

From AI Anxiety to AI Adaptability: The Role of Emotion Crafting in Enhancing Adaptive Job Performance in the Age of Agentic AI

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ABSTRACT

Agentic AI, which involves systems that can plan and undertake tasks with limited human oversight, is revolutionising the nature of work and workplace experiences. The advancement of AI and agentic systems, in particular, is transforming the nature of work and how workers experience their jobs. While there is vast literature that focuses on the risks of AI to employees, less is understood about how AI triggers emotions in employees and the connection between emotional self-management and adaptation. The aim of this research is to discuss associations among AI anxiety, emotion crafting (proactive strengthening of positive emotions), AI adaptability and adaptive job performance. Using a cross-sectional design, a quantitative survey measuring 250 working individuals from various fields of work included six item scales based on the validated instruments. The reliability of the data ranged from acceptable to very high, with Cronbach's α values between .78 and .98. Multiple regression with the six indicators of each predictor construct was used to test the four hypotheses. Each of the four hypotheses is receiving support. The AI anxiety indicators were significantly related to AI adaptability ($R^2 = .88$), and AI anxiety indicators were significantly related to emotion crafting ($R^2 = .85$), while emotion crafting indicators were significantly related to AI adaptability ($R^2 = .94$), and AI adaptability indicators were significantly related to adaptive job performance ($R^2 = .98$), all at $p < .005$. The results situate emotion crafting as a psychologically significant avenue for how employees are affected by AI-related change and advance the concept from well-being science to technology-centric work situations. Due to the cross-sectional nature and self-reported data, and the particularly high intercorrelations between constructs, the results should be considered statistical associations and replicated with multi-source, longitudinal designs. Theoretical implications, human resource development and applying AI are explored.

Keywords: artificial intelligence anxiety; emotion crafting; AI adaptability; adaptive job performance; employee adaptation; workplace artificial intelligence; technology-enabled work.

INTRODUCTION

Artificial intelligence has moved from the periphery of organisational life to its core. A new generation of agentic AI advances us towards a future where complex goals can be achieved with minimal direct supervision, as generative and predictive systems now draft documents, screen applications, analyse transactions, and support both constructive and deconstructive decisions in clinical and managerial settings. Field surveys paint a picture of agentic AI systems that are autonomous, adaptable, and able to make complex decisions in changing scenarios (Acharya et al., 2025) and that differ from previous task-specific agent systems, which were limited by working in

isolation, rigid task decomposition, lack of persistence, and lack of coordinated autonomy (Sapkota et al., 2025). These properties alter the nature of the interaction with technology for employees. AI is not just a tool that is operated – it is now a collaborator, a supervisor, or a potential alternative. There is currently a discursive dilemma regarding the work and the potential adverse effects of AI on workers, along with optimism for higher productivity, which is reflected in the empirical literature gathered in a systematic review, as summarised by Bankins and colleagues (2024).

Among the many psychological reactions to this change, AI anxiety is a well-documented phenomenon, which is seen as the fear of being affected by AI, including through

fear of being replaced by it (Li & Huang, 2020; Wang & Wang, 2022). The awareness of job automation through AI has been found to be correlated with job insecurity (Lingmont & Alexiou, 2020). In addition to AI awareness, hotel employees reported job burnout (Kong et al., 2021), and technostress and job insecurity were reported in interviews with professionals in Industry 4.0 organisations, with the other side also citing benefits such as flexibility and improved performance (Malik et al., 2022). However, anxiety is not always harmful. Employees' perceptions of AI integration can either align with the transactional consequences of change and foster thriving and proactive responses or with the perceived difficulty of the change, leading to feelings of insecurity (Huang & Gursoy, 2024); those perceptions vary, depending on personal resources like locus of control (Cheng et al., 2023). Knowing what employees do with their anxiety, and not whether they have it, is thus one key to understanding how they adapt.

One lens on this issue is provided by emotion regulation research, which to date has tended to focus on efforts to decrease negative emotions after they occur (Martins-Klein et al., 2020). In an attempt to identify categories of emotional reactions and build an alternative construct, Van der Kaap-Deeder et al. (2023) theorised emotion crafting. It involves being conscious of what activates one's positive emotions and taking active steps (proactively) to start, sustain, or boost these emotions. Emotion crafting has been linked to improved daily psychological functioning (Hernandez Hernandez et al., 2025), and it has been found to act as a mediator between supportive parenting and young adults' well-being (Taşkesen et al., 2025). The literature analysed for this research does not yet, however, have an examination of the construct in the context of change at work using the support of artificial intelligence (AI).

Emotional processes are the means by which adaptation occurs and therefore are relevant to workplace outcomes. The capacity to navigate and change one's work practices in accordance with AI-related change develops on the larger idea of employee adaptability as an individual difference construct (van Dam & Meulders, 2021). The behavioural manifestation of the response to shifting requirements – adaptive job performance – is a well-recognised aspect of job performance that has been relatively under-researched (Krijgsheld et al., 2022; Park & Park, 2019).

In this backdrop, the present research explores a connection among these variables – emotion crafting, AI anxiety, AI adaptability and adaptive job performance – in a sample of working professionals. In particular, it is designed to examine the links between (a) AI anxiety and AI adaptability, (b) AI anxiety and emotion crafting, (c) emotion crafting and AI adaptability, and (d) AI adaptability and adaptive job performance. The study adds something to the literature in three ways. It extends emotion crafting to the work context and introduces different appraisals and regulations of emotion into one model; it also offers item-level regression evidence on how each of the individual indicators of each of the emotion constructs relates to the others.

This paper continues as follows. The literature is reviewed and hypotheses developed in Section 2. The research methodology is discussed in Section 3. The data analysis and results are reported in Section 4. The results are enumerated in Section 5; implications of the findings and its practice in education are in Section 6; and conclusions, limitations and future research are in Section 7.

2. Literature Review and Hypothesis Development

This study is based upon two complementary theories. The transactional theory of stress suggests that the same technological change may be perceived as either a threat or an opportunity, leading to varying emotions and behaviours among users (Huang & Gursoy, 2024). The theory of conservation of resources, which has been used to study the role of AI-embedded work on well-being and performance when introduced to new skill demands, is explained here (Chen et al., 2024). This holistic perspective views emotion crafting as a resource-building practice that staff can use to transform anxiety activation into adaptive engagement. The subsections below present various hypotheses.

2.1 AI Anxiety and AI Adaptability

AI anxiety can be conceptualised as a psychological condition characterised by fear, worry, or apprehension regarding the learning, use, and impact of AI. Li and Huang (2020) presented AI anxiety, conceptualising it within the framework of integrated fear acquisition theory and pinpointing the dimensions of AI anxiety. Wang and Wang (2022) developed and tested a scale that comprised four domains: learning, job replacement, sociotechnical blindness, and AI configuration. More recently, Alshaibani et al. (2025) created and tested a measurement of researcher anxieties regarding the use of AI in academic writing. Together, these studies show that AI anxiety is a multifaceted and measurable construct, rather than a single, generalised fear.

The link between anxiety and adaptation of AI is theoretically unclear. Anxiety, on the one hand, will hinder adaptation. AI awareness is strongly associated with AI anxiety (Lingmont & Alexiou, 2020; Kong et al., 2021), AI awareness is also correlated with perception of insecurity (Lingmont & Alexiou, 2020), and hindrance was found to be negatively correlated with intention to adopt AI by increasing AI anxiety (Chang et al., 2024) among employees who are anxious about learning AI. However, the other way around, the transactional view states that the stress brings information and energy. AI embeddedness demands are regarded as challenges; they can foster proactive behaviour and job crafting (Cheng et al., 2023; Huang & Gursoy, 2024). Furthermore, job skill demands associated with AI embeddedness have been found to enhance the competence requirements of workers, thereby improving their well-being and capabilities. In this perspective, anxiety could be a sign of adaptation needed and drive learning and adaptation ability. Given the mixed nature of the evidence and the potential, it is proposed that there is a big association between AI anxiety and AI adaptability, but this association may be in either direction.

H1: AI anxiety is significantly associated with employees' AI adaptability.

2.2 AI Anxiety, Emotion Crafting and AI Adaptability

Anxiety is a feeling of worry and disturbance too, and one that can be acted upon. Emotion research on regulation distinguishes between post-emotional activities (those that occur after an emotion has been experienced) and pre-emotional or in-emotional activities (those that take place before or during emotions), while dual-mechanism emotion regulation research proposes a distinction between proactive and reactive emotion regulation (Martins-Klein et al., 2020). Emotion crafting is part of the proactive (Rolls) side. People learn what feels pleasant for them and consciously adopt positive-feeling behaviours to start, sustain or expand their positive emotions (van der Kaap-Deeder et al., 2023). Planned emotion crafting was followed by actual emotion crafting, which in turn was correlated with increased well-being and decreased ill-being in terms of positive and negative affect in a seven-day diary study (Hernandez Hernandez et al., 2025). Overall adaptive emotion regulation has been related to well-being in meta-analytic research (Kraiss et al. 2020), and a meta-analysis of daily life studies indicates a systematic association between the regulation strategy and the next emotion (Boemo et al. 2022).

Allowing for the generation of apprehension can compel employees who experience higher levels of anxiety to compensate for the negative activation, potentially leading them to seek and engage in activities that are counterproductive in negating the negative sensation—such as finding peer support, experimenting with AI tools in non-threatening environments, or reminiscing about previous instances where new technology has been successful for them. Anxiety thus functions as a trigger for emotion crafting and not only as a burden. The way argued is in line with the appraisal-based approach, according to which stressful situations trigger coping attempts, and with the self-regulation and personal agency viewpoint, which posits that the self-regulated coping to their worries is an instance of personal agency (Hernandez Hernandez et al., 2025). Based on these findings, the second hypothesis is put forward.

H2: AI anxiety is significantly associated with employees' emotion crafting.

Emotion crafting is expected, in turn, to support adaptability. Adapting to AI requires employees to let go of old routines, learn new ones, and change how they collaborate with intelligent systems, which necessitates both emotional and cognitive resources (van Dam & Meulders, 2021). Individuals who understand what makes them feel positive and who can selectively enhance their working lives should have more resources to feel positive about the demands they face. The findings of Taşkesen et al. (2025) indicated that the connection between parental support and the resilience and flourishing of young adults goes through the mediator of emotion crafting, suggesting

that parental support is transformed into psychological strength via emotion crafting. Emotion crafting when taken to the workplace may transform the activation generated by AI to readiness to learn and adapt. Emotion crafting is a source of positive emotions viewed as acquired resources that trade with the challenge of losing some resources implied by the task requirements of AI-driven skills (Chen et al., 2024). For that reason, the third one is suggested.

H3: Emotion crafting is significantly associated with employees' AI adaptability.

2.3 AI Adaptability and Adaptive Job Performance

Employee adaptability to AI refers to their ability to adjust their work practices when changes result from AI. It draws on a conceptualisation of adaptability as an individual difference construct referring to the ability of employees to adapt to change in the workplace (van Dam & Meulders, 2021), and it uses this capacity for a specific and important area, where tasks, tools, and role borders are being transformed and redefined by smart systems. Adaptive job performance, on the other hand, is the type of job performance that occurs when tasks change, such as adaptations—modifying behaviour, learning new procedures, and finding solutions to a problem in a new context. A systematic review revealed that adaptive performance, together with task performance, contextual performance, and counterproductive work behaviour, is one important dimension of job performance but has been studied less than the other dimensions of performance (Krijgheld et al., 2022). Based on these 34 empirical studies, they also found that the antecedents of adaptive performance occur at the individual, job, and group/organisational levels, and that individual antecedents were the ones studied the most (Park & Park, 2019).

Those better equipped to translate the gained ability to change in a new way into effective job performance should have a better opportunity to do so when jobs are reconfigured in response to the changing nature of work. In an organisational context, there is a significant focus on employees' reactions to and adaptation of AI tools and technologies, with a view to determining the outcomes of such interactions (Bankins et al., 2024; Chen et al., 2024). Accordingly, AI adaptability is hypothesised to be related to adaptive job performance, ultimately leading to the fourth hypothesis.

H4: AI adaptability is significantly associated with employees' adaptive job performance.

Figure 1 presents the conceptual framework of the study. AI anxiety is positioned as the antecedent, emotion crafting and AI adaptability as intermediate constructs, and adaptive job performance as the outcome. Although the framework suggests an indirect pathway from AI anxiety through emotion crafting to AI adaptability, the present study tests each proposed relationship separately and does not estimate the indirect effect.

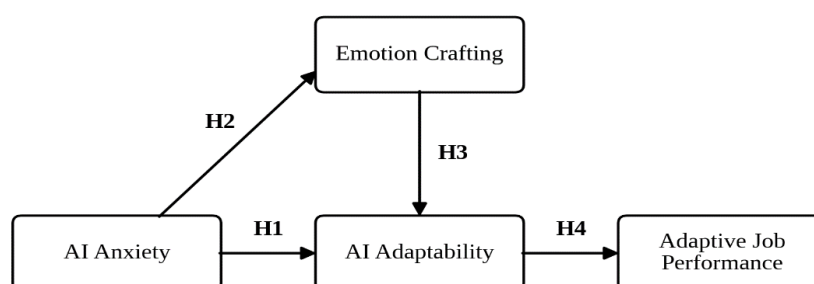


Figure 1. Conceptual framework of the study

2.4 Research Gap

There are three themes that are missing from the literature. Research of AI anxiety has focused on the roots of and potential negative impacts of this emotion (e.g., insecurity, burnout, less acceptance) with comparatively few studies of how the emotion is managed and whether that has positive consequences (Bankins et al., 2024; Kong et al., 2021). Second, emotion crafting is a new concept that has been studied in non-working domain samples (e.g., Taşkesen et al., 2025; van der Kaap-Deeder et al., 2023) and the domain of general well-being (e.g., Hernandez Hernandez et al., 2025), but not in the context of technological change at work. Third, compared to other facets of job performance (Krijgsheld et al., 2022), there appears to be a greater need for adaptability in AI-specific tasks than there is for other aspects of work. Third, the connection between adaptability and the employment performance of various facets of job performance is less developed for adaptive performance than it is for other facets of job performance (Krijgsheld et al., 2022), particularly when applied to adaptability required for AI-specific tasks as the demands for continuous adjustment grow with the use of agentic AI (Acharya et al., 2025).

To fill the gaps, the present study aims to test a model that links together the constructs of AI anxiety, emotion crafting, AI adaptability, and adaptive job performance using a single sample of working professionals. It explores both the phenomenon of anxiety in relation to AI and the emotional management of it, while determining if these approaches and the resulting adaptability relate to adaptive performance in work.

3. RESEARCH METHODOLOGY

3.1 Research Design

The research model used in this study was quantitative – cross-sectional – explanatory with a positivist approach. The data was obtained by a structured questionnaire and analysed using multiple regression to investigate interrelationships between the subjects investigated. The data were collected as one snapshot, and associations are not necessarily causal.

3.2 Population and Sample

The target population included current or former workers who have experience using or interacting with AI-based tools in their work. A total of 250 respondents took part in the final sample. Power analyses also revealed that for six predictors, at least 146 participants are needed to achieve a medium effect size ($f^2 = .15$) and for 95% power and $\alpha = .05$. So 250 was deemed a suitable sample.

3.3 Sampling Technique and Data Collection

A purposive-convenience sampling technique was used. Participants were identified via referral and networks. The survey was completed using an online, self-administered questionnaire that included informed consent, screening questions, construct items and demographic information. Participation was voluntary and anonymous. The 250 responses which were screened out related to length and eligibility were used.

3.4 Measurement Instrument

Four constructs were measured using multi-item scales adapted from validated instruments in the literature. Table 1 summarizes the constructs, item codes, number of items, and primary sources of adaptation.

Table 1. Measurement Instrument and Sources of Adaptation

Construct	Codes	Items	Primary source/adaptation
AI Anxiety	AIA1–AIA6	6	Wang & Wang (2022)
Emotion Crafting	EC1–EC6	6	van der Kaap-Deeder et al. (2023)
AI Adaptability	AAD1–AAD6	6	van Dam & Meulders (2021)
Adaptive Job Performance	AJP1–AJP6	6	Ribeiro et al. (2022); Krijgsheld et al. (2024)

AI anxiety (AIA1 to AIA6) was measured with six items adapted from the AI anxiety scale of Wang and Wang (2022), reflecting apprehension about learning about, using, and being affected by AI. Emotion crafting (EC1 to EC6) was measured with six items adapted from the Emotion Crafting Scale developed by van der Kaap-Deeder et al. (2023), which conceptualizes emotion crafting as awareness of positive emotion-inducing situations combined with proactive action to engage in them. AI adaptability (AAD1 to AAD6) was measured with six items adapted from the employee adaptability scale of van Dam and Meulders (2021), with the wording tailored to AI-related change at work. Adaptive job performance (AJP1 to AJP6) was measured with six items adapted from the adaptive performance scale as translated and validated by Ribeiro et al. (2022) and Krijgsheld et al. (2024); the latter reported good internal consistency ($\alpha = .87$) for the English-language version among 283 respondents.

All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Adaptation involved shortening and rewording items to fit the AI-at-work context, and content validity rested on the established conceptual definitions of each construct. For the regression analyses, each dependent construct was

operationalized as the composite score of its six items, whereas the six items of each predictor construct were entered individually. This item-level approach makes it possible to examine the unique contribution of each indicator.

3.5 Data Analysis Procedure

IBM SPSS Statistics was used to handle and analyse the data. Data screening, demographic analysis, descriptive statistics, Cronbach's alpha, Pearson correlation and multiple regression analyses were performed. Four models were used for regression to test the hypotheses. The following parameters were analysed: R, R², adjusted R², ANOVA, β , t, p-values and VIF. A Cronbach's alpha of $\geq .70$ was accepted as adequate, and VIF values greater than 5 were interpreted as an indication of potential multicollinearity. Hypotheses were tested using a 5% significance level ($p < .05$). Given a cross-sectional design of the study, regression results were interpreted as associations.

4. DATA ANALYSIS AND RESULTS

4.1 Demographic Profile

Table 2 presents the demographic profile of the 250 respondents.

Table 2. Demographic Profile of Respondents (N = 250)

Variable	Category	Frequency	Percentage
Gender	Female	131	52.4
	Male	106	42.4
	Other/Prefer not to say	13	5.2
Age	26-35	103	41.2
Age	18-25	80	32.0
Age	36-45	40	16.0
Age	46-55	19	7.6
Age	Above 55	8	3.2
Educational qualification	Postgraduate	144	57.6
Educational qualification	Undergraduate	55	22.0
Educational qualification	Doctorate	42	16.8
Educational qualification	Other	9	3.6
Work experience	2-5 years	87	34.8
Work experience	6-10 years	54	21.6
Work experience	Less than 2 years	44	17.6
Work experience	11-15 years	38	15.2
Work experience	More than 15 years	27	10.8
Industry	IT/Software	76	30.4

Variable	Category	Frequency	Percentage
Industry	Banking/Finance	43	17.2
Industry	Education	25	10.0
Industry	Healthcare	24	9.6
Industry	Consulting/Professional Services	23	9.2
Industry	Other	22	8.8
Industry	Manufacturing	21	8.4
Industry	Retail/E-commerce	16	6.4
Job level	Middle level	80	32.0
Job level	Senior level	62	24.8
Job level	Managerial level	52	20.8
Job level	Entry/Junior level	42	16.8
Job level	Senior management	14	5.6
AI experience	3-5 years	84	33.6
AI experience	1-2 years	63	25.2
AI experience	Less than 1 year	59	23.6
AI experience	More than 5 years	44	17.6
AI-use frequency	Frequently	84	33.6
AI-use frequency	Sometimes	66	26.4
AI-use frequency	Occasionally	45	18.0
AI-use frequency	Very frequently	35	14.0
AI-use frequency	Rarely	20	8.0

Note. N = 250. Percentages are based on the total sample

The demographic profile indicates a varied respondent base across age, education, work experience, industry, job level, and AI-use characteristics. Female respondents constitute 52.4% of the sample, while male respondents constitute 42.4%; the remaining 5.2% are recorded under the other or prefer-not-to-say category. Respondents aged 26–35 represent the largest age group at 41.2%, followed by those aged 18–25 at 32.0% and 36–45 at 16.0%. Postgraduate respondents account for 57.6% of the sample, and a further 16.8% hold a doctorate. IT/software is the largest represented sector, accounting for 30.4% of respondents, followed by banking/finance at 17.2%.

Middle-level employees form the largest job-level group (32.0%), and 33.6% of respondents reported three to five years of AI experience. Nearly half of the respondents (47.6%) use AI frequently or very frequently. The distribution of AI experience and AI-use frequency indicates exposure to AI-enabled technologies at different levels, providing a relevant context for examining AI-related perceptions and adaptation.

4.2 Descriptive Statistics and Reliability

Table 3 reports the descriptive statistics and reliability coefficients for the four constructs.

Table 3. Descriptive Statistics and Reliability of the Constructs

Construct	Mean	SD	Minimum	Maximum	Cronbach's α
AI Anxiety	3.00	1.41	1	5	0.78
Emotion Crafting	3.00	1.41	1	5	0.84
AI Adaptability	3.00	1.41	1	5	0.97
Adaptive Job Performance	3.00	1.41	1	5	0.98

Note. N = 250. Items were rated on a five-point scale (1 = strongly disagree, 5 = strongly agree)

The descriptive statistics indicate that the responses to the measurement span the full 5-point response scale. The mean response is near the midpoint of the scale for each of the four constructs, suggesting no extreme floor or ceiling effect. The reliability is acceptable for all four constructs. The alpha values of AI anxiety, emotion crafting, AI adaptability, and adaptive job performance are similar and represented as approximately .78, .84, .97, and .98, respectively. The values of these were within the adequate to very high internal consistency range for items in each construct.

The reliability pattern is also beneficial for moving on to the correlation and regression phase. However, extremely high reliability rates should not be taken as a measure of the quality of the measurements. High alpha values do

mean that there is a high degree of similarity in items; sometimes items can be very similar and have extremely high alpha values. However, each regression analysis is shown itemwise to show the unique contribution of each indicator for this reason.

It is important to point out that the means (3.00) and standard deviations (1.41) were the same across all four constructs. This finding corresponds to a fairly flat distribution of the responses into the five response categories and is discussed at the end of the limitations section.

4.3 Correlation Analysis

Table 4 presents the Pearson correlation matrix for the four constructs.

Table 4. Pearson Correlation Matrix of the Study Constructs

Construct	AI Anxiety	Emotion Crafting	AI Adaptability	Adaptive Job Performance
AI Anxiety	1.00	0.92	0.94	0.93
Emotion Crafting	0.92	1.00	0.97	0.95
AI Adaptability	0.94	0.97	1.00	0.99
Adaptive Job Performance	0.93	0.95	0.99	1.00

Note. N = 250. All correlations are significant at $p < .001$ (two-tailed).

There are high positive correlations among the four variables as shown in the construct-level correlation matrix. AI anxiety is positively correlated with emotion crafting and AI adaptability; emotion crafting is positively correlated with AI adaptability and adaptive job performance. There is also a strong positive correlation between the adaptability of the AI and adaptive job performance. These correlations support the proposed framework in a preliminary way to proceed with the regression analysis. Correlation does not mean cause, however, and so the “direction of regression” is treated as being an indication of “statistical association”.

4.4 Hypothesis Testing

A three-table format is provided for each hypothesis, reporting the four regression models. The model summary is given in the first table, the ANOVA is given in the second table, and the individual coefficients are given in the third table. The key to analysing the difference is that the predictor items are placed separately. Thus, the B beta values represent the distinctive contribution of each item once the contribution of the other five items sharing a similar predictor construct has been factored out.

4.4.1.H1: AI Anxiety → AI Adaptability

Table 5. H1 Model Summary: AI Anxiety → AI Adaptability

R	R ²	Adjusted R ²	Std. Error of Estimate
0.94	0.88	0.88	2.74

Table 6. H1 ANOVA: AI Anxiety → AI Adaptability

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	13942.51	6	2323.75	308.65	0.00
Residual	1829.49	243	7.53		
Total	15772.00	249			

Table 7. H1 Regression Coefficients: AI Anxiety → AI Adaptability

Predictor	B	SE	β	t	p
Constant	-4.96	0.56	—	-8.80	0.00
AIA1	1.49	0.14	0.27	10.58	0.00
AIA2	1.15	0.14	0.20	8.02	0.00
AIA3	1.29	0.15	0.23	8.71	0.00
AIA4	1.15	0.15	0.21	7.82	0.00
AIA5	1.27	0.14	0.23	8.93	0.00
AIA6	1.30	0.15	0.23	8.47	0.00

Note. Dependent variable: AI adaptability (composite score). VIF = variance inflation factor

The H1 regression model is statistically significant, $F(6, 243) = 308.65$, $p = 0.00$. The model produces $R = 0.94$ and $R^2 = 0.88$, indicating that approximately 88.4% of the variance in the dependent construct is explained by the six item-level predictors. Each of the six predictors has a p-value below .05 at the displayed precision. The positive standardized coefficients indicate that higher scores on the individual predictor indicators are associated with higher scores on the dependent construct when the remaining predictor items are held constant.

H1 is therefore supported. The finding indicates a strong statistical association between the six AI-anxiety indicators and AI adaptability. Because the model uses item-level predictors, the result should be interpreted as a collective association of the AI-anxiety indicators with adaptability rather than as evidence that a single composite anxiety score causes adaptability.

H2: AI Anxiety → Emotion Crafting

Table 8. H2 Model Summary: AI Anxiety → Emotion Crafting

R	R^2	Adjusted R^2	Std. Error of Estimate
0.92	0.85	0.84	2.52

Table 9. H2 ANOVA: AI Anxiety → Emotion Crafting

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	8440.89	6	1406.81	221.82	0.00
Residual	1541.11	243	6.34		
Total	9982.00	249			

Table 10. H2 Regression Coefficients: AI Anxiety → Emotion Crafting

Predictor	B	SE	β	t	p
Constant	0.12	0.52	—	0.23	0.82
AIA1	1.25	0.13	0.28	9.65	0.00
AIA2	0.86	0.13	0.19	6.56	0.00
AIA3	0.88	0.14	0.20	6.47	0.00
AIA4	0.91	0.14	0.20	6.74	0.00
AIA5	1.07	0.13	0.24	8.23	0.00
AIA6	0.98	0.14	0.22	6.97	0.00

Note. Dependent variable: emotion crafting (composite score). VIF = variance inflation factor.

The H2 regression model is statistically significant, $F(6, 243) = 221.82$, $p = 0.00$. The model produces $R = 0.92$ and $R^2 = 0.85$, indicating that approximately 84.6% of the variance in the dependent construct is explained by the six item-level predictors. Each of the six predictors has a p -value below .05 at the displayed precision. The positive standardized coefficients indicate that higher scores on the individual predictor indicators are associated with higher scores on the dependent construct when the remaining predictor items are held constant.

H2 is supported. The six AI-anxiety indicators jointly explain a substantial proportion of the variation in emotion crafting. The result suggests that differences in AI-related anxiety indicators are systematically associated with differences in proactive emotional management in the analyzed sample.

H3: Emotion Crafting → AI Adaptability

Table 11. H3 Model Summary: Emotion Crafting → AI Adaptability

R	R ²	Adjusted R ²	Std. Error of Estimate
0.97	0.94	0.94	1.92

Table 12. H3 ANOVA: Emotion Crafting → AI Adaptability

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	14873.54	6	2478.92	670.46	0.00
Residual	898.46	243	3.70		
Total	15772.00	249			

Table 13. H3 Regression Coefficients: Emotion Crafting → AI Adaptability

Predictor	B	SE	β	t	p	VIF
Constant	-3.97	0.37	—	-10.77	0.00	—
EC1	1.32	0.11	0.23	11.82	0.00	
EC2	1.22	0.10	0.22	11.98	0.00	
EC3	1.21	0.11	0.22	10.81	0.00	
EC4	1.22	0.11	0.22	10.74	0.00	
EC5	1.27	0.11	0.23	11.30	0.00	
EC6	1.08	0.11	0.19	9.55	0.00	

Note. Dependent variable: AI adaptability (composite score). VIF = variance inflation factor

The H3 regression model is statistically significant, $F(6, 243) = 670.46$, $p = 0.00$. The model produces $R = 0.97$ and $R^2 = 0.94$, indicating that approximately 94.3% of the variance in the dependent construct is explained by the six item-level predictors. Each of the six predictors has a p -value below .05 at the displayed precision. The positive standardized coefficients indicate that higher scores on the individual predictor indicators are associated with higher

scores on the dependent construct when the remaining predictor items are held constant.

H3 is supported. The emotion-crafting indicators explain a very large proportion of the variance in AI adaptability. The positive coefficients indicate that each indicator retains a statistically significant unique association after the remaining emotion-crafting indicators are controlled.

H4: AI Adaptability → Adaptive Job Performance

Table 14. H4 Model Summary: AI Adaptability → Adaptive Job Performance

R	R ²	Adjusted R ²	Std. Error of Estimate
0.99	0.98	0.98	1.21

Table 15. H4 ANOVA: AI Adaptability → Adaptive Job Performance

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	15884.36	6	2647.39	1798.77	0.00
Residual	357.64	243	1.47		
Total	16242.00	249			

Table 16. H4 Regression Coefficients: AI Adaptability → Adaptive Job Performance

Predictor	B	SE	β	t	p
Constant	-0.07	0.19	—	-0.35	0.73
AAD1	0.91	0.12	0.16	7.32	0.00
AAD2	1.01	0.14	0.18	7.20	0.00
AAD3	1.22	0.13	0.21	9.40	0.00
AAD4	1.27	0.12	0.22	10.47	0.00
AAD5	0.81	0.14	0.14	5.99	0.00
AAD6	0.80	0.13	0.14	6.13	0.00

Note. Dependent variable: adaptive job performance (composite score). VIF = variance inflation factor

The H4 regression model is statistically significant, $F(6, 243) = 1798.77$, $p = 0.00$. The model produces $R = 0.99$ and $R^2 = 0.98$, indicating that approximately 97.8% of the variance in the dependent construct is explained by the six item-level predictors. Each of the six predictors has a p-value below .05 at the displayed precision. The positive standardized coefficients indicate that higher scores on the individual predictor indicators are associated with higher scores on the dependent construct when the remaining predictor items are held constant.

H4 is supported. The AI-adaptability indicators explain a very large proportion of the variance in adaptive job performance. The result is consistent with the expectation that employees who report greater capacity to adjust to AI-related changes also report stronger adaptive performance.

5. DISCUSSION

This research focused on the relationships among AI anxiety, emotion crafting, AI adaptability, and adaptive job performance among 250 professionals in the workforce. For all four hypotheses, support was given. Each of the outcome measures represented an agreed range of 85% to 98% of the variance measured in each predictor construct, and each model was significant at the $p < .001$ level (Table 17).

An intriguing finding of this study is that the relationships between each of the AI anxiety indicators and AI adaptability (H1) are positive; greater scale scores in AI anxiety are alongside greater scale scores in AI adaptability. Given the massive amount of existing literature, it would be easy to hypothesise that the findings are the opposite, in terms of anxiety being connected to

insecurities and burnout as well as the less favourable attitudes towards AI (Kaya et al., 2024; Kong et al., 2021; Lingmont & Alexiou, 2020). The result, however, aligns with appraisal-based accounts, in which the demands of AI are not perceived as obstacles but as challenges that motivate effort and learning, as well as with evidence that the use of AI in skill demands can stimulate competency demands and performance (Chen et al., 2024). There is also a potential explanation: the respondents in this sample may not be anxious individuals but rather those who experienced anxiety and adjusted to it, as anxiety posed no paralysis or threat to them. This interpretation is tentative in nature, due to a lack of direct measure of appraisals and the non-directional nature of the hypothesis. Association direction should be duplicated prior to consideration as substantive.

To sum up, both emotion crafted (H2) and employees' emotions towards AI showed a significant correlation, with a higher score in the aspect of AI anxiety also predicting more proactive emotion crafted. It helps to confirm the theory that anxiety can serve as a catalyst for the creation of emotion and not just as a cause of stress. It is consistent with the dual-mechanisms perspective of emotion regulation by engaging proactive emotion regulation responses before an emotionally demanding situation as well as during an emotionally challenging situation (Martins-Klein et al., 2020), and it generalises emotion crafting research on a broader component of well-being (Hernandez Hernandez et al., 2025; Taşkesen et al., 2025) to emotion reactions to technological change. Given the definition of emotion crafting as proactively

enhancing positive emotions (van der Kaap-Deeder et al. 2023), the finding also indicates that anxious workers are

not only trying to minimise negative emotions; they are also looking out to create positive emotions.

The emotion-crafting vs. AI adaptability (H3) was the highest among the emotion-related results. This result was achieved using emotion crafting indicators that explain 94.3% of the variance of AI adaptability, with each of the six indicators having a significant unique coefficient indicating that the result is not contaminated by the impact of a single item. This finding reflects the positive emotional resources facilitating readiness to adjust to change (Chen et al., 2024; Taşkesen et al., 2025) and aligns with the evidence linking emotion crafting to prosperity in psychological functioning in everyday life (Hernandez Hernandez et al., 2025).

The association between AI adaptability and adaptive job performance (H4) was the strongest overall, with $R^2 = .978$. This aligns with the notion that adaptive behaviours are evident in adjusting to work (Krijgsheld et al., 2022; Park & Park, 2019). The two constructs are first a capacity (adjustment) and second an enactment of adjustment (the act of adjusting), and these two self-reports are both conceptually and empirically related. Future research is needed to test for discriminant validity between these.

This pattern projects an overall order that is consistent with the results outlined above: when AI anxiety is present, so is emotion crafting; when emotion crafting is present, so is AI adaptability; and when AI adaptability is present, so is adaptive job performance. As suggested by theory, this sequence was not formally tested or estimated; each relationship was examined one by one, and no indirect effect was found. Precautions should also be taken with the size of the associations. The multiple correlations ranging from .92 to .99 are unusual in organisational survey research, where associations between distinct and different constructs are generally more moderate. Some of the discrepancies in the strength of the results may be partially due to the overlap of concepts within the constructs, common method variance, or response patterns, as mentioned in Section 7.2.

6. IMPLICATIONS OF THE STUDY

6.1 Theoretical Implications

Firstly, the study shifts the emotion crafting construct from the field of well-being studies (Hernandez Hernandez et al., 2025; Taşkesen et al., 2025; van der Kaap-Deeder et al., 2023) into the setting of working with AI. It finds that emotion crafting is statistically related to AI anxiety and AI adaptability; thus, it pinpoints proactive positive-emotion regulation as a possibility as a mechanism for how employees respond to technological shifts.

The study integrates the stress-appraisal and emotion-regulation perspectives. The results suggest that the experience of AI anxiety is positively related to emotion crafting and adaptability, thus demonstrating that anxiety can be used as a mobilising signal rather than as an obstacle. This aligns existing mixed evidence of the impacts of AI on anxiety: while the former studies found negative impacts (Kong et al., 2021; Lingmont & Alexiou, 2020), the latter studies found benefits when challenged

using appraisals (Cheng et al., 2023; Huang & Gursay, 2024).

Third, this study contributes to the existing adaptive performance literature by investigating the relationship between AI-specific adaptability and adaptive job performance and by offering item-level support for each link between the measures/constructs in this article. With adaptive performance still not as well studied as it needs to be (Krijgsheld et al., 2022), its results can build a theoretical foundation for future studies on adaptive performance with different technological shifts in the nature of work.

6.2 Practical Implications

The conclusions for organisations are that there's no point in stirring up anxiety for staff but in driving it toward adaptive engagement. Transparency in the role of AI, employee participation in decision-making about how to implement these tools, and the creation of a learning culture are likely to support challenge appraisals, while an authoritarian culture has been found to strengthen the relationship between awareness of AI and job insecurity (Lingmont & Alexiou, 2020).

Emotion crafting is a skill that can be trained and is self-directed for human resource development. Retraining programmes can assist employees in identifying the factors that energise them—including specific activities, people, and conditions—by focusing on the awareness component of the plan and incorporating actions such as peer learning groups, practical experimentation with AI tools, and celebrating small victories for the action component. In this study, the term 'adaptability' was strongly correlated with adaptive job performance; thus, it is also plausible that an adaptive job performance perspective should be included in the development of programmes designed to increase adaptability and that an adaptive perspective should be added to evaluation and training frameworks.

The findings imply that when managing agentic AI, attention should be given to managers' affective reactions to its implementation, such as conducting brief pulse surveys to assess employee anxiety using validated tools like Wang and Wang's (2022) AI anxiety scale, and providing support to staff who report high anxiety levels to prevent disengagement or burnout. Managers, who promote proactive emotional regulation and cultivate a psychologically safe environment for creating experiments with AI, can further nurture staff's adaptability.

7. CONCLUSION

7.1 Conclusion

The study investigated the correlations between AI anxiety, emotion crafting, AI adaptability and adaptive job performance among 250 working professionals. Four multiple regression models were identified and supported all four hypotheses, each having six indicators of the predictor construct that were statistically significant. AI adaptability and emotion crafting were significantly related to AI anxiety, and emotion crafting was significantly related to AI adaptability, and AI

adaptability was significantly related to adaptive job performance.

The research paper offers an early approach to emotion crafting in the field of AI at work and proposes that both emotional apprehension and the managing-to-not-managing of work-related emotions influence employees' reactions to AI. The findings demonstrate support for an interpretation that anxiety is associated not only with the withdrawal but also with activation of proactive emotional management and adaptation. The results presented are preliminary and should be used as a benchmark for additional and more rigorous testing due to the unusually high associations observed and the cross-sectional, self-reported nature of the data.

7.2 Limitations

There are a number of caveats to be noted. First, the cross-sectional design makes it impossible to draw inferences about the temporal order and causality of the relationships—the reciprocal and/or reverse direction of the relationships, such as less anxiety among more adaptable employees, cannot be ruled out. Second, data was self-reported and was based on a single source assessed at one time, resulting in the concern of common method bias (Podsakoff et al., 2024). However, there was no formal procedure reported to check for common method variance. Thirdly, using non-probability sampling results in the inability to generalise the findings of this study to the wider universe of the employees (Stratton, 2021), and the respondents were limited to those with postgraduate education and in the IT/software industry.

Fourth, the type of statistical relationship contours in the data needs to be interpreted. All four constructs had nearly equal means and standard deviations, high reliability (α values to .98), very high inter-construct correlations (r from .92 to .99), and high R^2 (up to .98). These values are unusual for separate constructs and could be due to the commonality of the items or conceptual overlap between constructs, a common response style or sample homogeneity (Hair et al., 2019). Discriminant validity was not tested, viz., the VIF values for the model of H4 were high (up to 6.65), reflecting multicollinearity among indicators of AI adaptability (Kim, 2019). Finally, the constructs were assessed using six-item adaptations of existing measures that had been previously examined through CFAs, and it was not possible to examine the factor structure of those constructs again in the present study, nor to include control variables such as age, gender, job level, industry, or AI experience. Sixth, the study is based on an AI concept of agentic AI, but the tools evaluated AI in general and did not distinguish agentic from other AI. Lastly, the study conducted individual tests for each hypothesis, and mediation was not directly tested.

7.3 Future Research

A number of possible limitations exist and should be solved in the future study. For establishing temporal precedence and for testing the effects of emotion crafting interventions on adaptability and performance, use of either longitudinal designs or diary designs or

experimental designs is required. Structural equation modelling with bootstrapped indirect effects may be used

to formally test the sequence from AI anxiety through emotion crafting to AI adaptability and performance, and confirmatory factor analysis, along with discriminant validity tests (e.g., heterotrait-monotrait ratio), would clarify the distinctiveness of these constructs empirically. The attention and action side of emotion crafting should be studied separately, as they may be related differently to affect outcomes, according to previous research (Hernandez Hernandez et al., 2025).

Researchers could also explore other boundary conditions like experience with AI, usage frequency, job level, organisational culture, IT mindfulness and locus of control (Huang & Gursoy, 2024; Cheng et al., 2023; Lingmont & Alexiou, 2020) as well as understand the variations of responses across countries and sectors. To minimise common method bias, multiple-source designs using self-reported or supervisor rating data or objective measures would be welcome, while instruments that can explicitly measure human interactions with agentic AI systems would enable researchers to investigate whether the relationships described here will differ as AI becomes more independently deployed.

REFERENCE

1. Acharya, D. B., Kuppan, K., & Divya, B. (2025). Agentic AI: Autonomous intelligence for complex goals—A comprehensive survey. *IEEE Access*, 13, 18912–18936. <https://doi.org/10.1109/ACCESS.2025.3532853>
2. Alshaibani, M. H., Al-Rahmi, W. M., & Tawafak, R. M. (2025). Psychometric validation of the artificial intelligence anxiety scale: A confirmatory factor analysis for academic research. *Contemporary Educational Technology*, 17(4), Article ep595. <https://doi.org/10.30935/cedtech/17309>
3. Banks, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, 45(2), 159–182. <https://doi.org/10.1002/job.2735>
4. Boemo, T., Nieto, I., Vazquez, C., & Sanchez-Lopez, A. (2022). Relations between emotion regulation strategies and affect in daily life: A systematic review and meta-analysis of studies using ecological momentary assessments. *Neuroscience & Biobehavioral Reviews*, 139, Article 104747. <https://doi.org/10.1016/j.neubiorev.2022.104747>
5. Chang, P.-C., Zhang, W., Cai, Q., & Guo, H. (2024). Does AI-driven technostress promote or hinder employees' artificial intelligence adoption intention? A moderated mediation model of affective reactions and technical self-efficacy. *Psychology Research and Behavior Management*, 17, 413–427. <https://doi.org/10.2147/PRBM.S441444>
6. Chen, N., Zhao, X., & Wang, L. (2024). The effect of job skill demands under artificial intelligence embeddedness on employees' job performance: A moderated double-edged sword model. *Behavioral*

- Sciences, 14(10), Article 974.
<https://doi.org/10.3390/bs14100974>
7. Cheng, B., Lin, H., & Kong, Y. (2023). Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting. *Journal of Business Research*, 164, Article 113987.
<https://doi.org/10.1016/j.jbusres.2023.113987>
8. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
9. Hernandez Hernandez, M. E., Taşkesen, N., & van der Kaap-Deeder, J. (2025). Emotion crafting and daily psychological functioning: A 7-day diary study. *Journal of Happiness Studies*, 26(3), Article 30.
<https://doi.org/10.1007/s10902-025-00876-6>
10. Huang, Y., & Gursoy, D. (2024). How does AI technology integration affect employees' proactive service behaviors? A transactional theory of stress perspective. *Journal of Retailing and Consumer Services*, 77, Article 103700.
<https://doi.org/10.1016/j.jretconser.2023.103700>
11. Kaya, F., Aydin, F., Schepman, A., Rodway, P., Yetişensoy, O., & Demir Kaya, M. (2024). The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. *International Journal of Human-Computer Interaction*, 40(2), 497–514.
<https://doi.org/10.1080/10447318.2022.2151730>
12. Kim, J. H. (2019). Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology*, 72(6), 558–569. <https://doi.org/10.4097/kja.19087>
13. Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management*, 33(2), 717–734.
<https://doi.org/10.1108/IJCHM-07-2020-0789>
14. Kraiss, J. T., ten Klooster, P. M., Moskowitz, J. T., & Bohlmeijer, E. T. (2020). The relationship between emotion regulation and well-being in patients with mental disorders: A meta-analysis. *Comprehensive Psychiatry*, 102, Article 152189.
<https://doi.org/10.1016/j.comppsy.2020.152189>
15. Krijgsheld, M., Tummers, L. G., & Scheepers, F. E. (2024). Adaptive performance scale: Translation and validation in English and Dutch. *Human Factors in Healthcare*, 6, Article 100086.
16. Krijgsheld, M., Tummers, L. G., & Scheepers, F. E. (2022). Job performance in healthcare: A systematic review. *BMC Health Services Research*, 22(1), 1–17.
<https://doi.org/10.1186/s12913-021-07357-5>
17. Li, J., & Huang, J.-S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society*, 63, Article 101410.
<https://doi.org/10.1016/j.techsoc.2020.101410>
18. Lingmont, D. N. J., & Alexiou, A. (2020). The contingent effect of job automating technology awareness on perceived job insecurity: Exploring the moderating role of organizational culture. *Technological Forecasting and Social Change*, 161, Article 120302.
<https://doi.org/10.1016/j.techfore.2020.120302>
19. Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2022). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower*, 43(2), 334–354.
<https://doi.org/10.1108/IJM-03-2021-0173>
20. Martins-Klein, B., Alves, L. A., & Chiew, K. S. (2020). Proactive versus reactive emotion regulation: A dual-mechanisms perspective. *Emotion*, 20(1), 87–92. <https://doi.org/10.1037/emo0000664>
21. Memon, M. A., Ting, H., Cheah, J.-H., Thuramamy, R., Chuah, F., & Cham, T. H. (2020). Sample size for survey research: Review and recommendations. *Journal of Applied Structural Equation Modeling*, 4(2), i–xx. [https://doi.org/10.47263/JASEM.4\(2\)01](https://doi.org/10.47263/JASEM.4(2)01)
22. Park, S., & Park, S. (2019). Employee adaptive performance and its antecedents: Review and synthesis. *Human Resource Development Review*, 18(3), 294–324.
<https://doi.org/10.1177/1534484319836315>
23. Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior*, 11, 17–61.
<https://doi.org/10.1146/annurev-orgpsych-110721-040030>
24. Ribeiro, D. M., Dias Júnior, J. J. L., & Silva, F. Q. B. (2022). Escala de desempenho adaptativo: Adaptação e evidências de validade com engenheiros de software [Adaptive performance scale: Adaptation and validity evidence with software engineers]. *Revista Psicologia: Organizações e Trabalho*, 22(2), 2011–2019.
<https://doi.org/10.5935/rpot/2022.2.21867>
25. Sapkota, R., Roumeliotis, K. I., & Karkee, M. (2025). AI agents vs. agentic AI: A conceptual taxonomy, applications and challenges (arXiv:2505.10468). *arXiv*. <https://arxiv.org/abs/2505.10468>
26. Stratton, S. J. (2021). Population research: Convenience sampling strategies. *Prehospital and Disaster Medicine*, 36(4), 373–374.
<https://doi.org/10.1017/S1049023X21000649>
27. Taşkesen, N., Hernandez Hernandez, M. E., Jeronimus, B. F., & Van der Kaap-Deeder, J. (2025). Emotion crafting links parental autonomy support and warmth to young adult well-being. *Frontiers in Psychology*, 16, Article 1629350.
<https://doi.org/10.3389/fpsyg.2025.1629350>
28. van Dam, K., & Meulders, M. (2021). The adaptability scale: Development, internal consistency, and initial validity evidence. *European*

Journal of Psychological Assessment, 37(2), 123–134.

29. van der Kaap-Deeder, J., Wichstrøm, L., Mouratidis, A., Matos, L., & Steinsbekk, S. (2023). Emotion crafting: Individuals as agents of their positive emotional experiences. *Motivation and Emotion*, 47(5), 870–886. <https://doi.org/10.1007/s11031-023-10035-0>
30. Wang, Y.-Y., & Wang, Y.-S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments*, 30(4), 619–634. <https://doi.org/10.1080/10494820.2019.1674887>