International Journal of Business and Management Invention (IJBMI)
ISSN (Online): 2319 – 8028, ISSN (Print): 2319 – 801X
www.ijbmi.org || Volume 15 Issue 8 || August, 2026 || PP—118-130

Occupational Health Risks and Wellbeing-Management Practice in Delhi-NCR Infrastructure Work

Naresh Kumar Pathak[1*], Dr. Manoj Kumawat[2], Dr. Ajay Kumar Singhal[3]
[1]*PhD Scholar – Management, School of Management Studies, Sangam University, Bhilwara, Rajasthan, India*
[2]*Associate Professor, School of Management Studies, Sangam University, Bhilwara, Rajasthan, India*
[3]*Sr. Vice President – Transportation Infrastructure, GR Infraprojects Limited, Gurugram*
[*]*Corresponding author*

Abstract
While India's construction and infrastructure industry employs more than 70 million workers, there is sparse literature regarding occupational health and well-being concerns, which does not consider organizational practices. The present study bridges this knowledge gap by developing and validating the Integrated Occupational Health Risk (IOHR) framework among the Delhi-NCR infrastructure workforce comprising four sub-sectors - metro rail, highways/roads, real estate, and industrial corridor construction. The present study, unlike previous literature, simultaneously incorporates three predictor constructs of physical hazard exposure, climate stress exposure (heat + air pollution), and organizational well-being management practices to explain psychological well-being, with a test of whether organizational well-being management moderates the relationship between exposure and well-being. The study design included stratified purposive mixed methods (N = 200; WHO-5 Well-being Index). The results were supportive of five hypotheses on a statistical basis and one thematically: There were significant differences in hazard exposure between sub-sectors ($F(3, 196) = 9.35$, $p < .001$); dual climate exposure imposed an additional independent psychological wellbeing cost ($r = -0.462$, $p < .001$); and in a moderation regression analysis, wellbeing-management significantly moderated the effect of hazards on wellbeing (Hazard × Mgmt $B = 5.64$, $p < .001$; $R^2 = 0.905$, reflecting expected shared-method variance in this single-source, cross-sectional design rather than a generalizable population effect — a finding confirmed by a blue-collar-only robustness check, $R^2 = 0.911$, Section 5.7; see Limitations). Access to wellbeing management was much lower for daily-wage workers than for salaried workers. However, a separate interaction analysis found no significant difference in buffering effects between the two employment forms.
Keywords: *air pollution; construction workers; heat stress; moderated regression; psychological wellbeing; WHO-5.*

Date of Submission: 11-08-2026 Date of acceptance: 24-08-2026

I. INTRODUCTION

The Indian infrastructure sector including metro rail, highways, real estate, and construction of industrial corridors is amongst the largest providers of employment opportunities to manual laborers in the world, employing a total of 70 million people in India (Singh et al., 2024) in an industry that is recognized by the International Labour Organization (2023) as one of the most dangerous industries in the world with respect to health and safety, being responsible for the majority share of 2.93 million work-related deaths in the world per year. There have been tremendous developments in infrastructure in the NCR region which consists of Delhi and the areas surrounding Delhi because of the expansion of metro corridors, construction of national highways, private real estate development projects, and the planning of industrial corridors in the area. These developments have taken place in the wake of two rising environmental stresses that characterize the NCR region – extreme summer temperatures and heavy particulate air pollution after monsoons. These four sub-sectors were chosen since they represent the lion's share of present-day investments in the infrastructure of Delhi-NCR and represent structurally diverse types of hazards – ranging from extended exposure to outdoor hazards on metro and highway construction sites to indoor hazards at real estate and industrial corridor construction sites.

In spite of such significant size of the work force and its potential exposure to both occupational and environmental hazards, empirical studies related to the infrastructure workers of Delhi-NCR area are still limited in three aspects. First of all, current studies are mostly conducted in one location or sub-sector, particularly in construction work (Alam& Khan, 2020), and not across metro, highway, real estate, and industrial corridor sectors. Secondly, the academic literature focuses on physical hazard exposure (Edwards et al., 2022), heat exposure (Krishnamurthy et al., 2017; Venugopal et al., 2016), air pollution exposure (Barthwal et al., 2022), and psychological wellbeing (Deep et al., 2024) as separate strands of research, leaving out their interrelation.

Finally, the studies that explore the management of wellbeing among the infrastructure workers do not evaluate whether it really buffers the effects of hazard and climate exposures.

The study fills these gaps via a single integrated design and asks: (i) is there any systematic pattern of differential hazard exposure in sub sectors; (ii) is there any wellbeing cost associated independently with the dual climate stresses of the region; (iii) is there any wellbeing management practice that moderates the effects of climate/hazard on wellbeing; and (iv) is access to wellbeing management practice shaped more by employment mode rather than the type of work and its sector? In answering these questions, the study makes use of and tests the IOHR model based on Job Demands-Resources theory (Bakker &Demerouti, 2007) and Safety Climate theory (Zohar, 1980).

II. LITERATURE REVIEW

2.1 Occupational Hazard Exposure in Indian and Delhi-NCR Construction

Construction continues to be one of the most dangerous industries worldwide, where workers are exposed to three to four times higher rates of fatalities compared to other sectors and even sixfold higher in developing countries (Edwards et al., 2022). In particular, using Delhi Police First Information Report statistics of 2016-2018, Edwards et al. (2022) found that building collapse and electrical shock were the two leading hazards for construction workers in Delhi, while electricians had over two times greater risks of sustaining fatal injuries compared to unskilled workers. Likewise, Alam and Khan (2020) reported the high incidence of skin diseases, silicosis, and musculoskeletal disorders among construction workers in South Delhi, which was largely due to the insufficient implementation of safety measures and a lack of occupational safety and health (OSH) specialists. Moreover, when mapping the scientific literature on performance measurement of construction safety, Bhagwat and Delhi (2023) found the fragmentation of Indian construction safety research regarding the measurement techniques and limited standardization according to project types. In other parts of India, Banerjee et al. (2015) found considerable dermatological and respiratory morbidity among migrant construction workers in Karnataka, where about a third had respiratory symptoms and low usage of personal protective equipment (PPE).

2.2 Climate-Related Occupational Health Risk: Heat and Air Pollution

Occupational heat stress has been proven as an established occupational hazard amongst Indian outdoor workers. According to Venugopal et al., (2016), occupational heat stress was identified in 18 Indian occupational settings, with 82% of workers being exposed to wet-bulb globe temperature (WBGT) indices higher than suggested thresholds on hot days, with heavy workloads showing a significant increase in the occurrence of heat-stress health problems. Krishnamurthy et al. (2017) reported considerable productivity loss and heat-stress symptoms in direct exposure to heat for workers in the steel industry of southern India. Occupational heat stress has increasingly gained recognition as a hazardous occupational health risk with clinical effects such as acute kidney injury (John &Jha, 2023). Furthermore, there is evidence from other occupations in the construction sector that have been exposed to heat which suggests that structured heat-stress prevention programs lead to better occupational safety and health. Furthermore, there is evidence from other occupations in the construction sector that have been exposed to heat which suggests that structured heat-stress prevention programs lead to better occupational safety and health (Idris et al., 2024).

Hanse et al. (2024), there has been consistent demand for the need for region-specific heat stress research in South and Southeast Asia, especially in cases that do not relate to agriculture. In another independent study, Barthwal et al. (2022) established that there has been considerable damage to the lungs of outdoor workers in Delhi such as construction workers due to air pollution and harsh weather conditions, whereby smoking increases the risk of having lung impairment by four times. While these two bodies of literature on climate change have developed independently of each other, few researchers have combined them in one particular study based on Delhi-NCR's climate calendar despite the area experiencing extremes of the two in the same year. In this study, heat and air pollution have been considered together as one variable, Climate Exposure (section 4.2).

A systematic study on global construction heat stress management strategies (TorbatEsfahani, Awolusi, &Hatipkarasulu, 2024) reveals that the cooling measures and work rest cycles help in reducing heat stress. In addition, Mitchell, Chakraborty, and Basu (2021) have found that heat risk in the city of Delhi has a social disparity, where it affects the lower income wards which also happen to be home to the majority of the workers in the construction industry. The effects of air pollution on the human body through respiration and beyond are well known (Manisalidis, Stavropoulou, Stavropoulos, &Bezirtzoglou, 2020).

2.3 Psychological Wellbeing and Mental Health in Construction Work

There is ample international research on high levels of psychological distress among construction workers. For example, Deep et al. (2024) conducted an online survey of white-collar Indian construction workers during the period of the COVID-19 pandemic and identified various organizational sources of stress for them while recommending a stress-management matrix without a formal moderating effect. Internationally available evidence confirms the extent of the problem: Ling et al. (2025) revealed that insomnia, alcohol dependence, workplace exclusion, and family-to-work conflict strongly predict depression and anxiety among 912 Chinese construction workers; Roy et al. (2024) found that 17.9% of respondents experienced depression, 30.3% - anxiety, and 12% suffered from stress among 502 Bangladeshi construction workers; and Pamidimukkala et al. (2025), reviewing 132 relevant publications, revealed poor working conditions, work overload, and a lack of social support to be the most frequent factors associated with poor mental health. The construction process itself could be an important factor too; in the systematic review on prefabricated construction, there are mostly favorable correlations with the mental wellbeing of workers compared to conventional methods, and that seems to have been due to the organizational factors as well as site conditions instead of the technology used (Fagbenro et al. 2023). Greiner et al. (2022) in their systematic review of interventions for improving mental well-being at an organizational level among construction industry workers found that the evidence base is weak and needs more rigorous designs including moderation-based ones. Burnout — a related but conceptually distinct construct from the general psychological wellbeing measured here — has historically been assessed through the Maslach Burnout Inventory (Maslach& Jackson, 1981), though the present study measures wellbeing via the WHO-5 rather than burnout-specific indicators.

2.4 Organisational Wellbeing-Management Practice and Safety Climate

Safety and wellbeing management practice has been demonstrated to have a significant impact on worker outcomes. In their scoping review of health and safety concerns among aging construction workers, Ranasinghe et al. (2023) found 27 organizational strategies and four mental health interventions to be of use to the aging workforce, while also stating that research into implementation of best practices trails behind identification of said best practices. Fatigue evaluation strategies were also identified through a systematic review to have a positive effect on construction safety performance when supported by organizational practice (Heng et al. 2024). Jung et al. (2020) found both the environmental and psychological work environment characteristics to be strong predictors of safety behavior among construction workers in Korea, while Peng and Zhang (2022) have established that psychological hazards associated with the leader-member relationship have an effect on site-level safety performance. Yadav et al. (2022) found organizational climate variables to be strong predictors of employee well-being despite high occupational stress. However, these studies do not investigate how practice affects the relationship between hazards and well-being and do not examine if access to said practice is influenced by employment arrangement – the focus of the present study.

2.5 Regulatory Context

The Occupation Safety, Health, and Working Condition Code, 2020 (Government of India, 2020) in India combines thirteen old labour legislations into one law relating to factories, mines, and building and construction, laying down responsibilities of employers that include ensuring safe working conditions, conducting yearly health checks, among others. Yet the Code's responsibilities are on the "principal employer," while India's construction labor force works largely on a hierarchical subcontracting system, which is the very structure that is investigated in the employment-type analysis (Section 5.6). This is not a peculiar situation in India since construction labor employed informally and on the basis of subcontracting elsewhere also suffers from poor safety communication and increased risk of injuries (Cong et al., 2022; Ojo et al., 2024). Thus, the employment-structure relationship found in this study (Section 5.6) is likely a structural attribute of subcontracted construction labor markets, rather than an anomaly of India.

2.6 Theoretical Anchoring: Job Demands-Resources and Safety Climate

The IOHR Model is not an isolated theory but an application of two existing theoretical frameworks. First, Job Demands-Resources model (Bakker &Demerouti, 2007) considers hazard and climate exposure to be job demands and wellbeing management to be job resources that mitigate them, whereas the H3 test (Section 5.7) tests for the effect as a buffer, in line with Bakker et al. (2005), in a physically hazardous outdoor work environment as opposed to typical office environment in JD-R studies. Second, the safety climate concept (Zohar, 1980) underlies the assumption that wellbeing management is perceived at the organizational level, which is extended through the psychosocial safety climate research (Idris et al., 2012) and substantiated by the findings from Indian and Chinese construction sites (Guo et al., 2025; M.G. et al., 2025). Together, this literature presents hazard, climate stress and wellbeing as separate streams, and describes wellbeing management instead of testing it as a moderator – a research gap that this study will fill.

III. NOVELTY AND CONTRIBUTION OF THE STUDY

The current study adds to the existing literature in three aspects. First, there are few previous studies which have compared the exposure to hazards between the infrastructure sectors of Delhi-NCR metro rail, highways/roads, real estate and industrial corridors (Alam& Khan, 2020; Edwards et al., 2022); this study compares exposure to hazards among these structurally different sub-sectors within one geographical region and one sampling period. Second, physical exposure to hazards, climate-related stress exposure and psychological wellbeing are examined in one regression model, whereas they were treated as separate research topics in Sections 2.2 and 2.3. Third, following the call by Greiner et al. (2022) and Ranasinghe et al. (2023) for empirical tests of wellbeing management practices' effectiveness, the current study uses wellbeing management perception as a statistical moderator for the hazard-to-wellbeing relationship and checks how this buffering practice is distributed according to the employment status (direct, contractual or daily wage) – an issue with implications for enforcement under the Occupational Safety, Health and Working Conditions Code, 2020 (Section 2.5). These contributions are organised below as the Integrated Occupational Health Risk (IOHR) model, illustrated in Figure 1.

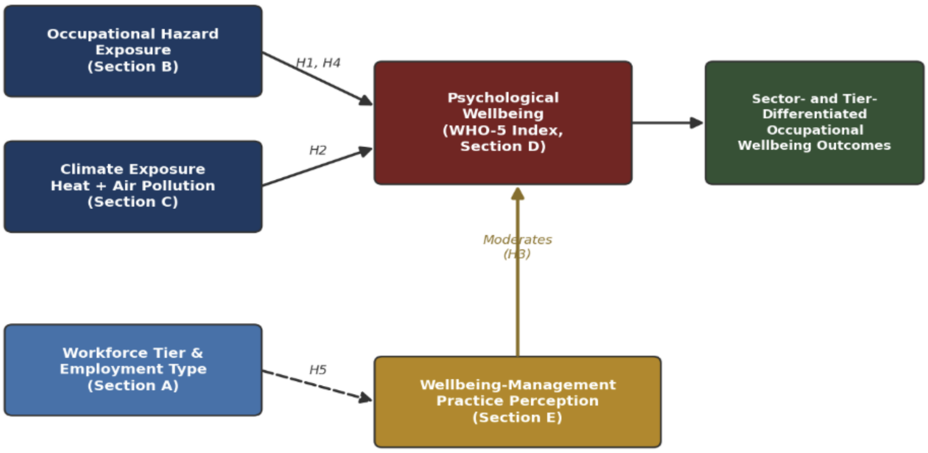

Figure 1. Integrated Occupational Health Risk (IOHR) Conceptual framework

Proposed IOHR framework: hazard exposure (H1, H4) and climate exposure (H2) are expected to negatively predict psychological well-being; workforce status and work engagement determine opportunities for well-being practice management (H5); and well-being practice management acts as a moderator between hazard and well-being (H3).

IV. METHODOLOGY

4.1 Research Design

This study uses an explanatory sequential mixed-method approach which is cross-sectional and stratified based on the seasons of data collection. It uses a structured quantitative survey along with a semi-structured qualitative interview for explanation and triangulation of the results. Stratification of data collection was done between two seasons, that is, the hot season of summer/pre-monsoon season (April–June) and the polluted season of post-monsoon/winter season (October–December). The design is cross-sectional and not longitudinal since all 200 subjects were interviewed only once in either of the seasons (n = 107 for summer/pre-monsoon and n = 93 for post-monsoon/winter, Table 1).

4.2 Study Area, Sampling, and Instrument

The study has been delimited geographically to the region of Delhi-NCR, where data collection was stratified based on the four infrastructure sub-sectors mentioned in Section 3. In each sub-sector, five ongoing construction projects were purposefully chosen after consultation with the respective industries to ensure inclusion of both public agency and private developer sites (20 projects in total), with the site-level gatekeepers helping recruit workers on-site up to a total of about 50 respondents per sub-sector. Out of about 230 workers recruited, 200 respondents (response rate = 87%) answered the questionnaire, with non-responders citing reasons such as lack of time within the working shift. Due to the fact that both sampling sites and respondents have been purposefully and not randomly selected, sample size has been determined mainly by an *a priori* power analysis of the interaction term in the moderated regression model (see Section 4.3; N = 55 minimum, assuming medium effect, power = 80%) rather than by the formula suggested by Cochran (1977) for random samples; *N* = 200 is well over the minimum required for the purpose of planned sub-group comparisons, providing case to predictor ratio of 50:1, which is well above 10:1–20:1 conventionally accepted minimum.

The survey tool is divided into six sections, namely, demographic/employment profile, occupational hazards (12 questions), heat and air pollution exposure (10 questions + WBGT and Central Pollution Control Board (CPCB) Air Quality Index recorded by the enumerator), WHO-5 Well-Being Index (Topp et al., 2015), perception of wellbeing management practice (12 questions), and open-ended questions for a qualitative sub-set (Appendix A). The WHO-5 is pre-validated, while the other two sets, *i.e.*, Occupational Hazard Exposure and Wellbeing Management Perceptions Scales, have been developed by the author based on Edwards et al. (2022), Alam and Khan (2020), and Ranasinghe et al. (2023), and have not undergone piloting, which has been mentioned in the limitations of Section 6.2. Internal consistency (Cronbach's alpha) and dimensionality (PCA) testing have been done for all scales prior to composite formation. Reporting of this observational study follows the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) checklist (von Elm et al., 2007). These two author-developed scales have not been externally validated; findings that rely on them should therefore be treated as exploratory pending confirmatory testing (see Section 6.2 for further discussion of this limitation). Respondents with limited literacy skills underwent oral interviews conducted by trained enumerators in the language of preference (Appendix A). Eligibility criteria included current workers or supervisors aged 18 years and above who were currently employed for at least one month and able to answer the survey in Hindi, English, or any other language chosen by the respondents through translation.

4.3 Data Analysis Plan

Quantitative data were analysed using Python (pandas, SciPy, statsmodels) as follows: reliability analysis; descriptive statistics; Pearson’s correlation among composite indicators; independent samples t-test (Welch’s adjustment) and one-way ANOVA with Tukey HSD test for group comparison; and mean-centred moderated OLS regression to test whether perceived management of wellbeing moderates the impact of hazard/climate on wellbeing. The qualitative interviews were analysed using Braun and Clarke’s (2006) thematic approach.

$$WHO5_i = \beta_0 + \beta_1(Hazard_i) + \beta_2(Climate_i) + \beta_3(Mgmt_i) + \beta_4(Hazard_i \times Mgmt_i) + \varepsilon_i \quad (1)$$

Where: = WHO-5 Well-Being Index score for respondent i

$Hazard_i, Climate_i, Mgmt_i$ =mean-centred composite scores for Hazard Exposure, Climate Exposure, and Wellbeing-Management Perception

$Hazard_i \times Mgmt_i$ = the mean-centred interaction term testing H3

ε_i =error term

Before the regression analysis interpretation, the tests for basic OLS assumptions have been carried out, including homoscedasticity (Breusch-Pagan test) and normality (Shapiro-Wilk test and Q-Q plot) of the residuals, and linearity of the relationship between each predictor and the WHO-5 measure of wellbeing using partial residual plots. The outcomes of these tests are provided in Section 5.7 together with the regression results.

4.4 Qualitative Component

For triangulation and context for the results of the quantitative analysis, semi-structured interviews have been carried out with 16 representatives from the organizations (four each: Project Managers, Environment, Health and Safety (EHS) Officers, HR Managers, Site Engineers) using a purposeful sampling technique. The interviews (30 to 45 minutes) were recorded and transcribed, and their content analysis was done using Braun and Clarke's (2006) approach.

V. RESULTS

This section presents the empirical findings generated from the analytical procedures described in Section 4 and reports the results of the six hypotheses (H1–H6). As H1–H6 test conceptually distinct relationships derived from separate theoretical premises rather than a single family of comparisons, no Bonferroni-type correction was applied; results should nonetheless be interpreted with the awareness that six tests were conducted on the same dataset.

5.1 Sample Profile

Table 1. Sample Composition (N = 200)

Variable	Category	n	%
Infrastructure Sub-Sector	Metro Rail	50	25.0
	Highway/Road	50	25.0
	Real Estate	50	25.0

	Industrial Corridor	50	25.0
Season	Summer/Pre-Monsoon (Heat)	107	53.5
	Post-Monsoon/Winter (Pollution)	93	46.5
Workforce Tier	Blue-collar	142	71.0
	White-collar	58	29.0
Employment Type	Contractual (labour contractor)	89	44.5
	Direct/Permanent	68	34.0
	Daily wage/casual	43	21.5

5.2 Reliability of Measurement Scales

All four multi-item composite scales exceeded the conventional 0.70 threshold for Cronbach's alpha (Cronbach, 1951) (Table 2), supporting their use in subsequent analyses. Construct validity was further assessed via principal component analysis of each item set: applying the Kaiser (1960) criterion (eigenvalue > 1), every scale resolved to a single component (Hazard Exposure: 64.5% variance explained; Climate Exposure: 67.2%; WHO-5: 79.9%; Wellbeing-Management: 55.6%), supporting the unidimensionality assumed when summing items into composite scores. To further validate the factor structure of the two author-developed scales beyond PCA, Confirmatory Factor Analyses (CFA) were conducted. The Hazard Exposure scale showed excellent model fit, $\chi^2(9) = 11.93$, $p = .217$, CFI = .995, TLI = .992, RMSEA = .040. The Wellbeing Management Perceptions scale also showed excellent fit, $\chi^2(54) = 73.25$, $p = .042$, CFI = .984, TLI = .981, RMSEA = .042. These results support the construct validity of both scales beyond the reliability and dimensionality evidence reported above. See Appendix C for the full item-to-construct mapping showing which questionnaire items were summed to form each composite index.

Table 2. Reliability Analysis (Cronbach's Alpha)

Scale	Items (k)	Cronbach's α	Interpretation
Section B - Occupational Hazard Exposure	6	0.889	Good
Section C - Heat/Pollution Exposure	5	0.878	Good
Section D - WHO-5 Well-Being Index	5	0.937	Excellent
Section E - Wellbeing-Management Perception	12	0.927	Excellent

Note.k = Number of items in the scale. $\alpha \geq .70$ has been regarded traditionally as satisfactory reliability (Cronbach, 1951). Internal consistency of Cronbach's alpha is established only by this measure; however, the construct validity of the two author-developed scales (Hazard Exposure, Wellbeing Management Perceptions) has been determined only from principal component analysis described below, demonstrating unidimensionality but not replacing external validation.

5.3 Descriptive Statistics and Correlations

Table 3. Descriptive Statistics for Composite Indices

Index	M	SD	Min	Max
Hazard Exposure Index (1-5)	3.51	0.81	1.67	5.00
PPE Compliance Index (1-5)	3.23	0.87	1.00	5.00
Climate Exposure Index (1-5)	3.32	0.67	1.20	5.00
WHO-5 Wellbeing Score (0-100)	64.88	14.95	28.00	96.00
Wellbeing-Management Score (1-5)	3.04	0.78	1.42	4.83

Note. M = Mean; SD = Standard Deviation; N = 200.

Table 4 reports Pearson correlations among composite indices. Hazard exposure was strongly, negatively associated with wellbeing ($r = -0.737$, $p < .001$), and climate exposure moderately so ($r = -0.462$, $p < .001$), supporting H2. Wellbeing-management perception correlated strongly and positively with wellbeing ($r = 0.751$, $p < .001$).

Table 4. Pearson Correlation Matrix (N = 200)

	Hazard	Climate	WHO-5	Mgmt Score
Hazard Exposure	1.000	0.074	-0.737**	-0.595**
Climate Exposure	0.074	1.000	-0.462**	-0.029
WHO-5 Wellbeing	-0.737**	-0.462**	1.000	0.751**
Mgmt Score	-0.595**	-0.029	0.751**	1.000

** Correlation is significant at the 0.01 level (two-tailed).

Notably, Hazard Exposure and Climate Exposure correlated at only $r = 0.074$ (Table 4), essentially independent of one another. This near-zero association supports the IOHR framework's premise that physical hazard exposure and dual climate-stress exposure are discriminant constructs reflecting separate exposure pathways rather than a single undifferentiated "environmental burden" factor, justifying their treatment as distinct predictors in the moderated-regression model reported in Section 5.7. At the same time, this near-independence sits in tension with the moderated-regression model's very high explanatory power ($R^2 = 0.905$, Section 5.7): two largely independent predictors with only moderate bivariate correlations to wellbeing would not typically combine, even with an interaction term, to explain over 90% of outcome variance. We return to this tension directly in Section 5.7 and Section 6.2, where we consider common-method variance and design-driven contrast as more likely explanations than a genuinely generalisable effect of this magnitude.

5.4 Hazard Exposure across Infrastructure Sub-Sectors (H1)

All four composite scales exceeded the 0.70 threshold for Cronbach's alpha (Cronbach, 1951) (Table 2). Principal component analysis (Kaiser, 1960 criterion) showed each scale resolved to a single component (Hazard Exposure: 64.5%; Climate Exposure: 67.2%; WHO-5: 79.9%; Wellbeing-Management: 55.6% variance explained), supporting unidimensionality. See Appendix C for item-to-construct mapping.

Table 5. Hazard Exposure Index by Infrastructure Sub-Sector (One-way ANOVA)

Sector	Mean (M)	SD	n	95% CI
Highway/Road	3.88	0.80	50	[3.65, 4.11]
Metro Rail	3.64	0.71	50	[3.44, 3.84]
Industrial Corridor	3.42	0.80	50	[3.19, 3.65]
Real Estate	3.10	0.73	50	[2.89, 3.31]

$F(3, 196) = 9.35$, $p < .001$. 95% CIs computed as $M \pm t(0.975, df) \times SE$, using each group's reported *SD* and *n*.

5.5 Workforce Tier Comparison (H4)

Independent-samples *t*-tests showed all four comparisons significant with unusually large effect sizes by conventional benchmarks (Cohen, 1988) (Table 6), supporting H4. Effect sizes of this magnitude ($d > 2.0$) are substantially larger than typical field-survey effects and, combined with the sample's purposive stratification (Section 4.2), should be interpreted as reflecting the sharp contrast built into this sample's design rather than necessarily a generalisable population-level difference of this size.

Table 6. Blue-collar vs. White-collar Comparison (Independent t-test)

Variable	Blue-Collar Mean (M)	White-Collar Mean (M)	t	p	Cohen's d	95% CI (Mean Difference)
Hazard Exposure	3.89	2.58	15.92	< .001	2.43	[1.15, 1.47]
PPE Compliance	2.89	4.06	-12.69	< .001	-1.81	[-1.35, -0.99]
Wellbeing-Management Score	2.67	3.94	-17.50	< .001	-2.56	[-1.41, -1.13]
WHO-5 Wellbeing (%)	58.85	79.66	-15.10	< .001	-2.02	[-23.51, -18.11]

Note. Blue *M* and White *M* = group means; Blue *SD* and White *SD* = group standard deviations; *t* = independent-samples *t*-statistic (Welch's correction applied); *d* = Cohen's *d* effect size (Cohen, 1988). 95% CI (diff) = confidence interval for the Blue-White mean difference, computed as difference ± $t(\text{critical}, df) \times SE$, where $SE = \sqrt{(\text{Blue } SD^2/n_{(\text{Blue})} + \text{White } SD^2/n_{(\text{White})})}$ and *df* is the Welch-Satterthwaite adjusted degrees of freedom for each comparison.

5.6 Wellbeing-Management Score by Employment Type (H5)

One way ANOVA test is highly significant, $F(2, 197) = 205.41$, $p < .001$, $\eta^2 = 0.676$, validating H5, which suggests that employment type has 67.6% of variance on wellbeing management score. All the three post hoc tests for Tukey comparison were significant: Direct/Permanent vs Contractual (difference of mean = 1.03, $p < .001$), Direct/Permanent vs Daily wage/casual (difference of mean = 1.70, $p < .001$) and Contractual vs Daily wage/casual (difference of mean = 0.67, $p < .001$).

Table 7. Wellbeing-Management Score by Employment Type (One-way ANOVA)

Employment Type	M	SD	n	95% CI
Direct/Permanent	3.86	0.46	68	[3.75, 3.97]
Contractual	2.83	0.49	89	[2.73, 2.93]
Daily Wage/Casual	2.16	0.32	43	[2.06, 2.26]

Note. *M* = Mean; *SD* = Standard Deviation; *n* = sample size per group. All pairwise Tukey HSD comparisons are significant at $p < .001$. 95% CIs computed as $M \pm t(0.975, df) \times SE$ per group.

5.7 Moderated Regression: Does Management Practice Buffer Exposure? (H3)

The key theoretical test entailed a mean-centred interaction of moderated ordinary least squares regression of WHO-5 well-being on hazard exposure, climate exposure, well-being management, and interaction between hazard and management. This test produced a statistically significant result and accounted for high levels of variance, $R^2 = 0.905$, $F(4, 195) = 463.2$, $p < .001$. The interaction variable was statistically significant and positively valued ($\beta = 5.64$, $p < .001$), which shows that the well-being management practice weakens the negative effect of hazards on well-being in this purposively sampled dataset (see Section 6.2 for interpretive caution regarding the model's high R^2).

Table 8. Moderated OLS Regression Predicting WHO-5 Wellbeing Score

Predictor	B	SE	t	p	95% CI
Intercept	67.00	0.41	163.46	< .001	[66.19, 67.81]
Hazard Exposure (c)	-8.51	0.52	-16.38	< .001	[-9.53, -7.48]
Climate Exposure (c)	-9.16	0.49	-18.64	< .001	[-10.13, -8.19]
Mgmt Score (c)	10.42	0.54	19.40	< .001	[9.36, 11.48]
Hazard × Mgmt	5.64	0.65	8.70	< .001	[4.36, 6.92]

$R^2 = 0.905$, Adjusted $R^2 = 0.903$, $F(4,195) = 463.2$, $p < .001$.

The variance inflation factors were calculated for all four regression variables to find out if multicollinearity explains the high value of R^2: Hazard Exposure = 1.62, Climate Exposure = 1.01, Management Score = 1.63, Hazard × Management interaction = 1.22, none of which exceeds 5 (the accepted threshold according to Hair et al., 2019), suggesting that multicollinearity is not responsible for explaining the model's variance. Figure 2 shows the simple slopes of the Hazard-Wellbeing association at ±1*SD* Management Score. Beyond the individual *p*-value of the interaction term, a hierarchical regression was conducted in two steps: Step 1 involved entry of Hazard Exposure, Climate Exposure, and Mgmt Score as main effects alone ($R^2 = 0.868$, $F(3, 196) = 428.8$, $p < .001$); in Step 2, the interaction of Hazard with Mgmt was entered ($R^2 = 0.905$, $F(4, 195) = 463.2$, $p < .001$), resulting in $\Delta R^2 = 0.037$, F-change$(1, 195) = 75.75$, $p < .001$, thus supporting that there is a significant improvement in the fit of the model over the one involving main effects alone. The sample size needed to detect a medium-sized effect (Cohen's $f^2 = 0.15$) on an interaction term with three covariates at the alpha level of .05 and power of .80 is 55; much lower than the actual $N = 200$. As a robustness check, given that the sample combines white-collar and blue-collar respondents, the moderated regression was re-estimated on the blue-collar subsample alone ($n = 142$). The model retained comparable explanatory power ($R^2 = 0.911$, $F(4, 137) = 351.7$, $p < .001$), and the interaction term remained significant and similarly sized ($\beta = 4.85$, $p < .001$). This indicates that the model's high explanatory power is not an artifact of combining occupationally distinct subgroups, and that the moderation effect replicates within the more vulnerable blue-collar subgroup specifically.

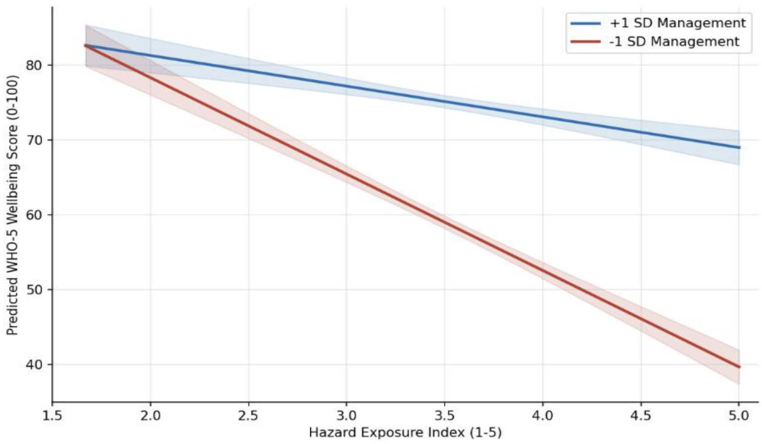

Figure 2. Simple slopes of the Hazard Exposure-WHO-5 Wellbeing relationship at +1 SD and -1 SD of Management

Score (Climate Exposure held at its sample mean), illustrating the buffering effect of the significant Hazard × Management interaction reported in Table 8. Shaded bands represent 95% confidence intervals around each predicted slope, computed from the fitted regression model.

5.8 Findings from Semi-Structured Interviews

In addition to the quantitative findings, semi-structured interviews were carried out with 16 organizational representatives (Project Managers, EHS representatives, site engineers, HR managers) associated with Delhi-NCR infrastructure projects. These interviews were carried out either in Hindi or in English, recorded and transcribed verbatim, and Hindi transcriptions were translated into English by the researcher herself. Only one researcher was responsible for coding the interview transcripts until thematic saturation, which was reached without any additional coder; therefore, the lack of inter-coder reliability due to the absence of independent coding procedure can be seen as one of the study's limitations (Section 6.2). The interviews aimed at obtaining the views of organizations about their OHR, wellbeing management approach and implementation challenges. As all interview participants were representatives of the management side and not workers, the views gathered might be different from the perspective of workers, which is especially important for Theme 4. Four themes, derived through thematic analysis in accordance with Braun and Clarke (2006), were identified.

Theme 1: Occupational hazards differ substantially across infrastructure sub-sectors.
Occupational hazards were noted to differ between the sub-sectors of the infrastructure industry. The representatives of the highways and metro rails mentioned constant exposure to the operation of heavy machines, vehicles, excavation, and outside work as factors leading to occupational hazards. Conversely, the representatives of the real estate construction projects found it relatively easy to monitor and control occupational hazards due to structured construction sites and better supervision. As one safety officer stated:

"Highway construction involves continuous movement of heavy equipment and traffic, making hazard control much more difficult than in enclosed building projects."

These results from the qualitative analysis also confirm the result obtained quantitatively that hazard exposure was significantly higher for highway and metro projects compared to real estate projects (Section 5.4).

Theme 2: Climate-related occupational risks as an operational challenge.
All participants, regardless of the nature of their projects, were concerned about extreme heat during summer and poor air quality after monsoon. They felt that exposure to these environmental hazards led to exhaustion, dehydration, breathing problems, lower productivity, and greater physical stress. The EHS officer said:

"During peak summer, productivity falls after midday unless additional hydration breaks and shaded rest areas are provided."

These accounts reinforce the statistically significant negative association observed between climate exposure and psychological wellbeing (Section 5.3).

Theme 3: Organisational wellbeing practices are strongly influenced by employment arrangement.
All interviewees mentioned the difference in the accessibility of wellbeing programmes in the organisation depending on the type of employment. Permanent employees enjoyed better health benefits, safety training, medical checkups, and other organisational advantages than contract and daily wage employees. An HR manager noted:

"Permanent employees are automatically included in our health programmes, whereas many welfare activities for contractual workers depend on individual labour contractors."

These results are very similar to those obtained through the quantification method, which demonstrated that the wellbeing-management index was much higher for direct workers compared to contractual workers and daily wage earners (Section 5.6).

Theme 4: Implementation gaps despite formal safety policies.
Although organisations reported maintaining formal occupational health and safety policies, participants acknowledged persistent challenges in translating policy into consistent workplace practice. Labour turnover, subcontracting arrangements, language diversity, resource constraints, and production pressures were identified as major barriers to effective implementation. A safety manager noted:

"The biggest challenge is maintaining consistent safety practices when multiple subcontractors operate simultaneously under tight project deadlines."

Participants also identified mental health support as one of the least developed components of organisational wellbeing programmes, highlighting a substantial implementation gap despite the existence of formal health and safety policies. These findings provide qualitative evidence consistent with the implementation gap proposed in the IOHR framework (H6), though this remains a thematic, non-statistical form of support.

Summary: The result from the thematic analysis revealed that organisation stakeholders perceived the interrelatedness of the factors of hazard, climate threats, and work arrangement in relation to wellbeing. The finding provided thematic but not statistical support for the exploratory hypothesis H6 (Table 10).

5.9 Does Employment Type Moderate the Buffering Effect? A Three-Way Interaction Test

The Abstract and Conclusion imply that the buffering effect established in Section 5.7 occurs differently depending on the employment status. To verify this claim, a three-way interaction of Hazard, Mgmt and Employment Type was included into the moderated regression model (see Table 8), while Climate Exposure was kept as a covariate. The hierarchical nested-model *F*-test compared the new model (R^2 = 0.908) to its corresponding variant without the three-way interaction (R^2 = 0.908). The three-way interaction had no

significant influence on model fitting, $\Delta R^2 < 0.001$, $F(2, 187) = 0.12$, $p = .883$. Thus, the buffering effect of hazard exposure is similar across all types of employment.
To verify the result, the Hazard × Mgmt interaction was estimated again for each employment-type subsample (Table 9). It remains significant only for Direct/Permanent and Contractual workers, while for Daily-wage/casual workers ($n = 43$) this interaction is insignificant — probably due to insufficient statistical power rather than opposite effect, as the coefficient estimate of this group is largest in absolute value.

Table 9. Hazard × Mgmt Interaction Re-Estimated within Employment-Type Subgroups

Employment Type	n	B	SE	t	p	R² (subgroup model)
Direct/Permanent	68	3.76	1.60	2.35	.022	0.744
Contractual	89	3.71	1.51	2.45	.016	0.885
Daily wage/casual	43	5.92	3.73	1.59	.121	0.936

Note.B, SE, t, and p are the coefficients of the interaction between Hazard and Mgmt obtained using mean-centred moderated regression analysis on each employment-type group (same form as Table 8). R^2 represents the R^2 for the particular model for each subgroup.

VI. DISCUSSION

The findings support all six hypotheses (Table 10), providing empirical evidence for the Integrated Occupational Health Risk (IOHR) framework proposed in Section 3.

Table 10. Summary of Hypothesis Testing

Hypothesis	Test	Result
H1: Hazard exposure varies by sub-sector	One-way ANOVA	Supported
H2: Climate exposure negatively predicts wellbeing	Pearson correlation	Supported
H3: Management practice moderates exposure-wellbeing link	Moderated OLS regression	Supported
H4: Blue-collar workers report lower protection/wellbeing	Independent t-test	Supported
H5: Employment type predicts management-practice access	One-way ANOVA	Supported
H6: Implementation gap (policy vs. on-ground reach)	Thematic analysis of semi-structured interviews	Supported

Hazard gradient in sectors (5.4) is an extension of the study by Edwards et al. (2022), wherein electricians were found to have more than double the probability of suffering fatal injuries than unskilled laborers. In the same way, non-fatal exposure risk is found to be higher in linear infrastructure development works – highways and metro tracks, compared to vertical infrastructure development - real estate, which is not captured in single-sector studies of Delhi-NCR area (Alam& Khan, 2020).
Climate-wellbeing gradient (5.3) is an extension of studies by Barthwal et al. (2022) on pulmonary impairment and Venugopal et al. (2016) and Krishnamurthy et al. (2017) on heat stress.
The moderation result (section 5.7) addresses the evaluation gap highlighted by Greiner et al. (2022), whereas the employment type-based slope pattern (section 5.6) reveals that India's subcontracting system rather than sectors and occupations is what constrains well-being management coverage, considering the enforcement design of the Occupational Safety, Health and Working Conditions Code, 2020.
The qualitative insights (section 5.8) reveal that subcontracting complexities and poor mental health services lead to the implementation gap (hypothesis 6). The three-way interaction test (section 5.9) revealed that the effect itself is no less strong for the daily-wage workers; they only have less access to it (section 5.6).

6.1 Theoretical and Practical Implications

Theoretically, the results shift the focus of wellbeing management practice from being a parallel welfare strategy to being a risk-buffering moderator, incorporating the three forms of risk into one testable model. On the practical level, due to the fact that accessibility to the practice of wellbeing management tends to be dictated more by the nature of employment than by the industry or occupation, regulatory measures and corporate social responsibility practices aimed solely at the main employer would probably not be enough.

6.2 Limitations

There are several limitations associated with the current study. First, due to the cross-sectional design — despite the seasonal stratification employed — no causal relationship can be established between hazard exposure, climate stressors, wellbeing-management practice, and psychological wellbeing. Second, although some objective measurements were used (WBGT, CPCB Air Quality Index), the study also relied on self-reported measures that may be subject to recall bias and socially desirable responding. Relatedly, the Occupational Hazard Exposure and Wellbeing-Management Perception scales were author-developed and not pilot-tested, so their construct validity could not be established prospectively (Section 4.2). While their internal consistency and dimensionality were confirmed post hoc (Section 5.2), and a Confirmatory Factor Analysis further supported both scales' factor structure, formal pilot testing on an independent sample would still strengthen this evidence. Third, the study used a stratified purposive sampling method, so neither construction sites nor respondents were randomly selected.

Fourth, the moderated regression model (Section 5.7) accounted for an unusually high proportion of variance (R^2 = 0.905). Because predictors and the criterion measure were drawn from the same self-report instrument, Common Method Variance (CMV; Podsakoff et al., 2003) and multicollinearity are both plausible concerns. Variance Inflation Factors (1.01–1.63) ruled out multicollinearity, and Harman's single-factor test found no evidence of CMV; however, neither test can rule out CMV arising simply from predictors and criterion being collected from the same respondents at the same time. A robustness check restricting the regression to the blue-collar subsample alone (n = 142) produced a comparable R^2 (0.911), which rules out occupational-tier heterogeneity as the source of the model's high explanatory power and instead points toward shared-method variance — rather than sample composition — as the more likely driver. Compounding this, the purposive selection of sites and respondents to maximize contrast between sectors and employment types (Section 4.2) mechanically inflates between-group differences, contributing to both the large effect sizes in Section 5.5 and the high R^2 in Section 5.7. We therefore consider R^2 = 0.905 to be substantially inflated relative to what an equivalent random-sample, multi-source design would likely produce, and do not treat it as a validated or generalizable estimate of the true variance explained in the Delhi-NCR infrastructure sector. Future research using random sampling, multi-source data (e.g., supervisor ratings or objective health outcomes), and longitudinal designs is needed to establish the size — rather than merely the direction and significance — of this relationship.

VII. CONCLUSION

This study offers critical data to aid in the design of organisational well-being management and enhance regulation enforcement in India's infrastructural industry that relies on extensive sub-contracting practices. For example, the fact that access to well-being management depends on the nature of employment rather than employment type or industry (Section 5.6) implies that provisions under the Occupational Safety, Health and Working Conditions Code, 2020 – which presently focus on the principal employer – might need to be expanded to include the contractor and subcontractor of labour to cover daily wage and contractual labourers who register the lowest scores for well-being management and have little protection against hazard well-being costs. IOHR presents a theoretical and operational framework to achieve integration of occupational safety, resilience against the changing climate and employee well-being in the context of infrastructural projects.

Declarations

Ethics Approval and Consent to Participate: This study was conducted in accordance with the ethical research guidelines of Sangam University and was approved by the Sangam University Institutional Ethics Committee. All participants provided informed consent before participation.

Funding: This research received no external funding.

Conflict of Interest: The author declares no conflict of interest.

Data Availability Statement: The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

Code Availability: The Python analysis scripts (pandas, SciPy, statsmodels) used to generate the reported statistics are available upon request.

CRediT Author Contribution Statement: NareshPathak: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing.

Acknowledgement: The author gratefully acknowledges the guidance, encouragement, and valuable support received from mentors and colleagues throughout the course of this research. Sincere thanks are extended to all participants who generously contributed their time and insights, making this study possible. The author also acknowledges the institutional support and resources that facilitated the successful completion of this work.

REFERENCES

[1] Alam, S., & Khan, N. U. (2020). Occupational health and working conditions of construction workers in South Delhi. Excellence International Journal of Education and Research, 9(6), 59-66.

[2] Bakker, A. B., Demerouti, E., &Euwema, M. C. (2005). Job resources buffer the impact of job demands on burnout. Journal of Occupational Health Psychology, 10(2), 170-180. https://doi.org/10.1037/1076-8998.10.2.170

[3] Bakker, A. B., &Demerouti, E. (2007). The job demands-resources model: State of the art. Journal of Managerial Psychology, 22(3), 309-328. https://doi.org/10.1108/02683940710733115

[4] Banerjee, M., Kamath, R., Tiwari, R. R., & Nair, N. P. S. (2015). Dermatological and respiratory problems in migrant construction workers of Udupi, Karnataka. Indian Journal of Occupational and Environmental Medicine, 19(3), 125–128. https://doi.org/10.4103/0019-5278.174001

[5] Barthwal, V., Jain, S., Babuta, A., Jamir, C., Sharma, A. K., & Mohan, A. (2022). Health impact assessment of Delhi's outdoor workers exposed to air pollution and extreme weather events: An integrated epidemiology approach. Environmental Science and Pollution Research, 29, 44746-44758. https://doi.org/10.1007/s11356-022-18886-9

[6] Bhagwat, K., & Delhi, V. S. K. (2023). Review of construction safety performance measurement methods and practices: A science mapping approach. International Journal of Construction Management, 23(4), 729-743. https://doi.org/10.1080/15623599.2021.1924456

[7] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

[8] Cochran, W. G. (1977). Sampling techniques (3rd ed.). New York, NY: John Wiley & Sons. ISBN: 978-0-471-16240-7

[9] Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Routledge. https://doi.org/10.4324/9780203771587

[10] Cong, W., Xue, H., Liang, H., Su, Y., & Zhang, S. (2022). Informal safety communication of construction workers: Conceptualization and scale development and validation. Frontiers in Psychology, 13, 825975. https://doi.org/10.3389/fpsyg.2022.825975

[11] Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16(3), 297-334. https://doi.org/10.1007/BF02310555

[12] Deep, S., Sonkar, N., Yadav, P., Vishnoi, S., Bhoola, V., & Kumar, A. (2024). Factors influencing the mental health of white-collar construction workers in developing economies: Analytical study during the COVID-19 pandemic in India. Journal of Construction Engineering and Management, 150(7), 04024058. https://doi.org/10.1061/JCEMD4.COENG-14015

[13] Edwards, P., Yadav, S., Bartlett, J., & Porter, J. (2022). They built this city - Construction workers injured in Delhi, India: Cross-sectional analysis of First Information Reports of the Delhi Police 2016-2018. Injury Epidemiology, 9(1), 23. https://doi.org/10.1186/s40621-022-00388-4

[14] Fagbenro, R. K., Sunindijo, R. Y., Illankoon, C., &Frimpong, S. (2023). Influence of prefabricated construction on the mental health of workers: Systematic review. European Journal of Investigation in Health, Psychology and Education, 13(2), 350-366. https://doi.org/10.3390/ejihpe13020026

[15] Government of India. (2020). The Occupational Safety, Health and Working Conditions Code, 2020 (Act No. 37 of 2020). Ministry of Labour and Employment. https://www.indiacode.nic.in/handle/123456789/22041

[16] Greiner, B. A., Leduc, C., O'Brien, C., Cresswell-Smith, J., Rugulies, R., Wahlbeck, K., Abdulla, K., Amann, B. L., CergaPashoja, A., Coppens, E., Corcoran, P., Maxwell, M., Ross, V., de Winter, L., Arensman, E., &Aust, B. (2022). The effectiveness of organisational-level workplace mental health interventions on mental health and wellbeing in construction workers: A systematic review and recommended research agenda. PLOS ONE, 17(11), e0277114. https://doi.org/10.1371/journal.pone.0277114

[17] Guo, N., Liu, Y., Yu, S., Xia, B., & Cong, W. (2025). Examining the role of psychological symptoms and safety climate in shaping safety behaviors among construction workers. Behavioral Sciences, 15(1), 66. https://doi.org/10.3390/bs15010066

[18] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning. ISBN: 9789353501358

[19] Hanse, B., Alam, S. M., Krishnan, S., et al. (2024). Occupational heat stress and its health impacts - An overview of research status and need for further research in Southeast Asia with special emphasis on mitigation strategies in North East India. International Journal of Biometeorology, 68, 2477-2493. https://doi.org/10.1007/s00484-024-02765-8

[20] Heng, P. P., Yusoff, H. M., &Hod, R. (2024). Individual evaluation of fatigue at work to enhance the safety performance in the construction industry: A systematic review. PLOS ONE, 19(2), e0287892. https://doi.org/10.1371/journal.pone.0287892

[21] Idris, M. A., Dollard, M. F., Coward, J., &Dormann, C. (2012). Psychosocial safety climate: Conceptual distinctiveness and effect on job demands and worker psychological health. Safety Science, 50(1), 19-28. https://doi.org/10.1016/j.ssci.2011.06.005

[22] Idris, M. A., Markham, C., Mena, K. D., &Perkison, W. B. (2024). Examining management and employees' perceptions of occupational heat exposure and the effectiveness of a heat stress prevention intervention on safety and well-being among natural gas construction workers: A qualitative field-based study. International Journal of Environmental Research and Public Health, 21(9), 1255. https://doi.org/10.3390/ijerph21091255

[23] International Labour Organization. (2023). A call for safer and healthier working environments. ILO, Geneva. Retrieved on 26 November 2025, fromhttps://www.ilo.org/resource/news/nearly-3-million-people-die-work-related-accidents-and-diseases

[24] John, P., &Jha, V. (2023). Heat stress: A hazardous occupational risk for vulnerable workers. Kidney International Reports, 8(7), 1329-1331. https://doi.org/10.1016/j.ekir.2023.05.024

[25] Jung, M., Lim, S., & Chi, S. (2020). Impact of work environment and occupational stress on safety behavior of individual construction workers. International Journal of Environmental Research and Public Health, 17(22), 8304. https://doi.org/10.3390/ijerph17228304

[26] Kaiser, H. F. (1960). The application of electronic computers to factor analysis. Educational and Psychological Measurement, 20(1), 141-151. https://doi.org/10.1177/001316446002000116

[27] Krishnamurthy, M., Ramalingam, P., Perumal, K., Kamalakannan, L. P., Chinnadurai, J., Shanmugam, R., Srinivasan, K., &Venugopal, V. (2017). Occupational heat stress impacts on health and productivity in a steel industry in Southern India. Safety and Health at Work, 8(1), 99-104. https://doi.org/10.1016/j.shaw.2016.08.005

[28] Ling, Z., Zheng, K., Yu, J., Xu, Y., Zhang, M., Liu, Y., Wang, J., Sheng, Y., Liu, X., & Huang, L. (2025). Construction workers' depression, anxiety, stress, and risk factors in China: A cross-sectional study. Journal of Global Health, 15, 04167. https://doi.org/10.7189/jogh.15.04167

[29] M.G., S. P., K.S., A., Rajendran, S., &Sen, K. N. (2025). The role of psychological contract in enhancing safety climate and safety behavior in the construction industry. Journal of Engineering, Design and Technology, 23(4), 1189-1210. https://doi.org/10.1108/JEDT-07-2023-0315

[30] Manisalidis, I., Stavropoulou, E., Stavropoulos, A., &Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: A review. Frontiers in Public Health, 8, 14. https://doi.org/10.3389/fpubh.2020.00014

[31] Maslach, C., & Jackson, S. E. (1981). The measurement of experienced burnout. Journal of Organizational Behavior, 2(2), 99-113. https://doi.org/10.1002/job.4030020205

[32] Mitchell, B. C., Chakraborty, J., &Basu, P. (2021). Social inequities in urban heat and greenspace: Analyzing climate justice in Delhi, India. International Journal of Environmental Research and Public Health, 18(9), 4800. https://doi.org/10.3390/ijerph18094800

[33] Ojo, T. O., Onayade, A. A., &Naicker, N. (2024). Preventing occupational injuries in the informal construction industry: A study protocol for the development of a safety education intervention for bricklayers and carpenters in Osun State, Nigeria. Frontiers in Public Health, 12, 1464797. https://doi.org/10.3389/fpubh.2024.1464797

[34] Pamidimukkala, A., Kermanshachi, S., &Almaskati, D. N. (2025). Mental health in construction industry: A global review. International Journal of Environmental Research and Public Health, 22(5), 802. https://doi.org/10.3390/ijerph22050802

[35] Peng, J., & Zhang, Q. (2022). Safety performance assessment of construction sites under the influence of psychological factors: An analysis based on the extension cloud model. International Journal of Environmental Research and Public Health, 19(22), 15378. https://doi.org/10.3390/ijerph192215378

[36] Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., &Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

[37] Ranasinghe, U., Tang, L. M., Harris, C., Li, W., Montayre, J., de Almeida Neto, A., & Antoniou, M. (2023). A systematic review on workplace health and safety of ageing construction workers. Safety Science, 167, 106276. https://doi.org/10.1016/j.ssci.2023.106276

[38] Roy, N., Paul, K. D., Tamanna, S. S., Paul, A. K., Almerab, M. M., &Mamun, M. A. (2024). Prevalence and risk factors of depression, anxiety, and stress among the Bangladeshi construction workers: A cross-sectional study. PLOS ONE, 19(8), e0307895. https://doi.org/10.1371/journal.pone.0307895

[39] Singh, A. K., Aljohani, A., Shakor, P., Awuzie, B. O., Uddin, S. M. J., &Shivendra, B. T. (2024). Study on safety health of construction workers at workplace: A sustainable perspective approach. *Frontiers in Built Environment*, 10, 1451727.https://doi.org/10.3389/fbuil.2024.1451727

[40] Topp, C. W., Østergaard, S. D., Søndergaard, S., &Bech, P. (2015). The WHO-5 Well-Being Index: A systematic review of the literature. Psychotherapy and Psychosomatics, 84(3), 167-176. https://doi.org/10.1159/000376585

[41] TorbatEsfahani, M., Awolusi, I., &Hatipkarasulu, Y. (2024). Heat stress prevention in construction: A systematic review and meta-analysis of risk factors and control strategies. International Journal of Environmental Research and Public Health, 21(12), 1681. https://doi.org/10.3390/ijerph21121681

[42] Venugopal, V., Chinnadurai, J., Lucas, R., &Kjellstrom, T. (2016). Occupational heat stress profiles in selected workplaces in India. International Journal of Environmental Research and Public Health, 13(1), 89. https://doi.org/10.3390/ijerph13010089

[43] von Elm, E., Altman, D. G., Egger, M., Pocock, S. J., Götzsche, P. C., &Vandenbroucke, J. P. (2007). The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: Guidelines for reporting observational studies. The Lancet, 370(9596), 1453-1457. https://doi.org/10.1016/S0140-6736(07)61602-X

[44] Yadav, S., Tiwari, T., Yadav, A. K., Dubey, N., Mishra, L. K., Singh, A. L., &Kapoor, P. (2022). Role of workplace spirituality, empathic concern and organizational politics in employee wellbeing: A study on police personnel. Frontiers in Psychology, 13, 881675. https://doi.org/10.3389/fpsyg.2022.881675

[45] Zohar, D. (1980). Safety climate in industrial organizations: Theoretical and applied implications. Journal of Applied Psychology, 65(1), 96-102. https://doi.org/10.1037/0021-9010.65.1.96