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Pathways to Career Adaptability in the Manufacturing Industry: Perceptions of Artificial Intelligence, Technical Anxiety and Job Crafting

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ABSTRACT

In the context of rapid technological advancement, artificial intelligence (AI) is transforming the manufacturing sector by redefining job requirements, restructuring resource utilization, and influencing how employees adjust to evolving career trajectories. This study investigates how individuals' perceptions of artificial intelligence (PAI) influence career adaptability (CA), with technological anxiety (TA) and job crafting (JC) serving as key mediating mechanisms in this relationship. Grounded in the Job Demands-Resources (JD-R) theory, this study investigates how employees' perceptions of artificial intelligence generate job demands that may lead to anxiety, while simultaneously offering opportunities for proactive engagement through job crafting. A cross-sectional survey was conducted among 397 employees working in the manufacturing sector. The data were analyzed using partial least squares structural equation modeling (PLS-SEM) to examine the hypothesized relationships. The results suggest that individuals' perceptions of AI exert a significant and positive influence on technological anxiety and job crafting. Moreover, job crafting has a significant and positive impact on career adaptability. In addition, job crafting positively mediates the relationship between perceptions of AI and career adaptability. This study contributes to the JD-R framework and offers practical insights for managing workforce transitions in environments where AI is integrated.

Introduction

The manufacturing sector is undergoing a significant transformation, driven primarily by the rapid advancement of artificial intelligence (AI), robotics, and automation technologies. The advancement reshapes traditional job roles while simultaneously enhancing efficiency and increasing precision within the production process (Kumar et al., 2023). Given this, AI technologies have gained momentum within modern organizational contexts and have deeply changed working practices, work functions, and decision-making procedures (Rajagopal et al., 2022). These developments signify enhancements in efficiency and productivity; however, they are also accompanied by underlying psychological and behavioural challenges that require employees to continuously adapt to evolving technological environments (Malik et al., 2022). While AI offers operational advantages, it also raises serious concerns among employees, including their role clarity and future employability. Many front-line workers and middle-skilled employees in manufacturing sector tend to see AI as a disruptive force rather than a helpful tool (Dwivedi et al., 2021). This gap between technological advancement and employees' perceptions of AI creates a critical challenge.

The introduction of AI into the workplace has sparked debates concerning job security, the growing risk of skill obsolescence, and the uncertainty surrounding future employment opportunities (McGuinness et al., 2023). Career adaptability refers to the readiness and resources needed to tackle present and future career challenges and transitions (Savickas, 2005). Career adaptability helps employees cope with changes in the workplace better by helping them acquire new skills and maintain long-term career development (Magnano et al., 2021; Takao & Ishiyama, 2021; Zhao et al., 2022). Hence, career adaptability is critical for employees to stay relevant and resilient in the face of AI-driven changes. Despite this, how career adaptability develops is still not fully explored. Two interesting factors that play a role in this process are technological anxiety and job crafting.

Technological anxiety refers to a stress that comes from feeling overwhelmed or threatened by new digital technologies, which can hinder a person's ability to adapt (Tarafdar et al., 2019). Conversely, job crafting refers to the proactive efforts of employees to alter their tasks and interpersonal interactions in the workplace, thereby enhancing their sense of autonomy and aligning their responsibilities with personal strengths, which can, in turn, foster greater adaptability (Wrzesniewski & Dutton, 2001). Through the examination of these two mechanisms, a more comprehensive understanding can be developed regarding how employees adapt to workplace transformations driven by artificial intelligence.

To advance understanding of how employees adapt to AI-driven transformations in the workplace, further research is required to address existing gaps in literature. Although awareness of technology- and AI-related anxiety is increasing, there has been limited research into how such anxiety may impede career adaptability, particularly in high-tech work environments where fear of AI can exacerbate stress levels (Dai et al., 2025). Although prior studies have established that job crafting positively influences employee outcomes such as innovation and engagement, its mediating role in the relationship between employees' perceptions of AI and their career adaptability, particularly within the manufacturing sector remains insufficiently understood (Khan et al., 2024). Additionally, previous research often examines psychological factors (e.g., anxiety) or behavioural factors (e.g., job crafting) separately, overlooking how these two interact to influence adaptability in the face of AI (Chen et al., 2025). Hence, there is a noticeable lack of empirical research in emerging economies where the rapid adoption of AI could replace how ready employees are, leading to even more uncertainty and challenge in adaptability (Chen et al., 2025; Hosen et al., 2025).

Even though previous research explored the way people and businesses perceive AI, less is known about the influence of employees' perceptions of AI on their personal work performance and emotional responses (Mantello et al., 2023). Most researchers neglect the behavioural impacts of AI, focusing instead on its performance (AI in predictive maintenance in manufacturing) and technical impacts (deep learning in natural language processing). The studies on the immediate and remote outcomes of AI perceptions on the attitude and behavior of employees should be conducted, especially in the corporate environment (Kim et al., 2024). The connection between how we perceive AI and our ability to adapt in our careers remains a mystery, particularly in the manufacturing sector, where automation is transforming the work landscape. Furthermore, many existing models do not account for both positive and negative psychological pathways, meaning researchers do not fully capture the complexity of employee experiences during technological change.

Based on the Job Demands-Resources (JD-R) theory, Bakker and Demerouti (2017) conceptualize the perception of artificial intelligence as a dual-faceted construct. When perceived negatively, it may be considered a job demand that contributes to technological anxiety; however, when viewed positively, it can serve as a job resource that promotes job crafting. Technological anxiety aligns with the health impairment process of the JD-R model, wherein psychological strain may hinder employees' capacity to adapt (Li & Liu, 2025). In contrast, job crafting facilitates the motivational pathway by enabling individuals to actively reshape their work in ways that strengthen their career adaptability (Viseu et al., 2025). Recent research indicates that AI-related threats may increase anxiety levels and reduce adaptability among employees, unless they employ proactive coping strategies (Chen et al., 2025). Furthermore, job crafting has been empirically established as a mediating mechanism linking digital transformation to favorable adaptive outcomes (Ali & Ishaq, 2025). The dual-pathway model provides a robust theoretical framework for examining how perceptions of AI influence adaptability through both psychological and behavioral mechanisms.

This study primarily seeks to examine how employees' perceptions of artificial intelligence influence their career adaptability, with particular emphasis on two key factors: technological anxiety and job crafting. The study investigates the direct influence of AI perceptions on career adaptability, the constraining effect of technological anxiety, and the role of job crafting as a resource-enhancing mechanism. In addition, the study examines dual-pathway mediation mechanisms as conceptualized within the framework of the Job Demands-Resources theory. This will provide a comprehensive understanding of employee responses to technological disruption within the manufacturing sector. This study contributes to the evolving discourse on the intersection of artificial intelligence and human resource development by offering both theoretical insights and practical implications for how organizations can address workforce anxiety, promote proactive work behavior, and foster long-term job resilience in an increasingly dynamic digital environment.

Literature review and hypothesis development

Job demand resource

The JD-R theory is an all-encompassing and versatile model in studying how the aspects of jobs affect the wellbeing of employees and their performance (Köroğlu, 2024). According to this theory, job demands, e.g., job-related anxiety, may cause strain and resultant burnout, whereas job resources, e.g., autonomy, social support, and job crafting opportunities may also increase motivation and employee engagement (Bakker & De Vries, 2021). Perception of AI in the current study can be thus modelled as a potential job demand (e.g., fear of being replaced by another worker with the help of AI processes, which leads to anxiety) and job resource (e.g., possibility to improve performance using AI tools) (LEE et al., 2025). JD-R theory also provides parallel

mediation by understanding that health impairment can work together with the motivational process, because of situations in workplaces. Job anxiety fits the health impairment path, whereas job crafting takes the form of the motivational route (Martínez-Díaz et al., 2023). Finally, it is career adaptability that emerges as the psychosocial facilitating variable that helps individuals to manage current and future career transitions. Such processes, in turn, affect how people handle career issues, which is a fundamental principle of career adaptability (Shabeer et al., 2023). The JD-R model can therefore be effectively used because it is a theoretical basis and tool of thinking about the subtle role of AI in the development of the modern career (Radic et al., 2025).

Technical anxiety as a mediator

AI perception refers to employees' cognitive understanding and evaluation of the role and implications of artificial intelligence within the workplace (Presbitero & Teng-Calleja, 2023). Technological anxiety occurs when employees feel threatened by AI, worrying about losing their jobs or becoming obsolete due to skills gaps; consequently, they develop fear, nervousness, and stress towards it (Goethals & Ziegelmayer, 2022). In the context of Pakistan's manufacturing sector, increasing automation has intensified such fears, creating distrust and emotional stress (Mahmood et al., 2021). Due to the JD-R model, such anxiety occurs when the demands within the job exceed the resources available (Demerouti & Bakker, 2023).

Despite the rising interest in AI and its effects on workplace psychology, there is still a surprising lack of concrete evidence connecting how we perceive AI to feelings of technical anxiety. Most existing studies tend to look at techno stress broadly, without really distinguishing the specific anxieties that come from our perceptions of AI, like concern about its autonomy, transparency, or ethical dilemmas. This leaves a gap in understanding how AI perception might uniquely lead to technical anxiety (Tarafdar et al., 2020). Moreover, while many studies explore AI perception in terms of trust, willingness to adopt, or performance, very few investigate whether negative or unclear perceptions of AI directly cause anxiety, rather than being influenced by things like job insecurity or digital fatigue (Stich et al., 2019).

Following the JD-R model, psychological strain occurs in circumstances where job demands outweigh or surpass the resources any employee has to engage (Köroğlu, 2024). Regarding the implementation of AI, employees face increased pressure to acquire new skills, learn new systems, and adapt to new role requirements. These demands come with significant responsibilities, including training, managerial backing, and understanding which role to play, which can be taxing and lead to emotional burnout and stress when left unattended. Therefore, it has been hypothesized that:

H1: Perception of AI has positively influenced technological anxiety.

Perceptions of AI influence the way people evaluate their working environment. By creating the perception of threat (e.g., it will likely automate activities, decrease the requirement of existing skills, or unknowingly stabilize job duties), AI prompts the negative appraisals of job insecurity and fear of skills obsolescence (Klein et al., 2024). Empirical studies recently and more conclusively indicate that AI-negative perceptions are linked with greater job-seeking anxiety, techno stress, and general fear about future work (Li et al., 2025). Empirical studies indicate that when the level of technological anxiety is high, motivation and self-efficacy, both being the most fundamental psychological processes concerning career adaptability, decrease (Khan et al., 2024). Psychological resilience, curiosity, and the prospective dimension of thinking is key to career adaptability, which is the ability and resources that individuals have to enable them to absorb the existing and future demands in their careers (Zyberaj et al., 2022).

Nonetheless, these qualities are also destroyed when anxiety is not overcome, and individuals lose their ability to handle change and make their careers long-lasting. Even though there has been a surge in research on techno stress, surprisingly few studies have investigated how it directly affects career adaptability. Specifically, we need to understand how stress from digital tools impacts key aspects like control and confidence (Tarafdar et al., 2020). Most of the existing research tends to focus on outcomes such as burnout or job satisfaction, missing out on its influence on career development. Moreover, while career adaptability is often viewed as a buffer against stress, the opposite, how ongoing techno stress might undermine adaptability, has not been thoroughly investigated (Calvard & Jeske, 2018). This highlights the significant gap in longitudinal and causal studies that link technical anxiety to diminishing adaptive skills in our tech-centric world.

Individuals who view AI as a threat, overly complicated, or something they cannot control are more likely to face techno stress, which can show up as feelings of being overloaded, confused, or uncertain (Tarafdar et al., 2020). These factors can ramp up technical anxiety, leading to feelings of inadequacy, mental fatigue, or the fear of being left behind (Ayyagari et al., 2011). This means that negative perceptions of AI do not always lead straight to anxiety; instead, they first create stress from using technology, which then shapes emotional responses. Still, the mediating effect of technical anxiety has not been deeply investigated in AI-specific situations, making it a promising avenue for future research.

In the light of the JD-R Theory, technological anxiety can be described as a job demand, which is an environmental circumstance that demands a prolonged, psychological resource in order to be able to deal with it and may result in being strained. Conversely, career adaptability is considered an individual resource that enables employees to effectively cope with those demands (Haenggli & Hirschi, 2020). Anxiety will worsen when there is inadequate organizational support, training programs, and effective communication regarding any AI-related changes introduced, particularly when job requirements are increasing at a higher rate than the available resources. Nevertheless, the development of adaptive abilities through the articulation of employers through developmental opportunities, emotional support, and learning interventions acts as a shield against the negative impacts of stressors. Going by the above discussion, the current research has the following hypotheses:

H2: Technological anxiety has negatively influenced career adaptability.

H3: Technological anxiety negatively mediates the relationship between perceptions of AI and career adaptability.

Job crafting as a mediator

The dynamic penetration of AI technologies into the manufacturing industry has changed the nature of work considerably and will offer opportunities as well as challenges to the employees. Although AI perception is considered both as an assistant and a disruptive element, it remains an important part of creating employee behaviors and attitudes (Verma & Singh, 2022). The studies indicate that positive perception of AI when the employees perceive AI as something that complements their possibilities but does not pose a specific threat to their jobs is linked with proactive workplace behaviors, including job crafting (Cheng & Liu, 2023). The perception of an employee in the manufacturing industry, which largely lacks the full potential of AI use, will become one of the key factors in deciding whether employees will strive to meet the emerging changes in the occupation or remain unresponsive to technological progress.

Nevertheless, self-initiated changes in the tasks, relationships or cognitive orientation toward the work can be categorized as job crafting, which becomes an important behavioral adaptation to perceived effects of AI (Kooij et al., 2022). The JD-R theory can provide an interesting approach

to this relationship. In line with the JD-R model, workers steer through shifting workplace environments, by, on the one hand, maintaining a balance between job demands (e.g., unpredictability, the acquisition of new technology) and, on the other, the job resources (e.g., freedom of decision making, and the support or training of managers) (Galli et al., 2023). Although AI perception can influence workplace behaviour, a noticeable shortage of empirical studies examines its direct effect on job crafting. Most researchers tend to focus on indirect factors like psychological empowerment or self-efficacy, without really isolating how AI perception directly impacts proactive job redesign. Moreover, there is a lack of exploration into how various dimensions of AI perception, such as trust versus fear, uniquely shape task, relational, and cognitive job crafting, particularly in settings where AI is becoming more prevalent (Kim et al., 2023). Therefore, the thought that AI perception is not a cognitive assessment only but a significant precursor of adaptive behaviors, such as job crafting, is backed by modern literature. This view is confirmed by the provision of favorable organizational environments and psychological resources at the basis of the discussion presented above. The study suggests the following hypothesis:

H4: Perception of AI has positively influenced job crafting**.**

Job crafting empowers employees to tailor their jobs to their strengths and values, fostering career adaptability and the ability to navigate career transitions and challenges (Federici et al., 2021). Job crafting enables employees to adapt to technological change in a rigid and standardized work environment, such as the manufacturing sector in Pakistan (Irfan et al., 2023). The proactive crafters possess higher levels of concern, control, curiosity, and confidence, all of which are key factors in career adaptability. The behaviors promote job resources that include autonomy, skill variety, and social support as well. A strong relationship exists between job crafting and career adaptability that has been elaborated using the JD-R theory. Employees in this framework will change elements of their jobs actively to affect the balance between job demands and job resources (Lopes et al., 2023). In resource-scarce settings such as the manufacturing area in Pakistan, job crafting becomes a key issue that employees should develop further resources, which help to bring adaptability and personal development, including a variety of skills, autonomy, and support.

Even though there is growing buzz about how AI is changing the workplace, how people perceive AI and how that affects their job crafting. Most research has not looked into how employees feel about AI, such as whether they trust it or are afraid of it, and how these feelings shape their proactive job crafting behaviours (John et al., 2025). The psychological pathways through which AI perception might influence career adaptability via job crafting are still largely uncharted, especially in workplaces that heavily rely on AI (Zhang et al., 2024). As stated in the JD-R theory, job crafting generates new resources (autonomy, feedback, etc.) to help one sustain career adaptability amidst AI-induced changes (Choi, 2024). The perceptions of the AI that employees hold influence the scope and quality of their job crafting process, which further builds the psychosocial resources upon which a career adaptability may be built (Doğan et al., 2025). Consequently, job crafting is a behavioral mechanism in which the perception of AI has an impact on career adaptability. Therefore, we hypothesized that:

H5: Job crafting has positively influenced career adaptability.

H6: Job crafting positively mediates the relationship between perception of AI and career adaptability.

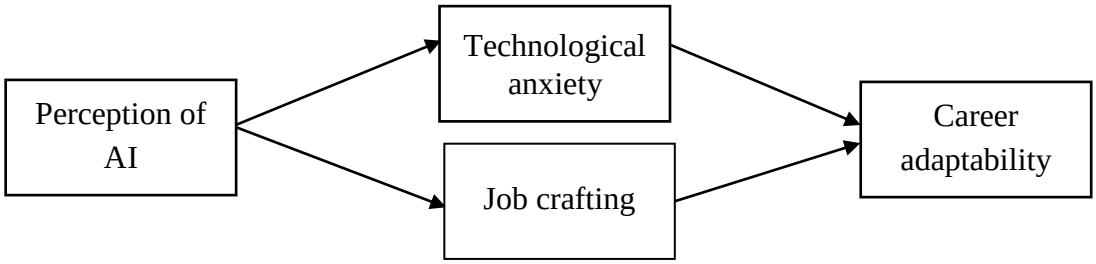


Figure 1: Theoretical model

Methodology

Sampling and procedure

To evaluate the theoretical framework of this study, the researcher surveyed employees from the manufacturing industries in Punjab, Pakistan. The current study targets full-time employees at both managerial and operational levels. The aim is to assess how these employees perceive AI, their psychological behaviors and their adaptability in their careers within the manufacturing sector in Pakistan. Thus, only those currently working in various manufacturing industries across different cities in Punjab, Pakistan is part of this research. However, more than that, the survey research was conducted on full-time employees only who were involved in on-the-job work, since the majority of studies suggest that the full-time employees may have a positive relationship with the organization (Braganza et al., 2021) and hence, their opinion can be more freely accepted. Besides that, organizations are paying extra attention to the full-time employee due to their increased level of commitment to the organization in comparison with the contractual one (Alshaabani et al., 2021). In this current research, the researcher includes 10 manufacturing industries (4 textiles, 2 fertilizers, 2 automations, and 2 cement industries) in a survey that is spread across the main areas in the Punjab province, namely in Lahore, Multan, and Faisalabad.

This quantitative study aims to examine how Artificial Intelligence usage influences career adaptability by analyzing the mediating effects of technological anxiety and job crafting. The inclusion criteria for the participants were: (1) the jobholders were currently employed at manufacturing units in Faisalabad, Multan and Lahore. (2) the employees having at least 1 year of job experience in their current organization, and (3) the jobholders must be using AI-enabled systems or technologies either directly or indirectly as a part of their job role. For this purpose, the convenience sampling technique was used. In this study, a cross-sectional approach was used, and the study was based on a self-report survey method. However, to gauge the perception of AI, the researcher examined two psychological behaviours - technical anxiety and job crafting that affect career adaptability by circulating a questionnaire among employees in various manufacturing industries. Employees from four textile industries - Sapphire Textile Mills, Lahore; Safa Textile Limited, Faisalabad; Hussain Industries Ltd., Faisalabad; and Gul Ahmad Group, Lahore are included in the survey. Furthermore, employees from two fertilizer industries, including New Agro King Chemicals, Multan, and Crop Care Solutions, Multan, are part of the survey. Additionally, two automation industries, Millat Tractors, Lahore, and Prop Pak Rizwan Autos, Multan, are included in the survey. Moreover**,** two cement industries, including Creative Construction Pvt. Ltd, Multan and Maple Leaf Cement Lahore, are also part of the survey.

Prior to distributing the surveys, we informed the respondents about the study's purpose and made it clear that their participation was voluntary. We also ensured that their responses would be kept confidential and completely anonymous. Participants provided their informed consent as well. Our data collection journey began with the distribution of questionnaires, which were accompanied by

a cover letter that detailed the objective of the study. The entire questionnaire was developed in English. Researchers decided to include operations managers as participants because they offer a unique perspective on the day-to-day functions of the industry. The 550 participants could not be exactly followed up to the end of the results, and out of the 550, only 442 participants responded according to the procedure, thus creating a sample size. The number of participants who did not fill out the questionnaire entirely was almost 108. However, 442 responses were received, of which 45 questionnaires were incomplete and discarded because of multivariate problems. The total number of participants with valid responses is 397, resulting in a response rate of 72.1%. Thus, Table 1 provides an overview of the demographic characteristics of the study sample. A process of acquiring the relevant information had to be error-free so that we were able to acquire the facts efficiently and effectively (Jayatilake & Ganegoda, 2021). The survey questionnaire had perceptions of AI, technological anxiety, job crafting, and career adaptability measures. As such, the research questionnaire was constructed based on 23 items to facilitate the goal of the study.

Measurement scale

To measure all constructs in our model, we drew on well-established scales from previous research. The researcher chose the Likert scale because it provides a quantitative way to gauge perceptions, opinions, or attitudes, which are usually used in social sciences to judge subjective experiences. In the present study, the researcher has chosen 5-point Likert-scale (according to the aim of the research and the objectives on the specific constructs), where a scale ranges between 1 (strongly disagree) and 5 (strongly agree). Nonetheless, PAI scale with four items was adopted from Presbitero and Teng-Calleja (2023). Moreover, job crafting with four items was adapted from He et al. (2024). In addition, technical anxiety with three items was adapted from Singh and Verma (2023). Likewise, the career adapting scale with 12 items was adopted from Maggiori et al. (2017).

Table 1. Demographics

Particulars	**Frequency**	**(%)**	**Particulars**	**Frequency**	**(%)**
Gender					
Male	296	74.5	Female	101	25.5
Age					
Below 30 years	87	21.9	31- 35 years	112	28.3
36 - 40 years	108	27.2	Above 40	90	22.6
Educational Level					
Bachelor's Degree	124	31.4	Master's Degree	143	33.6
MS/Mphil	75	21.5	Others	55	13.5
Industry type					
Textile	153	38.5	Fertilizer	81	20.4
chemical	87	21.9	Cement	76	19.2
Job duration					
2 – 5 years	87	21.9	6 - 10 years	121	30.4
11 – 15 years	115	28.9	Above 15 years	74	17.8
Note: n = 397					
Sources: Authors' work, SPSS – output					

Descriptive analysis

The descriptive analysis reveals that the average scores of job crafting, technical anxiety, perceptions of AI and career adaptability are from 3.45-3.57, which means moderate level of agreement. The standard deviations are quite low (0.63 to 0.75), indicating minimal variation in

the responses. According to George and Mallery (2010), the values of skewness and kurtosis for all variables must be in the range of (-2 to +2). In this current research, the values of skewness are (-0.610 to – 1.323) and the values of kurtosis are (0.575 to 1.898). Hence, all these values satisfy the normality requirement.

Table 2. Descriptive Statistics

Variables	Mean	SD	Skewness	Kurtosis
Technological Anxiety	3.53	0.75	-1.053	1.281
Job Crafting	3.45	0.70	-0.610	0.678
Perception of AI	3.53	0.74	-0.760	0.575
Career Adaptability	3.57	0.63	-1.323	1.898

Correlation

As mentioned in Table 3, the correlation matrix shows a positive correlation among all variables, especially at the $p < .01$ level. For instance, technological anxiety has a strong connection with the perceptions of AI ($r = .606$) and career adaptability ($r = .542$). Meanwhile, job crafting is also positively linked to both career adaptability ($r = .573$) and perceptions of AI ($r = .477$). These correlations are well within acceptable limits, suggesting that there are meaningful relationships among these constructs (Cohen, 1988).

Table 3. Correlation

Variable	TA	JC	PAI	CA
Technological Anxiety	1			
Job Crafting	.498**	1		
Perception of AI	.606**	.477**	1	
Career Adaptability	.542**	.573**	.541**	1

Common bias method

Since the researcher gathered both independent and dependent variables data from the same source, we adhered to Kock (2015) guidelines on collinearity to tackle the potential issue of common method bias (CMB). To evaluate the data on CMB, the researcher conducted two statistical tests. Firstly, the researcher carried out Harman's single-factor test, which indicated that the first factor accounted for 41.44% of the total variance, significantly lower than the 50% threshold (Podsakoff et al., 2003). Furthermore, the researcher extracted multiple factors with eigenvalues exceeding 1, which shows that a single factor does not dominate the variance. In the current study, to understand collinearity, we analyzed it through the variance inflation factor (VIF), average variance extracted (AVE), and composite reliability (CR) as mentioned in Table 4 and assessed how well we established discriminant validity through HTMT ratio (Table 5). These results indicate that the CMB and multicollinearity do not strongly affect the validity of our study.

Model Estimation

Structural equation modelling (SEM) serves as a widely accepted method for theory development and prediction model evaluation (Hair et al., 2021). The standard estimation methods for SEM include covariance-based SEM, known as CB-SEM, and partial least squares structural equation modelling (PLS-SEM). The researcher selected PLS-SEM for these main reasons: (1) the model contains multiple constructs and structural relationships; (2) the model is in its early stage of developing; (3) the focus in on predicting relationships; (4) PLS-SEM disregard to the extent that

CB-SEM does not allow researcher to concentrate on prediction accuracy over fir indices; (5) PLS-SEM resolves the factor indeterminacy problem that CB-SEM faces (Hair et al., 2021). Our decision to use Smart PLS 4 for hypothesis testing stemmed from these factors.

Measurement Model

In the PLS-SEM model, there are two key steps: the measurement (e.g., outer) model and the structural (e.g., inner) model. The outer illustrates how latent constructs relate to their indicators, while the inner model shows the connection between predictor and criterion variables (Hair et al., 2021). For this evaluation, the researcher employed the PLS algorithm technique, incorporating a weighted scheme for the paths and standardized results to assess the quality of the outer model. This process allowed us to evaluate the reliability and validity of the constructs. To check the reliability of inter-item correlations, the researcher analyzed the factor loading, using a threshold of ≥ 0.70 as a benchmark (Hair et al., 2021). As shown in Table 4 and Figure 2, the factor loading varied between 0.701 and 0.879, which is above the acceptable threshold. The researcher also performed an AVE method to evaluate convergent validity, yielding values from 0.585 to 0.737 for variables, all of which met the required threshold of ≥ 0.50 (Hair et al., 2021). Furthermore, we measured the internal consistency and reliability using composite reliability, ensuring that items were prioritized based on their reliability (CR) from 0.849 to 0.930, of all variables with values ≥ 0.70 (Hair et al., 2021).

Table 4. Average variance extracted, composite reliability and VIF

Construct	Item	Loading	AVE	CR	VIF
Perception of AI	PAI1	0.847	0.689	0.899	1.995
	PAI2	0.813			1.836
	PAI3	0.850			2.105
	PAI4	0.810			1.775
Technological anxiety	TA1	0.879	0.737	0.894	2.010
	TA2	0.820			1.633
	TA3	0.875			2.057
Job crafting	JC1	0.815	0.585	0.849	1.672
	JC2	0.762			1.401
	JC3	0.743			1.433
	JC4	0.739			1.466
Career adaptability	CA1	0.720	0.524	0.930	1.954
	CA2	0.715			1.838
	CA3	0.706			1.913
	CA4	0.787			2.451
	CA5	0.708			1.862
	CA6	0.701			1.969
	CA7	0.769			2.451
	CA8	0.705			1.950
	CA9	0.716			2.136
	CA10	0.745			2.215
	CA11	0.705			1.905
	CA12	0.708			2.043

Note(s): loading > 0.70; CR > 0.70; AVE > 0.50; VIF < 3.3.
Sources(s): Authors' work PLS-SEM measurement model output

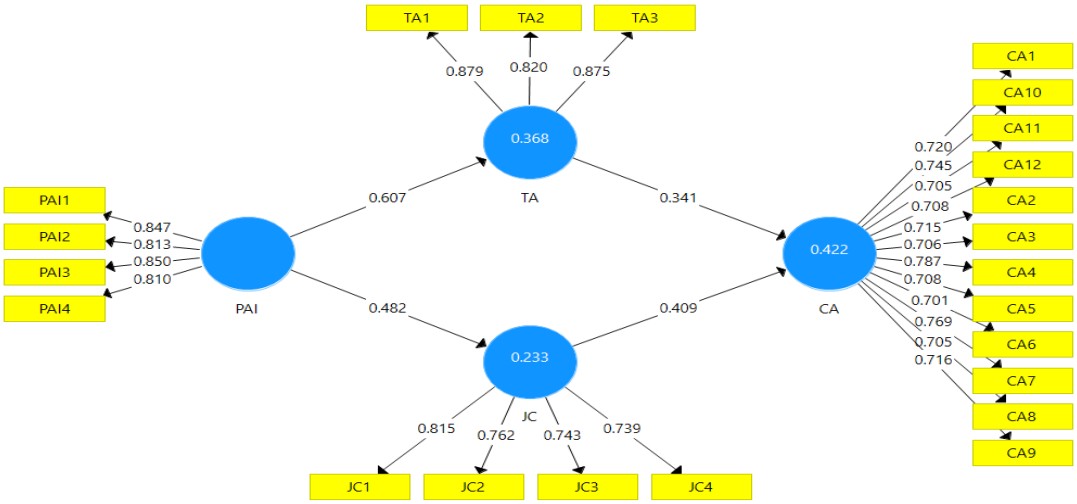


Figure 2. Measurement model

Sources (s): Author's work- Measurement model output

This study examined the discriminant validity of the measurement model by applying HTMT to assess the robustness (Henseler et al., 2015). As shown in Table 5, all HTMT values were below the threshold of 0.85 (Kline, 2015), which confirms that we achieved discriminant validity. Therefore, the outer model established good reliability and convergent and discriminant validity.

Table 5. Discriminant Validity (HTMT Ratio)

Construct	CA	JC	PAI	TA
Career adaptability				
Job crafting	0.685			
Perception of AI	0.615	0.594		
Technological anxiety	0.625	0.627	0.725	

Structural model

After the researcher was able to fulfill the requirements of the measurement model, the researcher examined the structural model in term of significance of path the coefficients (e.g., beta value), p-value, t-value, and coefficient of determination (R^2) by using a bootstrapping method with 5000 subsample (Henseler et al., 2009), and a two-tailed test at level of significance at 0.05. A visual representation of the complete set of proposed hypotheses within the single model is shown in Figure 3. The results in Figure 3 present the significance of path coefficient beta values, t-values and the explained variation of the endogenous construct (R^2).

Table 6 deals with the outcomes of the direct paths. The direct and indirect relationships in the model were statistically significant at $p < 0.001$, with t-values exceeding the critical threshold of 1.96, thus confirming the validity of all six hypotheses. For direct paths, PAI significantly predicted technological anxiety ($\beta = 0.607$, $t = 15.350$, $p < 0.001$), supporting hypothesis 1 (H1). This suggests that employees who perceive AI as highly impactful are more likely to experience an increased level of anxiety related to technology. Similarly, PAI significantly influences job crafting ($\beta = 0.482$, $t = 11.898$, $p < 0.001$), confirming hypothesis 4 (H4), indicating that employees respond to AI perception not only with concern but also by proactively modifying their work tasks and approaches. Furthermore, as initially proposed, TA has not negatively influenced

career adaptability (β = 0.341, t = 5.564, p < 0.001), thus, not supporting hypothesis 2 (H2), which indicates that a certain level of anxiety may serve as a motivator for employees to develop skills. Similarly, job crafting has a positive influence on career adaptability (β = 0.409, t = 8.409, p < 0.001), supporting hypothesis 5 (H5), reinforcing its role as an essential personal resource in enhancing adaptability.

Table 6. Direct path

Path	β (Beta)	SD	t-value	p-value	2.50%	97.50%	Decision
H1: PAI → TA	0.607	0.049	15.35	0.000	0.518	0.676	Supported
H2: TA → CA	0.341	0.040	5.564	0.000	0.201	0.447	Rejected
H4: PAI → JC	0.482	0.041	11.898	0.000	0.396	0.556	Supported
H5: JC → CA	0.409	0.061	8.409	0.000	0.310	0.501	supported

Note: PAI = perceptions of artificial intelligence, TA = technological anxiety, JC = job crafting, CA= career adaptability

According to Table 7, the mediation analysis shows that job crafting plays important role in mediating relationships between perception of AI and career adaptability. Hence, the indirect effect of PAI on CA through TA is not significant as initially proposed (β = 0.207, t = 4.612, p < 0.001), suggesting that when employees perceive AI more positively, it can lead to increased technological anxiety, which might push them to become more adaptable in facing career challenges. While the indirect effect of PAI on CA through JC is significant (β = 0.197, t = 6.482, p < 0.001). This means that employees who see AI as influential are more likely to engage in proactive job crafting, which ultimately boosts their career adaptability.

Table 7. Indirect path

Path	β (Beta)	SD	t-value	p-value	2.5%	97.5%	Decision
H3: PAI-> TA -> CA	0.207	0.045	4.612	0.000	0.112	0.289	Rejected
H6: PAI-> JC -> CA	0.197	0.030	6.482	0.000	0.142	0.261	supported

Note: PAI = perceptions of artificial intelligence, TA = technological anxiety, JC = job crafting, CA= career adaptability

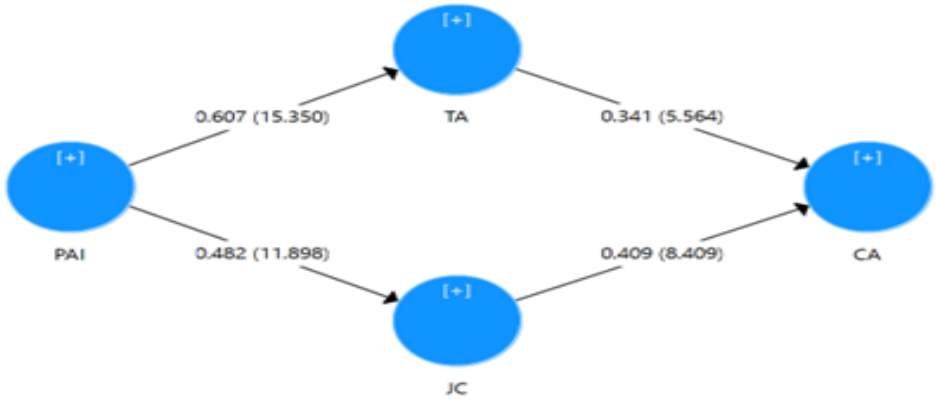


Figure 3. Structural model

Sources (s): Author's work- structural model output

Predictive relevance and model explanatory power

The model's explanatory power was assessed using the coefficient of determination (R^2), which indicates the proportion of variance in the endogenous constructs explained by PAI. For instance, the R^2 value for technological anxiety stands at 0.368, which means that 36.8% of the variance in TA can be attributed to its predictors, mainly AI usage. This points to a moderate level of explanatory power (Schmidt & Bohannon, 1988). On the other hand, the R^2 value for job crafting is 0.233, indicating that JC explains 23.3% of the variance explained by PAI. This suggests a moderate explanatory power, showing that the model effectively captures the factors that influence career. When we look at predictive relevance, the Q^2 value for TA is 0.260, while for JC is 0.130 and for CA is 0.220. Since both values exceed the threshold of 0 ($Q^2 > 0$), it shows that the model has a decent predictive relevance for both constructs. In summary, the model not only explains a meaningful portion of variance in the key construct but also demonstrates solid predictive capability supporting its overall robustness within the context of AI–driven changes in the manufacturing industry.

Table 8. Coefficients of determination (R^2) and predictive relevance (Q^2)

Construct	R- Square	Q-Square
Technical anxiety	0.368	0.260
Job crafting	0.233	0.130
Career adaptability	0.422	0.220

Discussion

This study dives into JD-R theory, aiming to discover how employees' attitude towards AI influences their careers adaptability. It focuses on the roles of technological anxiety and job crafting. JD-R posits that each job has its own specific associated with technical anxiety which can be divided into two broad categories: job demand (e.g., workload, uncertainty) and job resource (e.g., autonomy, skill variety). The interplay between job demand and job resources plays a crucial role in shaping employees' motivation, engagement and development (Bakker & Demerouti, 2007). The results indicate that technological anxiety supports a substantial psychological mechanism through which perceived AI influences career adaptability. Thus, from the JD-R perspective, technological change can serve as a challenge demand, which is a stressor that represents both an actual threat or a possibility of growth and adaptation (LePine et al., 2005).

While this study initially proposed that there would be a negative relationship between technical anxiety and career adaptability (H2). However, the results turned out to be quite opposite. They revealed a positive and statistically significant relationship suggesting that those with higher technical anxiety might be more adaptable in their careers, which is not what we expect at all. In this situation, technological anxiety may drive employees to become more aware of potential future disruptions, prompting them to build new skills or reconsider their career trajectories. Further the positive mediation effect implies that better understanding of AI might help ease technical anxiety or even flip it into a motivating force, ultimately improving career adaptability. Instead of serving as an obstacle as (H3), technical anxiety could drive people to actively seek out new skills in response to the evolving landscape of AI. Conversely, job crafting may serve as a powerful behavioral mediator. Employees who perceive AI positively are more inclined to proactively reshape their job roles to maintain alignment with changing expectations.

However, job crafting is conceptualized within the JD-R model as a self-initiated strategy to optimize resources and reduce demand (Tims & Bakker, 2010). This behaviour enhances not only engagement but also strengthens adaptability, particularly in dynamic environments like the

manufacturing sector undergoing digital transformation. The two mediation effects via crafting and anxiety show that the influence of AI in the development of a career is multifaceted. Anxiety is often framed so it is likely deficit-oriented and here it can be positive if combined with sufficient resources and resources. On the same note, job crafting shows how employees can exercise ownership of their working experience and meaningfully immerse themselves in the adaptive response to new technologies to and through AI in an adaptive manner to the new technology. All these mechanisms incline to support the idea that individuals' AI perceptions are accepted but are processed actively and reacted upon to generate factors that impact the career development of employees. It is worth noting these results have a considerable weight for organisations. The goal of the leadership must be to nurture the positive perception about AI as well as to develop support systems to manage anxiety and foster job crafting. By doing so, organisations can create a more resilient and adaptable workforce that can better face the current acceleration of technological advancement.

Theoretical implication

Research on JD-R theory published in recent years provides new insight into the field, especially regarding the perceptions of AI in the manufacturing business environment. The JD-R model has traditionally been applied to examine the issues concerning motivation, stress, and performance. Yet the present study goes further to recognize that AI has dual nature: it has the potential to create job demand, such as technological anxiety, as well as act as a resource that creates new opportunities and potentials to craft jobs in new ways signal roles bring up new opportunities to shape job-related resources in ways that benefit the individual and the organization alike (Bakker et al., 2023). The study outlines that an individual perception towards AI can result in varying psychological and behavioral responses. As an example, anxiety may become a motivational roadblock and job crafting an active coping strategy to address strategy. By defining perceptions of AI as cognitive evaluation that triggers the demand resource processes, the given study expands the application of the JD-R model to the digital transformation or the adaptability of workforce literature (Tims et al., 2022).

This study makes a unique contribution to the existing body of literature on career adaptability in that it has identified the psychological (technical anxiety) and behavioural (job crafting) mediation processes that demonstrate how our perception of technology reflects our ability to adapt to technology. Its discussion of technological anxiety as a mediator allows a more balanced perception of how our fears of the digital transformations can be seen as a driver of progress rather than only an obstacle to it (Koen). Furthermore, by viewing job crafting as a critical behaviour response, the role of personal agency and self-initiated change during career development is emphasized (Demerouti et al., 2025). Several disciplines come into play in this study; these include occupational health psychology, technology acceptance and career development. This offers a comprehensive model, which keeps in mind how our approach to AI may contribute to the future of employment and our willingness to use new devices.

Practical implication

The implications of the study are incredibly crucial to an organization, especially in the manufacturing sector as they go through the intricacies of an AI integration. It is important that leaders recognize that employee attitudes about AI are quite complex and not just negative or positive. Although AI can encourage such proactive actions as job crafting, it can also raise anxiety issues related to technology. Failure to manage anxiety well may actually result in the matter of disengagement or even opposition (Ivanov & Webster, 2019). In order to address these possible issues, organisations will have to work on open communication about the existence and adoption of AI, as well as training programs implementing AI in an organized manner to ensure that specific

roles and positions are defined. This approach can help employees feel more empowered and capable (van Vulpen & Jansen, 2025). When individual have a positive view of AI, it can significantly reduce the anxiety associated with technical anxiety, and it might even turn that anxiety into career advancement.

Employers really need to focus on fostering a positive environment that promotes a healthy attitude towards AI. This approach can make it much easier for employees to adapt to new technologies. It is crucial to cultivate a culture that supports job crafting and career flexibility. Managers should empower their employees to take ownership of their roles by fostering autonomy, promoting skill development and inspiring task innovation (van den Heuvel & Thomason, 2016). Implementing strategies such as job redesign workshops, peer mentoring, and feedback systems can significantly aid this effort. Organizations need to prioritize psychological safety and emotional support into changing management plans. This approach allows employees to shift their fear about technology into constructive actions (LePine et al., 2005). These efforts will not make the transition into enhanced AI workplaces smoother but also boost long-term workforce adaptability and retention among the workforce.

Limitations and direction for future research

Even though this research makes some important contributions, it does come with its limitations. Cross-sectional design, for instance, limits our ability to establish causal links between perceived AI, technical anxiety, job crafting, and career adaptability. Longitudinal studies make a smart move by tracking how these dynamics shift over time, particularly as AI continues to grow and integrate into our everyday lives. Moreover, since all the data were collected through self-reported questionnaires, there is a risk of social desirability bias or common bias method variance, even though we made efforts to mitigate these issues.

Looking ahead, researchers can expand on this study by investigating the model in various industrial and cultural environments. Since this research was limited to the manufacturing sector in a particular geographic area, its applicability might be somewhat restricted. By comparing different sectors, such as healthcare, education, and IT, or examining countries with diverse technological infrastructures, the researcher could gain broader insights into how employees perceive and adapt to AI. Additionally, future research could investigate other possible mediators or moderators, such as organizational support, AI literacy, or leadership style, which could impact the relationship between AI perception and career adaptability. Exploring these dimensions will enrich our understanding of how to nurture a resilient workforce in the age of intelligent automation.

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Appendix

	Survey Items
Perceptions of AI (Presbitero & Teng-Calleja, 2023)	
PAI1	I think many workplace systems will be replaced by artificial intelligence.
PAI2	What I do now in my job will be replaced by artificial intelligence.
PAI3	My future in my organization is being threatened by the introduction of artificial
PAI4	intelligence.
	My future in my industry is being threatened by the introduction of artificial intelligence**.**
Technological Anxiety (Singh & Verma, 2023)	
TA1	I am afraid that I will incorrectly use AI-powered digital platforms in my
TA2	professional tasks.
TA3	I feel anxious when I have to use AI-based tools or platforms for job-related activities.
	I feel uncomfortable relying on AI technologies integrated into digital platforms for my work
Job Crafting (He et al., 2024)	
	I will...
JC1	Introduce new approaches to improve my work.
JC2	Change minor work procedures that I think are not productive.
JC3	Change the way I do my job to make it easier to myself.
JC4	Rearrange equipment and change my working environment.
Career Adaptability (Maggiori et al., 2017)	
CA1	1. Thinking about what my future will be like.
CA2	2. Preparing for the future.
CA3	3. Becoming aware of the educational and vocational choices that I must make.
CA4	4. Making decisions by myself.
CA5	5. Taking responsibility for my actions.
CA6	6. Counting on myself.
CA7	7. Looking for opportunities to grow as a person.
CA8	8. Investigating options before making a choice.
CA9	9. Observing different ways of doing things.
CA10	10. Taking care to do things well.
CA11	11. Learning new skills.
CA12	12. Working up to my ability.