

AI Readiness and Personality

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Abstract

This research examines individual differences in readiness for artificial intelligence (AI). Across two studies, we developed and validated an Artificial Intelligence Readiness Scale and investigated its psychological correlates. Study 1 focused on scale construction and demonstrated satisfactory internal reliability and validity. Study 2 examined associations between AI readiness, a DISC-based behavioural style assessment (PPA), personality (HPTI), trait emotional intelligence (TEIQue), and cognitive ability (GIA). Correlational analyses indicated that AI readiness was related to both personality and intelligence; however, regression analyses showed that Curiosity (Openness) and Competitiveness (low Agreeableness) were the most consistent predictors. Implications of these findings are discussed.

Keywords

AI Readiness, Personality, Intelligence, Curiosity, Competitiveness

1. Introduction

The speed of research on the understanding and use of artificial intelligence (AI) is growing almost as quickly as the adoption of AI tools. Noticeably, there are many different reactions to the spread and use of AI tools, ranging from phobic anxiety to embracing enthusiasm. This study first develops and validates a measure of AI readiness and then looks at its individual correlates.

Differential psychologists have been particularly fascinated by individual difference correlates of attitudes to, and use of, AI (Gherheş, 2018; Ozbey & Yasa, 2025; Rhee & Rhee, 2019; Schepman & Rodway, 2020). Kaya et al. (2024) showed that positive attitudes toward AI were predicted by the level of computer use, level of knowledge about AI, and AI learning anxiety, while negative attitudes were predicted by agreeableness, AI configuration anxiety, and AI learning ability.

Stein et al. (2024) developed a novel psychologically informed questionnaire that captures attitudes towards AI as a single construct, independent of specific contexts or applications. In three studies, they examined several personality trait correlates—the Big Five, the Dark Triad, and conspiracy mentality—of AI-related attitudes. They predicted that all five-factor traits, except Neuroticism, would possess positive attitudes towards AI. They found that agreeableness and being younger in age predicted a more positive view towards AI technology, whereas the susceptibility to conspiracy beliefs was associated with a more negative attitude. They argued that agreeable individuals tend to perceive others more positively, and may, therefore, come to think more about the opportunities than the risks of a new invention when forming their opinion.

In a study similar to this, Liang et al. (2025) first developed and validated a scale to measure students' attitudes toward generative AI (GAI) in academic contexts. Next, they used hierarchical linear regression analyses to explore the relationship between personality traits and GAI attitudes. They found that Extraversion and Openness to Experience were significant positive predictors of favourable GAI attitudes. Honesty-Humility did not significantly predict GAI attitudes, while Machiavellianism was positively associated with favourable GAI attitudes, indicating that individuals high in this trait may perceive GAI as a strategic tool for personal gain.

Our aim in this research was first to develop a short and robust measure of what we call AI Readiness and then to examine its ability and personality correlates using three traits and one ability measure.

2. Study 1: Reliability and Confirmatory Factor Analysis of the AI Readiness Scale

In this study, we evaluated the reliability and construct validity of a brief, five-item AI Readiness scale, measured using a seven-point Likert-type response format. AI readiness was defined as an individual's psychological preparedness to understand, adopt, and effectively engage with artificial intelligence technologies in their work context. Unlike adjacent constructs such as AI attitudes (evaluative orientation), AI self-efficacy (confidence in ability), AI literacy (objective knowledge), or broader technology readiness (general predispositions toward technology), AI readiness integrates perceived understanding, perceived usefulness, confidence in learning and using AI tools, openness to adoption, and awareness of potential risks into a unified work-relevant construct. Conceptually, the scale draws on elements of the Technology Acceptance Model (perceived usefulness and openness), self-efficacy theory (confidence in capability), and risk perception research, reflecting a form of AI-specific preparedness.

The scale included the following statements: “*I understand the basic principles of how AI works and what it can do*”; “*I believe AI can improve outcomes in my current role or field of work*”; “*I feel confident in my ability to learn and use AI tools*”; “*I am open to using AI technologies in my work*”; “*I have concerns about the potential risks of AI*.”

2.1. Participants

In total, 2172 UK-based participants fully completed the scale, with no missing responses. The majority (61%) identified as male, 38% as female, and 1% did not indicate their gender. Just over one third (35%) reported being non-managers, 13% first-line managers or supervisors, 20% middle managers, and 18% senior or executive managers; 14% did not report their management level. Ages ranged from 18 to 72 years ($M = 38.10$, $SD = 11.30$). Participants were drawn from the Thomas International database. UK-based participants were invited to complete the Thomas Research Questionnaire after completing one of the other Thomas assessments (PPA, HPTI, TEIQue, or GIA; see Study 2).

2.2. Data Analysis

Reliability was assessed using Cronbach's alpha (α), McDonald's omega (ω), and the Rasch Person Reliability Index (PRI) to evaluate the internal consistency and measurement precision of the scale. Consistent with conventional guidelines, values of .70 or higher were considered acceptable (Bond et al., 2020).

Model fit was evaluated using standard confirmatory factor analysis (CFA) indices: a non-significant chi-square statistic, comparative fit index (CFI) and Tucker-Lewis index (TLI) values $\geq .90$, root mean square error of approximation (RMSEA) $\leq .08$, and standardized root mean square residual (SRMR) $\leq .06$. Model parameters were estimated using diagonally weighted least squares (DWLS), as it is better suited to Likert-type response scales (Hu & Bentler, 1999; Kline, 2016; Kyriazos & Poga-Kyriazou, 2023; Li, 2016). Standardised factor loadings were examined to evaluate the strength and adequacy of the relationships between observed indicators and their respective latent constructs.

3. Results and Discussion

The initial five-item model showed adequate reliability ($\alpha = .68$; $\omega = .72$; PRI = .65) and good fit, CFI = .990, TLI = .980, SRMR = .040, RMSEA = .090, 90% CI [.080, .110]). However, the model included an item with a negligible standardised loading ($\lambda_4 = .04$) and near-zero explained variance ($R^2 = .001$), suggesting that this item is a poor indicator of AI Readiness. This item (I have concerns about the potential risks of AI) may better reflect an independent construct of AI risk perception, distinct from readiness, and was therefore removed, and the CFA re-estimated with the four remaining indicators.

The final four-item model demonstrated good reliability ($\alpha = .80$; $\omega = .81$; PRI = .70). The fit statistics were as follows: $\chi^2(2) = 91.290$, $p < .001$ CFI = .992, TLI = .975, SRMR = .047, RMSEA = .143, 90% CI [.119, .169]. Although the RMSEA exceeds conventional cutoffs, this index is known to overestimate model misfit in models with very low degrees of freedom (Chen et al., 2008; Kenny et al., 2014). Given the excellent CFI and TLI values and low SRMR, the overall pattern of fit indices supports acceptable model fit in this context. All standardised factor loadings were statistically significant ($\lambda = .68 - .86$, $p < .001$), indicating strong relationships between the indicators and the latent factor. Overall, these results sup-

port the reliability and construct validity of the four-item AI readiness scale.

4. Study 2: Relationship between AI Readiness and Factors

In this study, we look at the relationship between our AI scale and four different individual difference measures. First, we evaluate the Personal Profile Analysis (PPA) or DISC measure, which has a long history of popular use. Next, we analyse the relationship between the measure and the HPTI, which has attracted a great deal of research (Cuppello et al., 2023a, 2023b; Furnham & Semmelink, 2026). This is essentially a version of the Big Five for use in work settings. Third, we used a measure of Emotional Intelligence and, finally, a measure of general intelligence (Furnham & Treglown, 2018; Treglown & Furnham, 2022, 2023).

Based on the above literature, we predict correlations with sex and age: men more than women, and younger people more than older people would be more AI-ready. We further predict that more Adjusted (less Neurotic), Curious (Open), and Competitive individuals would be more AI-ready. Finally, we predict that those with a higher IQ, at both the domain and facet levels, would be more AI-ready.

5. Method

5.1. Participants

Cohort 1: This cohort contains 2053 respondents who had completed the AI Readiness scale and the PPA. Most respondents indicated that they were male (61%), 38% were female, and 1% did not provide a response. Regarding management level, 35% indicated that they were non-management, 13% were first-line management/supervisors, 20% were middle management, 18% were senior/executive management, and 14% selected other/not applicable/no response. The age of the participants ranged from 18 to 72 ($M = 38.0$, $SD = 11.4$).

Cohort 2: This cohort comprises 121 respondents who had completed the AI Readiness scale and the HPTI. Most respondents indicated that they were male (56%), 42% were female, and 2% did not provide a response. Regarding management level, 32% indicated that they were non-management, 11% were first-line management/supervisors, 18% were middle management, 26% were senior/executive management, and 12% were other/not applicable/no response. The age of the participants ranged from 20 to 66 ($M = 40.5$, $SD = 10.0$).

Cohort 3: This cohort entails 128 respondents who had completed the AI Readiness scale and the TEIQue. Most respondents indicated that they were male (58%), and 42% were female. Regarding management level, 21% indicated that they were non-management, 18% were first-line management/supervisors, 31% were middle management, 24% were senior/executive management, and 5% selected other/not applicable/no response. The age of the participants ranged from 19 to 67 ($M = 42.6$, $SD = 9.2$).

Cohort 4: This cohort consists of 769 respondents who had completed the AI Readiness scale and the GIA. Most respondents indicated that they were male (70%), 29% were female, and 1% did not provide a response. Regarding management level, 32% indicated that they were non-management, 11% were first-line

management/supervisors, 16% were middle management, 13% were senior/executive management, and 18% chose other/not applicable/no response. The age of the participants ranged from 18 to 67 ($M = 35.5$, $SD = 11.9$).

5.2. Questionnaires

AI Readiness (see Study 1). The AI readiness scale is a four-item measure of one's belief in generative AI, with a five-point Likert scale. The reliability of the scale is presented in Study 1.

Personal Profile Analysis (PPA; Thomas, 2024a). The PPA is a 24-item, self-report instrument. It is designed to assess four work-related behavioural preferences: Dominance, Influence, Steadiness, and Compliance, linked to the early work of William Marston (1928) and Marston et al. (1931). The PPA has been evaluated to have sufficient internal consistency reliability (Dominance: $\alpha = .83$; Influence: $\alpha = .79$; Steadiness: $\alpha = .77$; Compliance: $\alpha = .80$).

High Potential Trait Indicator (HPTI; MacRae & Furnham, 2020). The HPTI is a measure of personality traits, specifically within a workplace context (Teodorescu et al., 2017). It is comprised of six factors, outlined above. The inventory is 78 items in length. Internal consistency reliability was evaluated using Cronbach's alpha (α) and McDonald's omega (ω). The Conscientiousness scale demonstrated acceptable reliability ($\alpha = .70$, $\omega = .74$). Adjustment showed good internal consistency ($\alpha = .77$, $\omega = .80$). Curiosity exhibited acceptable reliability ($\alpha = .73$, $\omega = .76$), as did Risk Approach ($\alpha = .73$, $\omega = .75$) and Ambiguity Acceptance ($\alpha = .74$, $\omega = .78$). Competitiveness revealed slightly lower but still acceptable internal consistency ($\alpha = .68$, $\omega = .71$).

Trait Emotional Intelligence Questionnaire (TEIQue; Petrides, 2012): The TEIQue measures emotional intelligence by identifying the ability to understand, respond, and interpret not only other people's emotions but also one's own, and further how one can manage their own feelings. TEIQue reflects how one thinks of themselves through looking into four broad factors which had been found to be reliable in its development (Well-being: $\alpha = .83$; Self-control: $\alpha = .83$; Emotionality: $\alpha = .80$; Sociability: $\alpha = .84$; Petrides, 2012). Internal consistency reliability in this study was evaluated using Cronbach's alpha (α) and McDonald's omega (ω). All scales demonstrated excellent internal consistency ($\alpha = .87 - .94$; $\omega = .88 - .95$).

General Intelligence Assessment (GIA; Thomas, 2024b): The GIA assesses individuals' cognitive abilities by measuring their speed and accuracy across five domains relevant to work contexts. In its development, the subtests of the GIA achieved excellent reliability. The reliabilities of the five subscales were estimated using split-half correlation with Spearman-Brown correction. The coefficients for each were: Verbal Reasoning (.85), Perceptual Speed (.86), Number Speed (.92), Word Meaning (.90), and Spatial Visualisation (.92). While a similar split-half exercise could not be conducted with the data in this study, the adjusted scores of the five subscales were entered into a confirmatory factor analysis to obtain the McDonald's omega and composite reliability ($cr.$) of the general factor. The rela-

bility estimates of the general factor were good ($\omega = .80$, $cr = .79$).

5.3. Procedure

The data for this study were sourced from the Thomas International Research Questions UK database, which comprises individuals who completed various Thomas assessments for applied purposes (e.g., recruitment, development) and who opted in to complete the voluntary Thomas Research Questions. The AI Readiness Scale items were embedded in this research section. Individuals were included if they had answered all AI Readiness items. However, not all participants completed every Thomas assessment, resulting in differing sample sizes across Thomas assessments. To address this, the sample was organised into four cohorts: Cohort 1 ($n = 2053$) included individuals who completed the PPA; Cohort 2 ($n = 121$) had completed the HPTI; Cohort 3 ($n = 128$) completed the TEIQue; Cohort 4 ($n = 769$) completed the GIA. Some participants completed more than one assessment, resulting in overlapping cohorts. The cohorts therefore represent partially overlapping convenience samples, rather than a single representative sample assessed with all measures. This introduces non-independence across the regressions and may slightly underestimate standard errors. In addition, each assessment cohort was formed based on a company's assignment rather than random selection, which may influence cross-cohort differences in predictor effects. Therefore, comparisons of predictor importance across assessments should be interpreted with caution, acknowledging potential cohort-specific selection effects.

6. Results

We correlated participant demography (sex and age) and all four test scores with the AI Readiness score. Both sex and age, as well as 3/4 of the DISC, 5/6 of the HPTI, none of the TEIQue, and all of the GIA, were significantly correlated. Highest correlations were for Traits Curiosity ($r = .32$) and Conscientiousness ($r = .22$).

The first regression, including sex, age, and the two DISC scores, indicated that younger individuals, those higher in Dominance, and lower in Steadiness reported higher AI Readiness. However, these variables accounted for only 3% of the variance ($R^2 = .03$), suggesting limited practical predictive power. The second regression included demographic variables and the HPTI traits and accounted for 17% of the variance in AI Readiness ($R^2 = .17$). Females and individuals scoring higher on Curiosity (Openness) and Conscientiousness reported higher AI Readiness. The third regression, involving demographic and TEIQue variables, did not reveal any significant predictors and explained minimal variance. The fourth regression indicated that one GIA subfactor, reasoning, related to the AI Readiness scores, but also explained minimal variance. The attenuation of cognitive predictors in the multivariable model likely reflects shared variance among the GIA subtests. When considered simultaneously, the regression coefficients represent only unique contributions beyond other cognitive factors and demographic variables, which substantially reduces their apparent predictive strength (Table 1 & Table 2).

Table 1. Means, standard deviations, and Pearson correlations.

	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. AI Readiness	16.22	2.81	—																						
2. Sex	.38	.49	-.05*	—																					
3. Age	38.08	11.35	-.10***	-.01	—																				
4. Dominance	-2.63	6.73	.14***	-.14***	.01	—																			
5. Influence	-.36	5.17	.02	.09***	-.03	-.06**	—																		
6. Steadiness	1.85	4.91	-.13***	.13***	-.01	-.75***	-.18***	—																	
7. Compliance	-.04	4.77	-.06**	-.05*	.00	-.37***	-.69***	.16***	—																
8. Conscientiousness	5.89	.51	.22*	.13	.06	.43***	-.17	-.49***	.13	—															
9. Adjustment	5.64	.66	.18*	-.06	.07	.16	.04	-.13	-.12	.31***	—														
1. Curiosity	5.48	.56	.32***	-.08	.09	.27*	-.12	-.21*	.03	.38***	.23*	—													
11. Risk Approach	5.39	.61	.18*	-.03	.20*	.47***	.04	-.42***	-.10	.53***	.43***	.41***	—												
12. Ambiguity Acceptance	4.25	.77	.16	-.19*	.07	.21	.01	-.14	-.15	.05	.47***	.26*	.39***	—											
13. Competitiveness	3.81	.69	.18*	-.10	-.13	.32**	.06	-.27*	-.18	.14	-.01	.04	.09	-.09	—										
14. TEIQue Overall	5.35	.60	.14	.05	.24**	.12	-.07	-.04	-.05	.77**	.13	.19	.72**	-.32	.06	—									
15. Well-being	5.63	.79	.09	.14	.20*	.05	-.01	-.01	-.08	.71**	.03	.07	.58*	-.47	.04	.86***	—								
16. Self-control	5.12	.79	.16	-.11	.32***	.16	-.31**	-.05	.16	.32	.58*	.39	.39	-.09	-.19	.85***	.66***	—							
17. Emotionality	5.54	.72	.10	.15	.10	-.10	.05	.17	-.12	.67*	-.17	.04	.55	-.65*	-.21	.85***	.63***	.59***	—						
18. Sociability	5.19	.57	.08	-.07	.18*	.38***	.08	-.28**	-.22*	.80**	.02	.07	.84***	-.06	.47	.79***	.58***	.60***	.60***	—					
19. GIA Overall	48.74	11.69	.14***	-.14***	-.16***	.06	-.06	-.06	.06	-.02	.05	-.02	.36*	-.07	-.08	-.16	-.16	-.05	.14	-.14	—				
2. Reasoning	38.97	9.60	.15***	-.05	-.23***	.09*	.02	-.09*	-.01	.07	-.01	-.04	.07	.32*	-.02	-.07	-.17	-.16	-.03	.17	.79***	—			
21. Perceptual Speed	41.56	7.16	.10**	-.10**	-.16***	.00	-.06	-.03	.08*	.11	.05	-.16	.07	.10	-.15	.02	.06	-.13	.04	.15	.79***	.56***	—		
22. Number Speed and Accuracy	13.65	7.06	.09*	-.17***	-.23***	.08*	-.08*	-.10**	.09*	-.37*	.01	.06	-.27	.40**	.00	-.33*	-.35*	-.32*	-.30*	-.10	.73***	.45***	.43***	—	
23. Word Meaning	28.22	5.94	.08*	-.09*	.05	.00	-.01	-.01	.01	.10	-.12	-.01	-.07	.16	-.04	.22	.12	.06	.15	.44**	.75***	.55***	.52***	.37***	—
24. Spatial Visualisation	9.85	5.38	.08*	-.12**	.03	.02	-.09*	.01	.06	.07	.26	.06	.02	.33*	-.05	-.08	-.24	.02	.01	-.12	.65***	.35***	.40***	.39***	.37***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$, Male = 0, Female = 1.

Table 2. Four multiple linear regressions with AI readiness as DV.

	PPA				HPTI				TEIQue				GIA							
	B	SE	β	t-value	p-value	B	SE	β	t-value	p-value	B	SE	β	t-value	p-value	B	SE	β	t-value	p-value
Sex	-.12	.13	-.02	-0.89	.373	1.14	.53	.20	2.14	.035	0.29	.58	.05	0.50	.615	0.00	.23	.00	0.00	.997
Age	-.03	.01	-.11	-4.83	<.001	0.01	.03	.04	0.43	.666	-0.02	.03	-.07	-0.67	.503	-0.02	.01	-.07	-1.88	.060
Dominance	.03	.01	.07	2.18	.029															
Steadiness	-.04	.02	-.07	-2.11	.035															
Conscientiousness						0.08	.64	.02	0.13	.896										
Adjustment						0.32	.45	.08	0.71	.480										
Curiosity						1.48	.51	.30	2.93	.004										
Risk Approach						-0.43	.56	-.09	-0.78	.439										
Ambiguity Acceptance						0.48	.40	.13	1.20	.234										
Competitiveness						0.79	.38	.19	2.08	.040										
Well-being											-0.17	.51	-.05	-0.33	.741					
Self-control											0.68	.53	.19	1.30	.197					
Emotionality											0.09	.53	.02	0.17	.863					
Sociability																				
Reasoning																0.03	.02	.10	1.99	.048
Perceptual Speed																0.00	.02	.00	0.16	.870
Numeric																0.01	.02	.02	0.42	.674
Word Meaning																0.00	.02	.01	0.20	.845
Spatial Visualisation																0.02	.02	.04	0.83	.405
<i>F</i> (df)																				
						15.64	(4, 1973)	***	2.77	(8, 104)**	0.51	(6, 116)								
<i>R</i> ²						.031			.176		.026									

Note. * $p < .05$, ** $p < .01$, *** $p < .001$, Male = 0, Female = 1.

7. Discussion

Essentially, this research trails the adoption of new technology literature (Williams et al., 2015; Yadegari et al., 2024). Researchers in this area have attempted to describe processes and models that describe and explain how, why, and when people are somewhere on a scale between enthusiastic “early adopters” vs those who avoid and shun adoption as long as possible. There are, however, not many studies on personality trait correlates of new technology uptake (Menon & Shilpa, 2023). Although personality studies done on the uptake of new technology, such as the use of social networks, have found that three traits appear relevant: Extraversion, Openness, and Conscientiousness (Lynn et al., 2017).

The present study examined individual difference correlates of AI readiness. At the bivariate level, results largely aligned with expectations. Emotional intelligence variables were unrelated to AI readiness, whereas all cognitive ability subtests were significantly correlated. The strongest association emerged for trait curiosity, consistent with the notion that individuals high in openness to new ideas are more inclined toward emerging technologies.

However, the multivariable regression analyses revealed a more nuanced pattern. When predictors were considered simultaneously, only Curiosity (Openness) and Conscientiousness demonstrated unique associations with AI Readiness. Importantly, although all GIA subtests were significantly correlated at the bivariate level, most cognitive effects attenuated in regression models. This reduction likely reflects shared variance among cognitive subtests, with Verbal Reasoning being the single subtest associated with AI Readiness. Indeed, these results are similar to other studies in the area, which failed to find many significant correlations between personality and AI attitudes (Kaya et al., 2024; Liang et al., 2025; Ozbey & Yasa, 2025; Stein et al., 2024), and even where predictors reached statistical significance, the overall variance explained was modest at best. The DISC and GIA models accounted for approximately 3% of the variance, and the HPTI model explained 17%. While statistically reliable, these effect sizes suggest limited practical significance in determining which traits impact one’s AI readiness.

Taken together, both the present findings and emerging literature indicate that personality and cognitive ability factors are not closely related to the uptake of AI. This opens the question as to what individual difference factors are related to AI Readiness. Instead, AI Readiness may be more strongly shaped by contextual and experiential variables. The absence of occupational and educational data in the present study limits interpretation; exposure to AI in one’s role, organizational culture, job demands, and social norms may exert stronger influence than dispositional traits. Future research should therefore examine environmental and situational determinants alongside individual differences to better understand the psychological and contextual foundations of AI adoption.

Like all studies, this one had limitations. The nature of the data collection resulted in the non-independence of the cohorts. Because individuals could complete multiple assessments and thus appear in more than one cohort, the regres-

sion models across cohorts cannot be formally compared using significance tests. The ranking of predictors (e.g. personality vs intelligence) is therefore indicative rather than definitive. Moreover, we did not have a measure of the participants' AI behaviours. Nevertheless, we believe this makes a modest contribution to the literature of this field.

Data Availability

This is obtainable from the first author upon request.

Registration

This paper was not pre-registered with the journal.

Ethics

This was sought and obtained (SLA/2022/02). The study involved secondary analysis of anonymised data, collected from a non-vulnerable population in a panel with informed consent that allowed the use of the data by third-party researchers.

Informed Consent

Participants gave consent for their anonymised data to be analysed and published.

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Authors' Contributions

A.F: Visualisation, Writing—review & editing; S.C: Data Curation; D.S: Data analysis, Writing, Proofing.

Conflicts of Interest

There is no conflict of interest or competing interests.

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