Mind Over Machine: Understanding Engineers' AI Opportunity and Risk Perceptions through Psychological Capital

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***Abstract*—The rapid spread of artificial intelligence (AI) is reshaping the workplace, generating responses that range from optimism about new opportunities to concerns over job insecurity. This study explores how engineers perceive AI opportunities (AIOP) and their associated unemployment risk perceptions (URP), with a focus on the mediating role of psychological capital (PsyCap). PsyCap comprising resilience, self-efficacy, optimism, and hope is positioned as a vital psychological resource enabling engineers to adapt to AI-driven disruptions, drawing upon Cognitive Appraisal Theory. The analysis was conducted using SmartPLS-4 with reliability indices (α, CR, AVE) and SRMR-based model fit. The sample consisted of 221 engineers (60% male, 50% aged 23–33 years) from Punjab, J&K and NCR-Delhi.**

The findings indicate that Psychological Capital exerts a significant indirect effect, confirming its mediating role between AIOP and URP. Higher levels of PsyCap appear to lessen anxiety regarding technological displacement by enabling individuals to perceive AI as an opportunity rather than a threat. These insights emphasize that preparing engineers for a digital and sustainable world requires more than technical upskilling; it also necessitates strengthening psychological preparedness. By integrating psychological empowerment with digital competence, the study highlights a dual pathway toward building resilient, future-ready engineers aligned with the vision of Industry 5.0. The results hold practical implications for educators, industry leaders, and policymakers in designing holistic strategies that merge emerging technologies with future skills to foster sustainable employability.

***Keywords*—Artificial Intelligence; Psychological Capital; Unemployment Risk Perception; Cognitive Appraisal Theory; Technological Disruption.**

ICTIEE Track—Emerging Technologies and Future Skills
ICTIEE Sub-Track: Preparing Engineers for a Digital and Sustainable World

I. INTRODUCTION

Amid rapid technological change, artificial intelligence (AI) has moved from theory to practice, emerging as a transformative force reshaping industries, reconfiguring work, and redefining organizational strategies. By 2027, nearly 74.9% of businesses worldwide are projected to adopt AI, with 59% expecting it to play a central role in business strategy (WEF, 2023a). From virtual assistants to predictive algorithms and machine learning applications, AI has become integral to enhancing productivity and innovation (McKinsey & Company, 2023; Brynjolfsson & McAfee, 2014). Yet, as AI increasingly performs tasks once reserved for humans such as data processing, speech recognition, and even creative problem-solving, concerns about technological unemployment have intensified (Bessen, 2019; Arntz et al., 2016). Routine and repetitive roles in sectors like manufacturing, logistics, data entry, and customer service are particularly vulnerable, with the Future of Jobs Report (2023) estimating that 83 million jobs could be lost globally over the next five years. In India alone, the loss may reach 5.1 million jobs by 2025, underscoring the acute risks faced by emerging economies that depend heavily on low- and semi-skilled labor.

These concerns are echoed globally, with the International Labour Organization (ILO, 2023) cautioning that AI adoption may exacerbate inequality, disproportionately affecting workers with limited education and restricted digital access. Empirical evidence supports this trend: Acemoglu and Restrepo (2020) found that the introduction of one robot per 1,000 workers in the United States reduced the employment-to-population ratio by 0.2 percentage points, underscoring the tangible erosion of job opportunities linked to automation. Beyond outright displacement, AI is also contributing to job polarization, where high-skill, high-pay roles expand while

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middle-skill jobs decline, leaving workers squeezed between specialized technical roles they cannot access and precarious low-wage work (OECD, 2023). Such structural transformations amplify job insecurity, economic anxiety, and psychological stress among large sections of the workforce (Al-Ghazali & Afsar, 2022).

However, the discourse on job displacement only captures part of the picture. AI is also generating new employment opportunities in areas such as data science, cybersecurity, and digital innovation (Bughin et al., 2018; OECD, 2023). Moreover, human-centric roles that emphasize creativity, critical thinking, and emotional intelligence remain largely irreplaceable by machines (Frey & Osborne, 2023; Autor, 2015). This duality indicates that the future of work is not solely about technological substitution but about adaptation, requiring workers to complement technical upskilling with psychological readiness. As Jarrahi (2018) observes, the key challenge lies less in technological change itself and more in how effectively individuals and organizations respond to it.

This recognition brings Psychological Capital (PsyCap) to the forefront. PsyCap comprising optimism, hope, self-efficacy, and resilience equips individuals with the psychological resources to embrace disruption, sustain adaptability, and maintain a growth mindset (Luthans et al., 2007). Workers with high PsyCap are more likely to interpret AI as a source of opportunity rather than a threat, enhancing their openness to reskilling and innovation (Hu et al., 2025). Conversely, individuals with low PsyCap may perceive AI adoption with fear and resistance, leaving them more vulnerable to job insecurity (Al-Ghazali & Afsar, 2022). Organizations increasingly acknowledge this dual challenge, with 69% of CEOs identifying employee upskilling both technical and psychological as critical for AI readiness (PwC, 2024). This organizational concern is complemented by broader economic projections, with McKinsey & Company (2023) estimating that AI is projected to boost the global economy by approximately $2.6 trillion to $4.4 trillion each year. Together, these insights emphasize the urgent need to cultivate a psychologically empowered workforce that can navigate the disruptions of an AI-driven economy.

Despite the growing body of work on the economic implications of AI adoption, limited focus has been paid to the psychological process that shape how employees perceive AI as either a threat to job security or a source of opportunity. The mediating role of Psychological Capital in this relationship remains underexplored, particularly in emerging economies where both digital transformation and employment vulnerability are highly pronounced.Very limited work explains how PsyCap reduces unemployment fear in AI-exposed engineering contexts, particularly in emerging economies like India. The present study addresses this gap by modelling AIOP → PsyCap → URP.

In Addressing this gap, the present study examines how AI Opportunity Perception influences Unemployment Risk Perception, with special emphasis on the role of PsyCap among engineers. It further investigates how the four components of PsyCap hope, optimism, self-efficacy, and resilience enable engineers to adapt more effectively to AI-driven workplace changes.

In line with these aims, the study seeks to address the following research questions: How does AI Opportunity Perception influence Unemployment Risk Perception among employees in the context of technological innovations? What is the mediating role of Psychological Capital in this relationship? And how do the components of Psychological Capital help employees adapt to AI-driven changes in the workplace?

II. Theoretical Foundation, Literature Review, and Hypotheses Development

AI is deeply rooted in our day-to-day life. It is no longer a futuristic thought it's here, and everywhere, reshaping the way engineers work. It has transformed our lives by enhancing efficiency, fostering innovation, boosting productivity, and improving overall performance. It has not only impacted an individual but also the economy as a whole. It has become deeply entrenched in everyday business operations, generating both positive and negative outcomes for individuals, society, and the economy (Lee, 2017; Lev-Ram, 2017). Given its pervasive impact, this research intends to explore how engineers perceive AI and how they cope with the challenges posed by it. The Cognitive Appraisal Theory, developed by Richard Lazarus(Lazarus & Folkman, 1984), lays the foundation for understanding the constructs for the research. In the past, it has been used to study how employees assess and respond to job stressors (Lazarus & Folkman,1984; Narayanan et al., 1999; Searle & Auton,2015), explaining employee reactions to automation, digital transformation, and AI adoption (Turel & Serenk,2012; Meijerink et al., 2021; Guo et al,2020); unemployment and economic uncertainty (McKee-Ryan et al., 2005; Wanberg et al., 2012). In the present research, it has been used to understand how especially engineers assess events emotionally based on their personal evaluation of those events, such as the growing adoption of artificial intelligence(AI), which has a direct impact on Unemployment risk and is strongly shaped by psychological capital. The theory describes that an individual appraises situations in two stages, i.e., primary evaluation, where they assess whether AI poses a threat or an opportunity to their job security, and secondary evaluation, where they evaluate their ability to cope with or leverage the situation. This dual evaluation determines their emotional and behavioral responses to AI-driven changes. AI-driven disruptions can lead to job insecurity (Yam,K.C et al., 2022) whereas employees who view AI as an opportunity will adopt proactive approach to cope up with the new challenges (Nguyen,L.T.et al.,2024) Thus, this theory provides a foundational framework for understanding how individuals assess AI implementation within an organization, and how their levels of hope, self-efficacy, optimism and resilience, influence their perception of potential job loss. In the context of AI opportunity risk perception, psychological capital (PsyCap), and unemployment risk perception, Cognitive Appraisal Theory offers a robust framework to study the relationship between them by emphasizing how engineers interpret and respond to stressors like technological advancements.

III. AI Opportunity Perception and URP

AI represents both opportunities and uncertainties, and individuals' perceptions of these vary significantly. While some engineers believe AI is a tool for progress, others view it as a potential threat to their profession and occupational security (Acemoglu & Restrepo, 2018; Aghion et al., 2017). Though AI may lead to the displacement of some jobs, it is also expected to create new job opportunities, specifically in emerging areas like Business Intelligence, AI Modelling, etc. (WEF, 2023a). It has created anxiety among individuals who fear that their roles may become obsolete, raising worries about unemployment risk (Yam, K.C.et al., 2022) while others take it as a facilitator for long-term progress and development (Nguyen, Luan-Thanh et al, 2024). Engineer's perceptions of AI differ depending on their cognitive perspective and their readiness to handle AI-related challenges in practical workplace environments.

AI has transformed the employment landscape not only in India but all over the world, creating a challenging environment. It has designed the machines in such a way that they are a perfect replacement of human beings as they can think and work like humans. It possesses the ability to learn from experience, make informed decisions, and carry out tasks that traditionally demand human intelligence. Many economists believed that automation technology is designed to make work easier by taking over tasks that people used to do themselves, but this can also mean fewer jobs for human workers (Acemoglu & Restrepo, 2018; Aghion et al., 2017).

With the advent of rapid advancement of artificial intelligence (AI), technologies have led to substantial opportunities across various sectors. However, alongside these opportunities, there are considerable risks that need to be understood and managed. Unemployment Risk Perception (URP) is described as a fear of losing a job. It describes an individual's subjective assessment or concern regarding the likelihood of losing their current job or being unable to secure employment in the future. It is increasingly relevant in the digital age, where rapid technological advancements especially in AI and automation have revolutionized numerous industries, at the same time, have intensified fears around job displacement across industries (Tschang and Almirall,2021).

This literature review explores the perception of AI opportunity, focusing on how young individuals and organizations evaluate the benefits and potential problems. Accordingly, the following hypothesis has been proposed:

H1: AI Opportunity Perception is negatively related to Unemployment Risk Perception

Psychological Capital

Psychological capital is the person's psychological ability that may be measured, established, and controlled for performance enrichment (Paul, F.A. et al, 2023). It includes self-efficacy, optimism, hope, and resilience (Avey et al., 2023; Luthans and Youssef, 2004, 2007), and serves as a mediator in this relationship by influencing how young engineers perceive and cope with AI-related risks.

Studies have shown that Psychological Capital is referred to as a positive psychological capacity playing a distinct role in moderating the effect of perceived risks and uncertainties in the workplace, as stated by Luthans et al. (2007). When perceiving AI as a potential threat to job security, psychological capital buffers negative emotional and behavioral responses by facilitating adaptive responses. Hope enables employees to plan and develop backup plans to overcome perceived barriers (Snyder, 2002), while self-efficacy facilitates confidence in being able to learn new competencies or transition to other employment roles (Bandura, 1977). Optimism affects positive assessments of AI opportunities so that they can focus on potential benefits rather than threats (Youssef & Luthans, 2007). Whereas resilience helps individuals adapt to disruptive changes, like AI-driven automation, by enabling them to reframe threats into opportunities (Youssef-Morgan & Luthans, 2013) and recover from hindrances, difficulties, and transform themselves, which leads to personal growth (Avey et al., 2023; Luthans & Youssef, 2004, 2007). Employees high in Psychological Capital have more positive attitudes toward AI and lower negative attitudes toward AI (Carter, J.W.,2024). Therefore, Psychological Capital facilitates the secondary evaluation process, reducing perceived risks and enhancing coping strategies to mitigate the impact of AI among individuals. Hence, the following hypotheses have been developed:

H2a: AI Opportunity Perception (AIOP) is positively related to Hope.

H2b: AI Opportunity Perception (AIOP) is positively related to Optimism.

H2c: AI Opportunity Perception (AIOP) is positively related to Self-Efficacy.

H2d: AI Opportunity Perception (AIOP) is positively related to Resilience.

Unemployment Risk Perception

Unemployment risk perception is the subjective anticipation of job loss, influenced by individual cognition and external factors (Zhang & Liu, 2015). It stems from job insecurity but represents a broader psychological state, encompassing uncertainty about future employment. According to cognitive appraisal theory, the anticipation of unemployment can have severe consequences, such as stress, reduced mental health, and decreased job performance (Zhang & Liu, 2015).AI intensifies unemployment risk perception by emphasizing uncertainty about job security in a rapidly evolving technological landscape. Workers may perceive AI as a threat to their roles, particularly in sectors undergoing significant automation (Danaher, 2017). The inability to predict or control these changes heightens fears and creates a persistent sense of insecurity (César, 2023). Gomes and Santos (2023) highlight that while AI enhances efficiency and accuracy, it also replaces human roles, fueling fears of obsolescence among workers. Similarly, César (2023) points out that AI's potential to disrupt job markets intensifies feelings of uncertainty, further linking technological advancements to unemployment risk perception, but psychological capital often conceptualized as including hope, optimism, self-efficacy, and resilience buffers stress effects by nurturing perceived control and adaptive coping. For example, among young adults and university students, higher levels of hope and resilience predict the use of effective coping strategies, which in turn are linked to lower perceived stress (Gupta,P et al., 2019; Esteban Moreno-Montero, Mara-del-Mar Ferrads, & Carlos Freire, 2024). Individuals with high Psychological capital are more likely to engage in positive evaluations, viewing AI as an opportunity for growth and skill enhancement rather than a threat to their employment. For example, self-efficacy gives individuals confidence in their *ability to acquire new skills, while optimism fosters a belief in* favourable outcomes even amidst uncertainty (Luthans et al., 2004). Conversely, individuals with low Psychological capital may appraise AI advancements as a challenge, intensifying unemployment risk perception and inducing stress or resistance to change(Bidi Badrinath\et al. 2024).PsyCap not only reduces perceived stress but also mediates its effect on occupational well-being, burnout, and job satisfaction. Through the integration of PsyCap in organizational programs, organizations can build resilience and adaptability, thereby reducing turnover intentions, mitigating stress, and improving overall employee well-being (Luthans & Youssef-Morgan, 2017; Ferradás et al., 2019)

Thus, the following hypotheses have been derived:

H3a: Hope is negatively related to Unemployment Risk Perception (URP).

H3b: Optimism is negatively related to Unemployment Risk Perception (URP).

H3c: Self-efficacy is negatively related to Unemployment Risk Perception (URP).

H3d: Resilience is negatively related to Unemployment Risk Perception (URP)

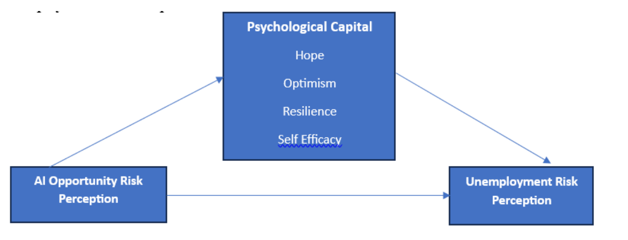
Psychological Capital as a Mediator Between AI Opportunity Perception and Unemployment Risk Perception

The Cognitive Appraisal Theory (Lazarus & Folkman, 1984) provides the theoretical basis for understanding how psychological capital explains the mediation between AI opportunity perception and Unemployment risk perception. Individuals with higher psychological capital will more likely appraise AI as a manageable challenge rather than an existential threat, thereby buffering against unemployment anxiety and psychologically preparing them for change (Luthans et al., 2007). For instance, employees with high psychological capital have improved mental health, reduced job insecurity, and greater openness to change (Al-Ghazali & Afsar, 2022). Furthermore, Psychological capital development through special intervention, such as resilience training or goal-setting workshops, has been shown to reduce job loss fear by enhancing individuals' capacity to deal with uncertainty (Shahzad, 2022).

Psychological capital also enables individuals to remain motivated and concentrated in the face of change, which is necessary to deal with the psychological and practical implications of AI-induced disruptions (Di Fabio & Tsuda, 2018; Youssef-Morgan & Luthans, 2013). In summary, psychological capital not only cushions the adverse effect of AI opportunity risk perception on unemployment fear but also equips engineers with the emotional and cognitive skills to thrive in rapidly changing working environments.

Hence, Psychological Capital (PC) serves as a vital mediator in the association between artificial intelligence opportunity perception (AIOP) and unemployment by affecting how engineers assess, deal with, and respond to AI-driven change (Luthans et al., 2007; Shin et al., 2020). Based on the preceding discussion, the following hypothesis is proposed:

H4: Psychological Capital Mediates the relationship between AI Opportunity Perception and Unemployment Risk Perception



III. RESEARCH METHODOLOGY

Data synthesis and scale used

The study employed an online questionnaire with a seven-point Likert scale to obtain responses from young professional engineers. The research questionnaire includes a demographic profile of the respondents and research components developed from the existing scales. Every question was adapted from previously published research on the concepts of AI Opportunity Perception(AIOP), Psychological Capital (PC), and Unemployment Risk Perception (URP). The items to measure AI opportunity perception were measured by using a scale from Highhouse and Payam (1996). Psychological capital, including constructs like hope, optimism, self-efficacy, and resilience, was adopted from Luthans et al. (2007), and the construct of unemployment risk perception was adapted from Hovick et al. (2011). A structured questionnaire (see Appendix) was framed to collect data from 250 engineer professionals as recommended by Hair et al. (2010), who suggest that for a basic mediation model, 250 respondents can be considered statistically sufficient. The data was captured from Punjab, J&K, and NCR-Delhi to get diverse socioeconomic, industrial, and urban-rural backgrounds, ensuring relevance to the study of AI adoption and workplace psychological dynamics within the Indian setting (Budhwar, Pawan, et al. 2023). This multi-region approach enhances the generalizability of findings by comparing responses of engineers from diverse industries (Vrontis et al., 2022).Purposive sampling was adopted to identify engineers with relevant exposure to AI-enabled tools, ensuring that the respondents possessed the necessary experience and awareness aligned with the study's objectives (Campbell et al., 2020). A total of 250 survey links were circulated, out of which 221 valid responses were obtained after screening, resulting in an effective response rate of approximately 88%, which is considered adequate for statistical analysis.

Based on the demographic data, the majority of the engineers are young, as 50 % of the respondents were between the age group of 23 -33, with 60% of the respondents being men. Additionally, the analysis showed that 48% of engineers earn between 41000 and 50000 per month, and 55% of them work in a private organization. These demographic trends reflect the perceptions of a relatively young, professionally active, and educated population, which is relevant when evaluating the association between AI opportunity perception (AIOP), psychological capital (PC), and unemployment risk perception (URP) in an evolving employment landscape.

IV. MEASUREMENT MODEL ASSESSMENT

The measurement model is assessed through lower-order constructs that include the complete details of all the constructs, including the dimensions. For the second time, the measurement model is assessed by conducting a higher-order constructs model. It included only the outer model, which comprises only the major constructs.

Reliability and Validity of Lower Order Constructs

Reliability and validity are checked through the measurement model assessment. Indicator reliability is seen through Factor loadings which should be larger than 0.708 (Hair et al., 2022). The results showed all factor loadings are above the threshold values except URP3 which has 0.702 but as the AVE is 0.601 (above 0.50) so the item was retained. Cronbach's Alpha values should be larger than 0.650 (Henseler et al., 2009). The threshold value for the composite reliability is 0.70 (Hair et al. 2019).The internal consistency of the constructs was ensured through the Cronbach's Alpha and Composite reliability check. The Convergent validity was measured using average variance extracted (AVE). The outcomes of the data demonstrated support for convergent validity, as evidenced by AVE standards above the threshold of 0.50 (Hair et al., 2019). The results show that all the values are within the prescribed limits (Table 1).

TABLE I
RELIABILITY AND VALIDITY OF LOWER ORDER CONSTRUCTS

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIOP	0.918	0.944	0.938	0.752
PC HOPE	0.869	0.909	0.920	0.794
PC OPTIMISM	0.912	0.922	0.945	0.850
PC RESILIENCE	0.866	0.867	0.918	0.789
PC SELF EFFICACY	0.892	0.897	0.933	0.824
URP	0.665	0.667	0.818	0.601

Discriminant Validity

Moreover, discriminant validity is checked through both HTMT and Fornell and Larcker criterion. For HTMT the threshold value is 0.90 i.e. all the values should be less than 0.90 (Henseler et al., 2009). And for Fornell and Larcker criteria, the square root of the AVE (i.e. diagonal values in the table) value for each construct exceed its correlation estimates (Fornell & Larcker, 1981). Tables 2&3 below show the successful fulfillment of discriminant validity by both methods.

TABLE 2
HTMT DISCRIMINANT VALIDITY

	AIOP	PC HOPE	PC OPTIMISM	PC RESILIENCE	PC SELF-EFFICACY	URP
AIOP						
PC HOPE	0.661					
PC OPTIMISM	0.486	0.675				
PC RESILIENCE	0.476	0.813	0.545			
PC SELF-EFFICACY	0.424	0.749	0.506	0.895		
URP	0.483	0.799	0.695	0.724	0.732	

TABLE 3
FORNELL AND LARCKER DISCRIMINANT VALIDITY

	AIOP	PC HOPE	PC OPTIMISM	PC RESILIENCE	PC SELF-EFFICACY	URP
AIOP	0.867					
PC HOPE	0.612	0.891				
PC OPTIMISM	0.470	0.618	0.922			
PC RESILIENCE	0.442	0.696	0.489	0.888		
PC SELF-EFFICACY	0.394	0.657	0.459	0.786	0.908	
URP	0.386	0.617	0.544	0.549	0.564	0.775

Variance Inflation Factor (VIF)

VIF is used to check the multicollinearity among the constructs.

It should be below 5 (Hair and Alamer, 2022) and the results (annexure) shows that all the VIF values are less than 5.

Reliability and Validity of Higher Order Construct

Reliability and validity are checked through measurement model assessment. Indicator reliability is seen through Factor loadings which should be larger than 0.708 (Hair et al., 2022). The results showed all factor loadings are above the threshold values except URP3 which has 0.702 but as the AVE is 0.601 (above 0.50) so the item was retained. Cronbach's Alpha values should be larger than 0.650 (Henseler et al., 2009). The threshold value for the composite reliability is 0.70 (Hair et al. 2019). Both Cronbach's Alpha and Composite reliability is used to ensure the internal consistency of the constructs. Convergent validity was measured using average variance extracted (AVE). The results demonstrated support for convergent validity, as evidenced by AVE values exceeding the threshold of 0.50 (Hair et al., 2019). The results in the table 4 shows that all the values are within the prescribed limit.

TABLE 4
RELIABILITY AND VALIDITY OF HIGH ORDER CONSTRUCTS

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIOP	0.918	0.945	0.938	0.752
PC	0.866	0.875	0.909	0.715
URP	0.665	0.667	0.818	0.601

Discriminant Validity

Moreover, discriminant validity is checked through both the HTMT and the Fornell and Larcker criteria. For HTMT, the threshold value is 0.90, i.e., all the values should be less than 0.90 (Henseler et al., 2009). Moreover, the Fornell and Larcker criteria require that the square root of the AVE (i.e., diagonal values in the table) value for each construct exceed its correlation estimates (Fornell & Larcker, 1981). Tables 5 and 6 below show the successful fulfillment of discriminant validity by both methods.

TABLE 5
HTMT DISCRIMINANT VALIDITY

	AIOP	PC	URP
AIOP			
PC	0.617		
URP	0.483	0.888	

TABLE 6
FORNELL AND LARCKER DISCRIMINANT VALIDITY

	AIOP	PC	URP
AIOP	0.867		
PC	0.576	0.846	
URP	0.386	0.675	0.775

STRUCTURAL MODEL ASSESSMENT

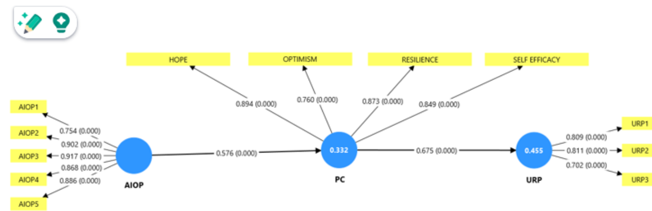


Figure 3: Structural Model Assessment

VARIANCE INFLATION FACTOR (VIF)

VIF is used to check the multicollinearity among the constructs. It should be below 5 (Hair and Alamer, 2022). And results (Annexure) show that all the VIF values are less than 5.

MODEL FITNESS

In the assessment of structural model table 7, the model fitness is ensured by standardized root mean square residuals (SRMR) which was found to be 0.08, that is acceptable and at par with the critical value of 0.08 (Hair et al., 2019) representing goodness of fit model. Results are depicted in the table 8 below:

TABLE 7
STRUCTURAL MODEL

model	Saturated	Estimated model
SRMR	0.08	0.08
d_ULS	0.529	0.529
d_G	0.225	0.225
Chi-square	234.578	234.600
NFI	0.835	0.835

HYPOTHESES RELATIONS

Thus, from the above analysis, it can be concluded that AI Opportunity risk perception has a significant positive impact on Psychological Capital (β Value = 0.576, t value = 13.079, and p value = 0.000). Further, Psychological capital has a substantial positive and significant impact on Unemployment Risk Perception (β Value = 0.675, t value = 14.843, and p value = 0.000).

TABLE 8
HYPOTHESIS RELATIONS

Variables	Path Coefficients (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIOP -> PC	0.576	0.581	0.044	13.079	0.000
PC -> URP	0.675	0.678	0.045	14.843	0.000

Justification of hypotheses

Hypothesis H1 proposes that AI Opportunity Perception (AIOP) is negatively connected to Unemployment Risk Perception (URP). Table 4 confirms that both constructs are statistically comprehensive, with AIOP demonstrating high composite reliability (0.938) and AVE (0.752), and URP also meeting acceptable thresholds (composite reliability = 0.818, AVE = 0.601). Discriminant validity(Table 5) is established through HTMT (0.483) and the Fornell-Larcker criterion (Table 6), confirming that AIOP and URP are conceptually distinct. The structural model reveals a significant negative path coefficient between AIOP and URP, validating the proposed inverse relationship.. Thus, the hypothesis is strongly justified.

The results of the data analysis strongly support hypotheses H2a through H2d, confirming that AI Opportunity Perception (AIOP) is positively related to the four dimensions of Psychological Capital: Hope, Optimism, Self-Efficacy, and Resilience. First, the measurement model (Table 1) results show high reliability and convergent validity for each of these constructs, with AVE values well above the 0.50 threshold—Hope (0.794), Optimism (0.850), Self-Efficacy (0.824), and Resilience (0.789)—and composite reliability scores all exceeding 0.90. Additionally, HTMT values (Table 2&3) for the relationships between AIOP and each psychological dimension (Hope = 0.661, Optimism = 0.486, Self-Efficacy = 0.424, Resilience = 0.476) are all below the 0.90 threshold, confirming discriminant validity and suggesting that while the constructs are related, they are distinct. Crucially, the structural model (Table 8) shows a significant and positive relationship between AIOP and overall Psychological Capital ($\beta = 0.576$, $t = 13.079$, $p = 0.000$), which comprises the four sub-dimensions. This indicates that individuals who perceive AI as an opportunity tend to possess higher levels of Hope, Optimism, Self-Efficacy, and Resilience, thereby empirically supporting hypotheses H2a, H2b, H2c, and H2d.

The findings of the data analysis support hypotheses H3a through H3d by demonstrating that the four components of Psychological Capital (PC)—Hope, Optimism, Self-Efficacy, and Resilience—are negatively related to Unemployment Risk Perception (URP). Although the structural model reports (Table 8) shows the association between overall Psychological Capital (PC) and URP ($\beta = 0.675$, $t = 14.843$, $p = 0.000$), further evidence from the HTMT and Fornell-Larcker discriminant validity results confirms conceptual separation between each PC sub-dimension and URP. Specifically, the HTMT values (Table 2&3) between URP and Hope (0.799), Optimism (0.695), Self-Efficacy (0.732), and Resilience (0.724) all fall below the threshold value, i.e., 0.90, supporting discriminant validity. Additionally, Fornell-Larcker values reinforce this by showing that the square roots of AVE for each construct are higher than their correlations with URP. These findings indicate that individuals with higher levels of Hope, Optimism, Self-Efficacy, and Resilience tend to perceive lower unemployment risk, thereby supporting H3a, H3b, H3c, and H3d.

H4: Psychological Capital Mediates the relationship between AI Opportunity Risk Perception (AIOR)and Unemployment Risk Perception (URP)

The analysis provides strong support for Hypothesis H4, which posits that Psychological Capital (PC) mediates the association between AI Opportunity Perception (AIOP) and Unemployment Risk Perception (URP). The structural model (Table 8) demonstrates that AIOP significantly and positively influences PC ($\beta = 0.576$, $t = 13.079$, $p = 0.000$), and in turn, PC significantly and negatively impacts URP ($\beta = 0.675$, $t = 14.843$, $p = 0.000$). This pattern of relationships confirms a significant indirect effect, indicating mediation. Although the direct correlation between AIOP and URP is weakly positive (0.386), the mediation through PC reveals the underlying mechanism: individuals who view AI as an opportunity tend to develop greater Psychological Capital (PC), which in turn reduces their perceived unemployment risk. This mediating effect is theoretically supported by Cognitive Appraisal Theory and empirically validated by the model's strong fit indices (e.g., SRMR = 0.08), confirming that PC acts as a key psychological buffer in this relationship, thereby supporting H4.

V. DISCUSSION

The existing research studies the complex connection between AI Opportunity Perception (AIOP), Psychological Capital (PC), and Unemployment Risk Perception (URP) using PLS-SEM. The measurement model demonstrated strong validity and reliability, with all constructs meeting the prescribed values i.e. Composite Reliability, and AVE (Hair et al., 2019).

The results of the analysis provide strong support for the proposed hypotheses. AIOP was found to be negatively related to URP, suggesting that those engineers who perceive AI as beneficial are less likely to fear job displacement. This is consistent with earlier studies that report opportunity-focused AI perceptions reduce anxiety about technological unemployment (Schepman & Rodway, 2020; Zhang et al., 2019). Further, supported by Schepman and Rodway (2020), who suggest that engineers with positive perceptions of AI report lower fears of employment disruption. Additionally, the results are strengthened by the findings of Xu, G., Xue, M., & Zhao, J., (2023) which highlights that grasp of AI-relevant competencies among employees may contribute to career resilience and reduced feelings of job insecurity Moreover, Cognitive Appraisal Theory also emphasizes that individuals perceiving AI as an opportunity are less likely to perceive it as a threat, thereby reducing their unemployment risk perception.

Furthermore, AIOP showed significant positive effects on all four dimensions of Psychological Capital (Luthans et al., 2007), which in turn were negatively related to URP. These relationships align with Cognitive Appraisal Theory by Lazarus & Folkman (1984, which suggests that how people interpret external stimuli (e.g., AI) determines emotional and behavioral outcomes. Thus, individuals especially engineers are more likely to appraise AI positively if they have high psychological capital, thereby reducing their perception of employment risk (Luthans et al., 2007; Lazarus & Folkman, 1984). Further, the research conducted by (Lazarus & Folkman, 1984) emphasizes that strong psychological capital is more inclined to see AI advancements as enablers rather than displacers, thereby reducing anxiety over employment security in the workplace. The study by Hou, Y., & Fan, L. (2024) highlights the importance of nurturing psychological capital to help employees adapt to AI-driven changes. Thus, supporting the results that psychological capital can have a positive impact on AI opportunity perception among employees.

Further, the findings support the hypotheses that substantial Psychological capital reduces Unemployment risk perception. The studies in the past show that higher levels of Hope, Optimism, Self-Efficacy, and Resilience core dimensions of Psychological Capital significantly reduce Unemployment Risk Perception (Luthans et al., 2007; Bandura, 1997; Snyder, 2002; Cheng & Chan, 2008). These results are consistent with Cognitive Appraisal Theory, which posits that positive psychological resources lower threat perceptions in uncertain employment contexts (Lazarus & Folkman, 1984; Wang et al., 2021).

Finally, the mediation effect of Psychological Capital (PC) in the association between AIOP and URP reveals a significant underlying mechanism. The path analysis demonstrated that AIOP influences URP not only directly but also indirectly by enhancing an individual's positive psychological resources. This dual pathway confirms that Psychological Capital (PC) serves as a critical mediator in adapting to technological change, consistent with prior research on emotional resilience and change readiness in work settings (Brougham & Haar, 2018) among engineers. Practically, these findings emphasize the importance of designing interventions and policies that promote opportunity-driven narratives and strengthen psychological readiness to reduce fears of job loss in an AI-driven future (World Economic Forum, 2020). By promoting a more empowered outlook, engineers are better equipped to adapt and thrive in evolving labor markets.

CONCLUSION

The study concludes that AI Opportunity Perception (AIOP) significantly influences Unemployment Risk Perception (URP) through the mediating role of Psychological Capital (PC). While direct relationship among AIOP and URP is minimal, individuals who perceive AI as an opportunity tend to develop stronger psychological resources which in turn buffer against the fear of unemployment. This mediating mechanism, grounded in Cognitive Appraisal Theory, highlights the importance of internal psychological appraisal in shaping responses to external technological disruptions.

The findings provide both theoretical and empirical evidence that Psychological Capital mediates the relationship between AI perceptions and unemployment risk, suggesting that building psychological strength among engineers are crucial for navigating the uncertainties of an AI-driven labor market. The validated model, with strong reliability, validity, and fit indices, reinforces the critical role of psychological empowerment in facilitating positive adaptation to AI adoption.

IMPLICATIONS

Social Implications

The study's findings underline the critical role of perception and psychological readiness in navigating the societal impacts of AI adoption. Even technical people are afraid of losing their jobs when they see AI as a danger rather than an opportunity. Accordingly, society needs to change its narrative from one of job loss brought on by AI to one of innovation, growth, and skill development. A future-focused mindset should be fostered by educational institutions, the media, and public policy initiatives that raise awareness of AI's potential advantages and give people the psychological tools they need to cope with change. Improving psychological capital which might help people better adjust to changes in the labor market, lessen social anxiety related to automation, and encourage equitable economic participation. Such proactive, community-level psychological reinforcement can be crucial in fostering societal resilience as AI continues to transform occupational positions.

Managerial Implications

The findings give firms important information on how HR procedures and leadership can allay concerns about technology change. Supervisors should understand that cultivating AI Opportunity Perception in staff members involves more than simply skill improvement; it also entails changing employees' perspectives. Employees' perceived risk of losing their jobs can be considerably reduced by enhancing their psychological capital through training initiatives, mentorship, encouraging communication, and courses on transition preparation. Furthermore, engagement and trust can be increased by incorporating staff members in AI adoption procedures and outlining the benefits of new technology in enhancing rather than replacing human responsibilities. Managers may increase organizational agility, retain talent, and develop a workforce that is not only technically proficient but also emotionally prepared to succeed in an AI-driven environment by incorporating psychological readiness into strategic planning.

LIMITATIONS AND FUTURE IMPLICATIONS

The research paper despite offering meaningful insights, is subject to certain limitations. First, the data is collected from geographically confined specific regions in India—Punjab, Jammu & Kashmir, and the NCR-Delhi area. Thus, limiting the generalizability of the research findings to broader national or international situations. Secondly, the measurement of AI Opportunity Perception without considering respondents' actual exposure to AI technologies in their professional environments may significantly shape their perceptions and psychological responses. Moreover, while the study approves the mediating role of Psychological Capital as a composite construct, it does not explore the distinct mediating effects of its individual dimensions—Hope, Optimism, Self-Efficacy, and Resilience which may yield more nuanced insights. Finally, the research work does not focus on moderating variables such as age, job type, or industry sector, which could further influence how individuals perceive AI and its impact on employment. These limitations offer directions for future research to enhance the depth and relevance of the findings.

Consistent with current research, the implications for the future highlight the increasing need to combine technical-non technical and psychological readiness when handling workplace changes brought about by AI. Moreover, future research employing longitudinal and multi-variable techniques could offer a more nuanced and dynamic understanding of workforce preparation in the AI-driven era. Also, future work can test moderators such as AI literacy or experience, and run longitudinal intervention designs to strengthen PsyCap training outcomes among engineers.

References

Acemoglu, D., & Restrepo, P. (2018). Artificial Intelligence, Automation, and Work. NBER Working Paper.

Aghion, P., Jones, B. F., & Jones, C. I. (2017). Artificial Intelligence and Economic Growth. NBER Working Papers 23928, National Bureau of Economic Research, Inc.

Al-Ghazali, B. M., & Afsar, B. (2022). Impact of psychological capital on mental health, readiness for organizational change, and job insecurity: Hotel employees' perspective in COVID-19. Journal of Tourism Futures, ahead-of-print(ahead-of-print).

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis (OECD Social, Employment and Migration Working Papers No. 189.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of Economic Perspectives, 29(3), 3–30.

Avey, J. B., Reichard, R. J., Luthans, F., & Mhatre, K. H. (2011). Meta-analysis of the impact of positive psychological capital on employee attitudes, behaviors, and performance. Human Resource Development Quarterly, 22(2), 127–152.

Avey, J., Newman, A. and Herbert, K. (2023),Fostering employees' resilience and psychological well-being through an app-based resilience intervention, Personnel Review, 52 (9), 2229-2244

Budhwar, Pawan, et al. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT Human Resource Management Journal, 33(3), 606–659.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. Psychological Review, 84(2), 191–215

Bessen, J. E. (2019). AI and jobs: The role of demand. NBER Working Paper No. 24235.

Bidi, Shilpa Badrinath, Bhat, Vrinda, Chandra, Sachin R., Dmello, Venisha Jenifer, Weesie, Edwin, Gil, Mathew Thomas, Kurian, Simmy, and Rajendran, Ambigai. (2024). Decoding occupational well-being of teachers: does psychological capital and coping mechanism impact perceived stress?. Cogent Psychology.

Brougham, D., & Haar, J. (2018). Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees' perceptions of our future workplace. Journal of Management & Organization, 24(2), 239–257.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton & Company.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., & Trench, M. (2018). Skill shift: Automation and the future of the workforce. McKinsey Global Institute. Retrieved from https://www.mckinsey.com/featured-insights/future-of-work/skill-shift-automation-and-the-future-of-the-workforce.

Campbell, Steve, Greenwood, Melanie, Prior, Sarah, Shearer, Toniele, Walkem, Kerrie, Young, Sarah, Bywaters, Danielle, and Walker, Kim. (2020).Purposive sampling: complex or simple? Research case examples. SAGE Publishing.

Carter, Justin. (2024). Enhancing student performance in business simulation games through psychological capital and flow. The International Journal of Management Education. 22.

César, J. (2023). Elon Musk wants to pause ChatGPT and Artificial Intelligence in a letter. São Paulo: g1.

Danaher, J. (2017). Will life be worth living in a world without work? Technological unemployment and the meaning of life. Science and Engineering Ethics, 23(1), 41–64.

Di Fabio, A., & Tsuda, A. (2018). The Psychology of Harmony and Harmonization: Advancing the Perspectives for the Psychology of Sustainability and Sustainable Development. Sustainability, 10(12), 4726.

Ferradás, M. D. M., Freire, C., García-Bértoa, A., Núñez, J. C., and Rodríguez, S. (2019). Teacher profiles of psychological capital and their relationship with burnout. Sustain. For. 11:5096.

Frey, C. B., & Osborne, M. A. (2023). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280.

Future of Job Reports (2023). Retrieved from https://www.weforum.org/publications/the-future-of-jobs-report-2023/

Gatlin, M. (2023). Assessing pre-service teachers' attitudes and perceptions of using artificial intelligence in the classroom. Texas Educator Preparation, 7(2), 1–8.

Gomes, C., & Santos, R. (2023). AI and the Future of Human Employment.

Gupta, Pragati, De, Nikita, Hati, Subhalina, Saikia, Chayanika, and Karmakar, Rita. (2019). The Relationship between Positive Psychological Capital and Coping Styles: A Study on Young Adults. Scientific Research Publishing.

Guo, L., Xiao, J., & Li, J. (2020). Employees' perceptions of AI and their job insecurity: Evidence from a multi-source survey. Computers in Human Behavior, 106, 106259.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Upper Saddle River, NJ: Pearson Prentice Hall.

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2019). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). SAGE Publications

Hair, J. F., & Alamer, A. (2022). Partial least squares structural equation modeling: Guidelines for selecting appropriate model fit indices. Journal of Applied Structural Equation Modeling, 6(1), 1–14.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. Advances in International Marketing, 20, 277–319

Highhouse, S.; Yüce, P.(1996). Perspectives, Perceptions, and Risk-Taking Behavior. Human Decision Process.65, 159–167.

Hovick, S., Freimuth, V. S., Johnson-Turbes, A., & Chervin, D. D. (2011). Multiple health risk perception and information processing among African Americans and Whites living in poverty. Risk Analysis, 31(11), 1789–1799.

Hou, Y., & Fan, L. (2024). Working with AI: The Effect of Job Stress on Hotel Employees' Work Engagement. Behavioral Sciences, 14(11), 1076.

Hu, C., Mohi Ud Din, Q., & Tahir, A. (2025). Artificial intelligence symbolic leadership in small and medium-sized enterprises: Enhancing employee flexibility and technology adoption. Systems, 13(4), 216.

International Labour Organization (ILO). (2023). Reskilling and upskilling for the digital economy: Policy challenges and opportunities. https://www.ilo.org/global/topics/future-of-work/publications/WCMS_831982/lang--en/index.htm

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586.

Lazarus, R. S., & Folkman, S. (1984). Stress, Appraisal, and Coping. Springer.

Lee, K. (2017). Artificial intelligence, automation, and the economy. Chinese American Forum,32(3),22–23.

Lev-ram, M. (2017). Tech's magic 8 ball says embrace the future. Fortune, 176(5), 28–29.

Luthans, F., Youssef, C. M., & Avolio, B. J. (2007). Psychological capital: Developing the human competitive edge. Oxford University Press.

Luthans, F., Avolio, B. J., Walumbwa, F. O., & Li, W. (2004). The psychological capital of Chinese workers: Exploring the relationship with performance. Management and Organization Review, 1(2), 249–271.

Luthans, F., & Youssef-Morgan, C. M. (2017). Psychological capital: An evidence-based positive approach. Annual Review of Organizational Psychology and Organizational Behavior, 4, 339–366.

Martinez, Hector, Rochford, K., and Bergeron, Diane(2025). Helping You, Helping Me? The Mediating Role of Organizational Citizenship Behavior in the Relationship Between Psychological Capital and Social Network Positions.

McKee-Ryan, F. M., Song, Z., Wanberg, C. R., & Kinicki, A. J. (2005). Psychological and physical well-being during unemployment: A meta-analytic study. Journal of Applied Psychology, 90(1), 53–76.

McKinsey & Company. (2023). The state of AI in 2023: Generative AI's breakout year. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

Meijerink, J., Bondarouk, T., & Lepak, D. (2021). When employees shape HRM: Exploring the antecedents and outcomes of employee empowerment strategies. Human Resource Management Review, 31(1),

Moreno-Montero, E., Ferradás, M. M., & Freire, C. (2024). Hope and resilience as predictors of coping strategies and perceived stress in university students. Current Psychology. Advance online publication.

Narayanan, L., Menon, S., & Spector, P. E. (1999). Stress in the workplace: A comparison of gender and occupations. Journal of Organizational Behavior, 20(1), 63–73.

Nguyen, Luan-Thanh, Dang, Tri-Quan, and Duc, Dang Thi Viet.(2024).The Dark Sides of AI Advertising: The Integration of Cognitive Appraisal Theory and Information Quality Theory. Social science computer review.

OECD. (2023). Artificial intelligence in work, innovation, productivity and skills. Retrived from https://www.oecd.org/employment/ai-at-work.htm

Paul FA, Banerjee I, Ali A(2023). Psychological capital and well-being beyond the workplace: A conceptual review. Indian Journal of Psychatric Nursing;20:76-84.

PwC. (2024). 25th CEO survey: Winning today's race while runningtomorrow's. https://www.pwc.com/gx/en/issues/c-suite-insights/ceo-survey.html

Schepman, A., & Rodway, P. (2020). Initial validation of the General Attitudes towards Artificial Intelligence Scale. Computers in Human Behavior, 106, 106190

Shahzad, M.B. (2022), Role of Psychological Capital in the Curvilinear Association between Job Autonomy and Job Performance. Perf Improvement Qrtly, 34: 603-625.

Shin, Y., Hur, W. M., & Kang, S. (2020). Employees' perceptions of the impact of artificial intelligence on the workplace: The mediating role of psychological capital. Sustainability, 12(4), 1692.

Snyder, C. R. (2002). Hope Theory: Rainbows in the Mind. Psychological Inquiry.

Tschang, F. T., & Almirall, E. (2021). Artificial intelligence as augmenting automation: Implications for employment. Academy of Management Perspectives, 35(4), 642–659.

Vrontis, D., Chaudhuri, R., & Chatterjee, S. (2022). Adoption of digital technologies by SMEs for sustainability and value creation: Moderating role of entrepreneurial orientation. Sustainability, 14(10), 6149..

Wang, H., Hall, N. C., & Taxer, J. L. (2021). Hope, self-efficacy, and optimism: A systematic review of positive psychological capital as a mediator of work outcomes. Psychological Reports, 124(5), 1741–1776.

Yam, K. C., Tang, P. M., Jackson, J. C., & Gray, K. (2022). The rise of robots increases job insecurity and maladaptive workplace behaviors: Multimethod evidence. Journal of Applied Psychology, 107(7), 1141–1159.

Youssef-Morgan, C. M., & Luthans, F. (2013). Psychological capital theory: Toward a positive holistic model. Advances in Positive Organizational Psychology, 1(1), 145–166.

Youssef, C. M., & Luthans, F. (2007). Positive Organizational Behavior in the Workplace.

Wanberg, C. R., Zhu, J., Kanfer, R., & Zhang, Z. (2012). After the pink slip: Applying dynamic motivation frameworks to the job search experience. Academy of Management Journal, 55(2), 261–284.

WEF (2023a).Future of jobs report 2023. World Economic Forum. Retrieved from https://www3. weforum.org/docs/WEF_Future_of_Jobs_2023.pdf.

World Economic Forum. (2020). The Future of Jobs Report 2020.Retrievedfrom https://www.weforum.org/reports/the-future-of-jobs-report-2020

Xu, G., Xue, M., & Zhao, J. (2023). The Relationship of Artificial Intelligence Opportunity Perception and Employee Workplace Well-Being: A Moderated Mediation Model. International Journal of Environmental Research and Public Health, 20(3).

Zhang, B., Dafoe, A., & Dafoe, A. (2019). Artificial Intelligence: American Attitudes and Trends. University of Oxford.

Zhang Huachu, Liu Shenglan(2015). The impact of unemployment Risk on Floating population consumption. Economic Review.192(02), 68-77

Zhang, M., & Liu, G. (2015). The effect of perceived job insecurity on employees' unethical behavior: The mediating role of unemployment risk perception. Social Behavior and Personality: An International Journal, 43(10)