effects depend on how it is implemented and how employees interpret it. These insights highlight the importance of designing AI-enabled work environments that are transparent, autonomy-supportive, and responsive to diverse employee needs.

Future research should employ longitudinal and experimental designs to examine whether the autonomy- and motivation-related effects of AI use persist over time and whether AI use shapes stable or context-sensitive technology attitudes. Sector-specific studies are needed to clarify how digital infrastructures, job demands, organizational maturity, technological readiness, and task complexity influence employees' responses to AI. Building on the role of personality traits, intervention studies should test whether more personalised training and communication can reduce perceived AI-related threat, particularly among individuals high in neuroticism. Methodological refinements, including improved autonomy measures, data sources beyond self-report, more heterogeneous industry samples, and qualitative approaches, would further strengthen the evidence base. Overall, a nuanced understanding of how AI interacts with motivation, autonomy, and personality will be essential for designing work environments that support well-being, acceptance, and sustainable technological integration.

Ethical Impact Statement

Participation was voluntary and based on informed consent. The survey was conducted anonymously, and no directly identifying personal data was collected. Participants could discontinue participation at any time without providing a reason. Data were stored securely and used exclusively for research purposes in accordance with applicable data protection regulations.

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