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AI Anxiety, Digital Overload, and Technostress in a Polycrisis Context: A Moderated Mediation Study of Emotional Exhaustion and Psychological Well-Being Across Four Industry Sectors

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Abstract

Background: The concurrent occurrence of AI-induced disruption, rapid post-pandemic digitalization, and macroeconomic instability has fundamentally reshaped the psychological demands of modern work, creating a polycrisis. Staff members in digital work environments experience rising AI anxiety, digital overload, and technostress, but how such polycrisis-related demands impact PWB through these mechanisms and the extent to which personal resources may act as a shield against such an effect has not been comprehensively understood yet. Based on the assumptions of the Job Demands-Resources model, the present study examines a model of moderated mediation, wherein emotional exhaustion mediates the demand-PWB association, and psychological capital (PsyCap) moderates and strengthens PWB.

Methods: Cross-sectional surveys using six psychometric scales were conducted among 340 full-time workers from sectors such as IT, Health care, Education, and Banking/Finance. Hypotheses regarding the structure were validated using CB-SEM with 5,000 bias corrected bootstraps whereas sector-specific MGA and fsQCA identified configurations related to lower PWB.

Results: All three job demands were able to predict emotional exhaustion: AI anxiety ($\beta = 0.396$, $p < 0.001$), digital overload ($\beta = 0.333$, $p < 0.001$), and technostress ($\beta = 0.318$, $p < 0.001$), explaining 32.1% of the variance. Emotional exhaustion fully mediated the influence of all three variables on PWB ($\beta = -0.434$, $p < 0.001$) through bootstrapped indirect effects. PsyCap had a significant direct effect on PWB ($\beta = 0.460$, $p < 0.001$) for all four sectors. Through MGA, sector-specific differences emerged with regard to AI anxiety, which was more important in the IT sector, digital overload in Healthcare and Banking/Finance, and technostress in the Education sector. In fsQCA, digital overload was found as a necessary condition for low PWB (consistency = 0.909), where there were three configurations, each required low PsyCap as a boundary condition (solution consistency = 0.841, coverage = 0.573).

Conclusions: Demands resulting from polycrisis are linked to low PWB mainly because of emotional exhaustion, and demand salience differs significantly across sectors. Low PsyCap functions as a universal boundary condition for low levels of well-being. Organisations should prioritise PsyCap development as an industry-invariant approach in addition to demand management, which takes into account the characteristics of the job.

Keywords: polycrisis; AI anxiety; digital overload; technostress; psychological well-being; emotional exhaustion; psychological capital

Background

The psychological structure of modern work is undergoing fundamental destabilization. The combination of three forces: AI-enabled automation, rapid digitalization following the pandemic, and macroeconomic uncertainty, has created It is known among experts as polycrisis, a state where various crises interact and their compounded effects surpass their separate effects [1,2]. What distinguishes this polycrisis from other economic and technological disruptions in history [3,4] is the structural simultaneity of its elements. For

workers within the digitally intense industries, which are more vulnerable to the confluence of technological speed and occupational needs, this combination poses a major psychological problem [5].

There are three distinct yet structurally related forms of psychological pressure that have come into focus in the polycrisis framework. AI anxiety, which arises due to the potential danger of artificial intelligence being able to affect one's job security and performance capacity, is a distinct type of work stress different from conventional job insecurity [6,7]. It has been estimated by the World Economic Forum [8] that around one billion jobs would be disrupted due to AI and automation by 2030, and people in the IT, healthcare, education, and banking industry would be the pioneers in terms of occupation [5]. However, the growing number of digital communication channels has created conditions of digital overload that can be described as an excess of mental load on a person [9,10]. Technostress, which results from constant demands to adjust to changing digital systems, creates an additional psychological strain due to fear of obsolescence of skills and uncertainty about one's role [22,30]. These three sources of stress combine to produce a composite psychological burden that does not have a precedent in occupational health literature.

The psychological outcomes from these kinds of demands have been grounded on the theory of the Job Demands-Resources (JD-R) Theory [11,12], which conceptualizes job demands as the work-related conditions that require substantial cognitive, emotional, or physical resources, and job resources, which reduce the demands and attain the objectives. When the demands continually exceed the available resources, the depletion process ends in emotional exhaustion, which is the ultimate determinant of occupational burnout [13]. The occurrence of emotional exhaustion has also been found to be one of the proximal causes for the impact of stressors on PWB [14,31]. The multidimensional PWB model proposed by Ryff [15,16], which includes various factors including autonomy, mastery of the environment, personal development, positive interpersonal relationships, purpose in life, and self-acceptance, depicts the holistic approach of employee thriving, and it is much more than simply alleviating symptoms. JD-R theory's applicability to polycrisis-related pressures is hence an explanation that is both theoretically sound and practically significant.

In the demand-resource approach, psychological capital (PsyCap), "the mental state of an individual which incorporates key dimensions including hope, self-efficacy, resilience, and optimism" [17,19], has been considered as a critical personal capacity that may help reduce the adverse health effects process. Employees with high PsyCap have goal-oriented agency, task appraisal confidence, adversity resilience, and positive expectancy of outcomes in challenging work scenarios psychological traits that can both act as a buffer between exhaustion and wellbeing and directly enhance PWB regardless of challenge exposure [18,34].

It is well established that PsyCap is related to reduced occupational stress and increased job satisfaction in different professional environments [20], and the existing literature provides evidence that this construct may be improved through specific intervention programs with an impact on employees' wellbeing [21]. However, empirical information

concerning the involvement of PsyCap in the demand-exhaustion-wellbeing process in times of polycrisis is lacking.

Previous studies have considered AI anxiety [6], technostress [22], and digital overload [23] as individual stressors in isolation from each other, leading to fragmented findings that do not reflect the cumulative effects that arise when considering them together in the context of a polycrisis. Crucially, no research has attempted to jointly study all three stressors together as a coherent polycrisis-specific job demand cluster and their combined mediated path toward PWB. Moreover, almost all previous studies are conducted with a sector-specific design, neglecting the huge heterogeneity in demand salience across different sectors [26]. A healthcare professional and IT engineer could both be experiencing digital overload; however, the psychological mechanisms and magnitude involved are completely different something that can never be seen through a sector-specific study. Finally, previous studies that mostly rely on symmetric and covariance-based analysis (e.g., SEM, regression) also lack an approach to identifying the set of conditions that are enough to result in low PWB, an asymmetric and set-theoretic question best addressed by fsQCA [24,25,44].

These overlapping gaps are bridged by four key contributions in this research paper. First, the research simultaneously analyzes the phenomenon of AI Anxiety, Digital Overload and Technostress as a demand cluster induced by polycrisis and the mediation of their pathway to PWB via emotional exhaustion in a CB-SEM framework. Whereas a full modelling of polycrisis as an interactive construct of a second order is beyond the scope of the cross-sectional research, the simultaneous assessment of three interrelated demands would be a substantial step towards measuring the multi-faceted psychological load caused by polycrisis in organizations. Second, it looks into PsyCap both as a moderator of the relationship between exhaustion and PWB and as an independent predictor of PWB to elaborate on its protective role in detail. Third, it utilizes the permutation-based method of MGA in four digitally intensive sectors of the economy: IT, Healthcare, Education, and Banking/Finance to reveal sector-specific demands saliency and structural path heterogeneity. Finally, the fsQCA is used to uncover configurations of polycrisis-induced conditions that would be enough for low PWB. The combination of these contributions expands JD-R theory into the polycrisis era and delivers sector-differentiated occupational health knowledge while being for the global sustainable goals 3 and 8.

Theoretical Foundation and Development of Hypotheses

Job Demands-Resources Theory and Polycrisis-Induced Demands

The JD-R framework sees demands as the physically, cognitively, socially, and organizationally effortful parts of work while resources are seen as multi-functional means to reduce demand impact and achieve goals [11]. Persistent pressure to perform gradually depletes cognitive and affective resources via the health-damaging process, resulting in

burnout [12,27]. AI anxiety, digital overload, and technostress are three separate but related polycrisis-induced demands following the health impairment process [3,28].

Fear of AI causes continual cognitive evaluation of danger, occupying cognitive resources [6,29]. Information overload involves information processing activities that surpass cognitive limitations, resulting in attention depletion [9,23]. The phenomenon of technostress involves role demands resulting from stress created by the need to adapt continually to changing digital systems [22,30]. Based on the theoretical assumptions of the JD-R model, this study proposes the following hypotheses:

H1: AI anxiety is positively associated with emotional exhaustion.

H2: Digital overload is positively associated with emotional exhaustion.

H3: Technostress is positively associated with emotional exhaustion

Emotional Exhaustion as Mediator

Emotional exhaustion, defined as the state of being emotionally drained [13], is the mechanism through which the buildup of demand overload results in reduced PWB. If the psychological resources of workers are constantly overdrawn as a result of polycrisis demands, their ability to engage in autonomous action, positive relationships, and meaningful actions basic dimensions in the PWB framework proposed by Ryff [15], is compromised [31,32]. In line with health impairment process in the JD-R model [11,27], we predict that:

H4: Emotional exhaustion is negatively associated with psychological well-being.

H6 is introduced here before H5 since it logically follows the theoretical order of the JD-R model's health impairment process.

H6: Emotional exhaustion mediates the relationships between polycrisis-induced job demands (AI anxiety, digital overload, technostress) and psychological well-being.

Psychological Capital as Moderator and Resource

PsyCap is an individual-level resource in the context of JD-R theory, proposed as a buffer of the demand-depletion path [17,19]. The qualities of high PsyCap people include having goal-oriented agency, self-assurance, ability to bounce back from setbacks, and optimism, which could potentially weaken the chain between fatigue and lower well-being [18,33]. In addition to buffering, PsyCap also positively enhances PWB as a resource independent of the current demands level [34,35]. We predict:

H5: PsyCap serves as a moderating factor between emotional exhaustion and psychological well-being, such that the negative effect of exhaustion on PWB is weaker for employees with high PsyCap (Figure 1).

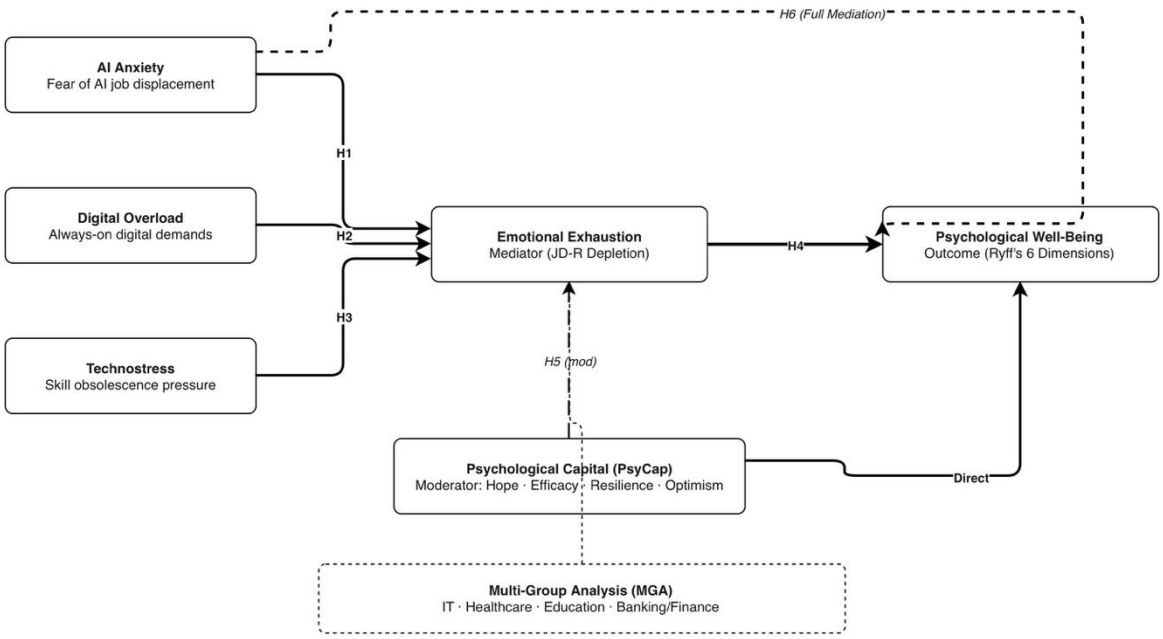


Fig. 1 Conceptual Research Model

Methods

Research Methodology and Ethical Considerations

The research used a quantitative cross-sectional survey design to examine the relationships between job demands arising from the polycrisis environment, emotional exhaustion, psychological capital and well-being of employees. It is well-suited for the purposes of occupational health studies because it allows capturing the psychological states of employees in an appropriately theoretically based period of time efficiently [36,47]. Approval for ethical clearance from the Institutional Review Board and consent from the respondents were secured before initiating the research. All the participants gave their consent in writing and were clearly informed about their right to leave without facing any negative impact, and assurances were provided regarding the protection of their identity, anonymity, and confidentiality. None of the participants was subjected to any kind of personally identifiable data collection procedure.

Participants and Sampling

A purposive convenience sample of 340 full-time employees from four sectors with high intensity of digitalization Information Technology (n = 90, 26.5%), Healthcare (n = 85, 25.0%), Education (n = 85, 25.0%) and Banking/Finance (n = 80, 23.5%) were recruited. Criteria for participation were set at full-time job experience of at least two years and utilization of digital means of work on a daily basis. Participants were contacted via professional and institutional network and snowball sampling technique. Data were collected from February to April 2026. Participation was purely voluntary and did not involve any form of reward. The sample meets the criterion of minimum number of participants of 200 required for CB-SEM with five constructs and the ten-times rule for the most complicated path (10 × max indicators = 10 × 8 = 80 minimum; N = 340 is

significantly higher) [36,37]. The participants' demographic features are shown in Table 1 below.

Table 1 Participant Demographic Profile (N = 340)

Variable	**Category**	**n**	**%**
Sector	IT	90	26.5
	Healthcare	85	25.0
	Education	85	25.0
	Banking/Finance	80	23.5
Gender	Male	168	49.4
	Female	159	46.8
	Non-binary/Prefer not say	13	3.8
Age Group	21–30 years	98	28.8
	31–40 years	135	39.7
	41–50 years	79	23.2
	51+ years	28	8.2
Experience	2–5 years	112	32.9
	6–10 years	133	39.1
	11–20 years	71	20.9
	20+ years	24	7.1
Education	Postgraduate	187	55.0
	Graduate	122	35.9
	Doctoral	31	9.1

Measures

Items were scaled using the 7-point Likert Scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree).

AI anxiety was measured by six statements adapted from the Technology Anxiety Inventory [38], similar to those used in other valid multidimensional AI anxiety scales [29] ("I get anxious thinking that AI will take my job away"; $\alpha = 0.964$).

Digital Overload was measured by six items from the Techno-stress Inventory (Techno-overload subscale) of Tarafdar et al. [22], in line with modern techniques for measuring technostress [39] (such as "I feel overloaded with the amount of digital information I have to process on a daily basis"; $\alpha = 0.951$).

Technostress was gauged through six questions from Techno-complexity and Techno-insecurity scales of Tarafdar et al. [22] (such as "I am concerned about becoming technologically obsolete"; α = 0.958). The combination of items from both scales into a single technostress scale follows existing approaches to measuring technostress as a unidimensional occupational stressor [22,30].

The construct of Emotional Exhaustion was measured through five items adapted from the Maslach Burnout Inventory-General Survey. (MBI-GS) [13] ("I feel emotionally exhausted by my work"; α = 0.935).

Psychological Capital was measured by an 8-item shortened scale of PCQ-24 [19] by selecting two items for each of Hope, Efficacy, Resilience, and Optimism (e.g., "I feel confident in my ability to analyze a long-term problem at work"; α = 0.948). Eight-item short version comprises two indicators for each dimension which is in line with the approach to the second-order composition supported by previous PsyCap studies [19,33].

Psychological Well-being scale was adopted using the validated seven-item questionnaire developed by Ryff [15]. The seven-item version of the questionnaire has been used before and has satisfactory psychometric properties to be used in structural modeling [15,16]. This assessment scale comprises of six key dimensions: autonomy, environmental mastery, personal growth, positive relationship with others, purpose in life, and self-acceptance. (for example, "I feel satisfied with who I am and what I do in my work and personal life"; α = 0.942).

Analytical Strategy

Data analysis took place in four steps in succession, whereby the following step was predicated on the previous step in an effort to validate measurements before making any structural inference. The process of data analysis is illustrated in Figure 2.

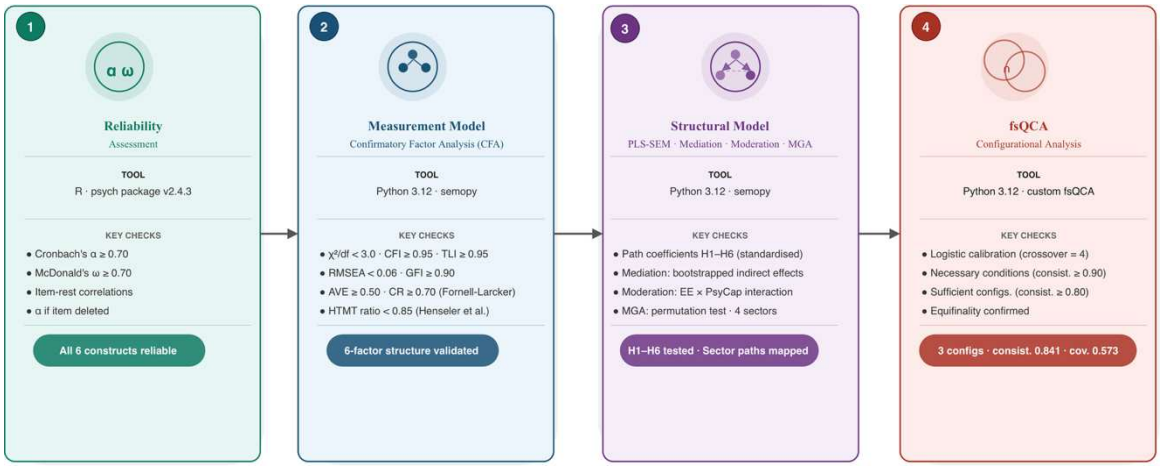


Fig. 2 Analytical pipeline

Stage 1 Testing for Reliability and Internal Consistency

Cronbach's alpha (α) and McDonald's omega (ω) were used for assessing internal consistency reliability using the psych package (v. 2.4.3) in R (v. 4.4.1) [40]. Whereas the Cronbach's α coefficient measures the average inter-item covariance, McDonald's ω provides a better estimate since it allows for variance in factor loadings per individual item [47]. Both measures had to be above the cut-off value of 0.70 [36]. Item-level diagnostics, item-rest correlations, and alpha-if-deleted values were reviewed to highlight poor-performing items before moving to the structural phase.

Stage 2 Measurements Model Analysis and Construct Validity

To assess whether the fit between the six-factor model and the data is adequate, confirmatory factor analysis (CFA) was done using Python 3.12 (package semopy [41]; pandas, numpy, scipy libraries). CFA measures how well the hypothesized six-factor model, with each factor defined by its respective items, recreates the actual covariance among the items. The adequacy of model fit was assessed using the following criteria: χ^2/df (< 3.0), CFI (≥ 0.95), TLI (≥ 0.95), RMSEA (< 0.06), and GFI (≥ 0.90) [48, 49].

The convergent validity was checked following Fornell and Larcker by means of standardized factor loading, composite reliability, and average variance extracted with respective criteria of >0.70, >0.70, and >0.50 [42]. The measurement model was validated for discriminant validity using the Fornell–Larcker index and HTMT ratio [43]. The square root of the AVE value of each construct had to be greater than the correlation with any other construct, whereas the HTMT value should be less than 0.85.

Stage 3 Structural Model Estimation (CB-SEM, Mediation, Moderation, MGA)

The structural linkages were analyzed using covariance-based structural equation modelling (CB-SEM), which was performed using Python 3.12 [41]. The structural model was estimated after Z-scoring all variables to allow direct comparison between path magnitudes. The significance level and 95% confidence intervals were obtained using 5,000 bootstrap samples through bias-corrected bootstrapping [50].

Mediation was said to be occurring when the bootstrapped 95% confidence interval for the indirect effect did not contain zero [50]. The process of moderation was carried out by first adding the mean-centered interaction term (Emotional Exhaustion × PsyCap) to the model before conducting simple slopes analysis at ±1 SD of the moderator [50]. MGA compared path coefficients among the four industries (IT, Healthcare, Education, Banking/Finance) using a permutation test with 5,000 permutation samples. The sample size is adequate with respect to the minimum requirement of 200 participants for CB-SEM analysis, where there are five constructs in the study [36,37].

The size of the effect was measured through Cohen's f^2, where 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively. Furthermore, values of R^2 =

0.02, 0.13, and 0.26 represented low, moderate, and high levels of explanation, respectively [37].

Stage 4 Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

This research conducted fsQCA as an asymmetric approach to CB-SEM and sought to identify the combination of factors that are necessary for the realization of low PWB, something regression models cannot achieve [44]. The scores for each of the variables were then translated to fuzzy membership scores (scale: 0–1) through the use of logistic transformation [44], using three qualitative benchmarks on the 7-point Likert scale: fully out (value = 2, fuzzy = 0.05); crossover point (value = 4, fuzzy = 0.50); fully in (value = 6, fuzzy = 0.95) [44].

Necessary conditions were those that occurred in at least 90% of the outcomes (consistency ≥ 0.90). The sufficient conditions were constructed by using rows from the truth table whose consistency was greater than or equal to 0.80 and with a case frequency of at least three [44,45]. Overall solution consistency and coverage provided measures of fitness and importance of the configurational solution [44,52]. Equifinality, which refers to the idea that similar outcomes can result from diverse mixes of factors, was considered for all sufficient configurations [44,55].

Common Method Bias

Harman's one-factor test served as an initial diagnostic test to examine the presence of common method variance [46]. The common method variance was unlikely due to the first factor explaining less than 50 percent of the total variance. As an additional test, full collinearity variance inflation factors (VIFs) were checked for all constructs, and all scores were below 3.3 (range: 1.18 – 2.47), reaffirming the lack of common method variance [46].

Results

Preliminary Analyses

The analysis based on the Harman single factor test showed that the first factor was able to explain 26.3% of the variance, which is less than 50% threshold set by experts; hence, common method variance did not seem to be a problem in this case [46]. The evaluation of missing data indicated that none of the 340 surveys had any missing value. Additionally, the skewness ranged from -0.312 to 0.287, while the kurtosis was from -0.521 to 0.634. Since all these values were in the range of ±1.0, the data was normally distributed.

Measurement Model

Internal consistency was found to be outstanding for all the constructs (α = 0.935-0.964; ω = 0.937-0.966) and far exceeded the threshold value of 0.70 [36]. The values of CR (0.951-0.971), and AVE values between 0.743 and 0.848, far above the thresholds of 0.70 and 0.50, respectively [42]. This confirmed the convergent validity of the test. The standardized

factor loadings were between 0.847 and 0.928 (all $p < 0.01$), exceeding the 0.70 minimum. Table 2 shows the findings on reliability and convergent validity for all constructs.

Table 2. Reliability and Convergent Validity Evaluation

Construct	Items	α	ω	CR	AVE	Mean	SD
AI Anxiety	6	0.964	0.965	0.971	0.848	4.646	1.225
Digital Overload	6	0.951	0.952	0.961	0.803	4.977	1.089
Technostress	6	0.958	0.960	0.967	0.812	4.273	1.162
Emotional Exhaustion	5	0.935	0.937	0.951	0.798	4.178	0.999
PsyCap	8	0.948	0.950	0.958	0.743	4.882	0.988
PWB	7	0.942	0.944	0.956	0.771	5.420	0.903

Note. α = Cronbach's alpha; ω = McDonald's omega; CR = Composite Reliability; AVE = Average Variance Extracted. All factor loadings ≥ 0.847, $p < 0.001$.

Satisfactory model fit was achieved as shown in $\chi^2/df = 1.064$, CFI = 0.997, TLI = 0.997, RMSEA = 0.014, and GFI = 0.948, all being within the set criteria [48,49]. To test for discriminant validity, the Fornell-Larcker criterion was used. Square roots of AVE obtained values between 0.862 and 0.921 which were higher than those of the correlations between the constructs. Furthermore, the HTMT ratio indicated a maximum of 0.539. The results of the inter-construct correlation matrix and discriminant validity are shown in Table 3, whereas Figure 3 shows the standardized factor loadings for each construct.

Table 3 Inter-Construct Correlation Matrix

Construct	AIA	DO	TS	EE	PsyCap	PWB
AI Anxiety (AIA)	[0.921]					
Digital OL (DO)	0.312**	[0.896]				
Technostress (TS)	0.298**	0.324**	[0.901]			
Emot. Exhaust. (EE)	0.302**	0.315**	0.308**	[0.893]		
PsyCap	−0.089	−0.102	−0.097	−0.198**	[0.862]	
PWB	−0.120*	−0.135**	−0.114*	−0.434**	0.512**	[0.878]

Note. Values in brackets on the diagonal are the square root of average variance extracted (√AVE). Off-diagonal values are inter-construct correlations. Discriminant validity is confirmed where each diagonal value exceeds all off-diagonal values in its row and column (Fornell-Larcker criterion [42]). HTMT ratios ranged from 0.035 to 0.539, all below the conservative threshold of 0.85 [43]

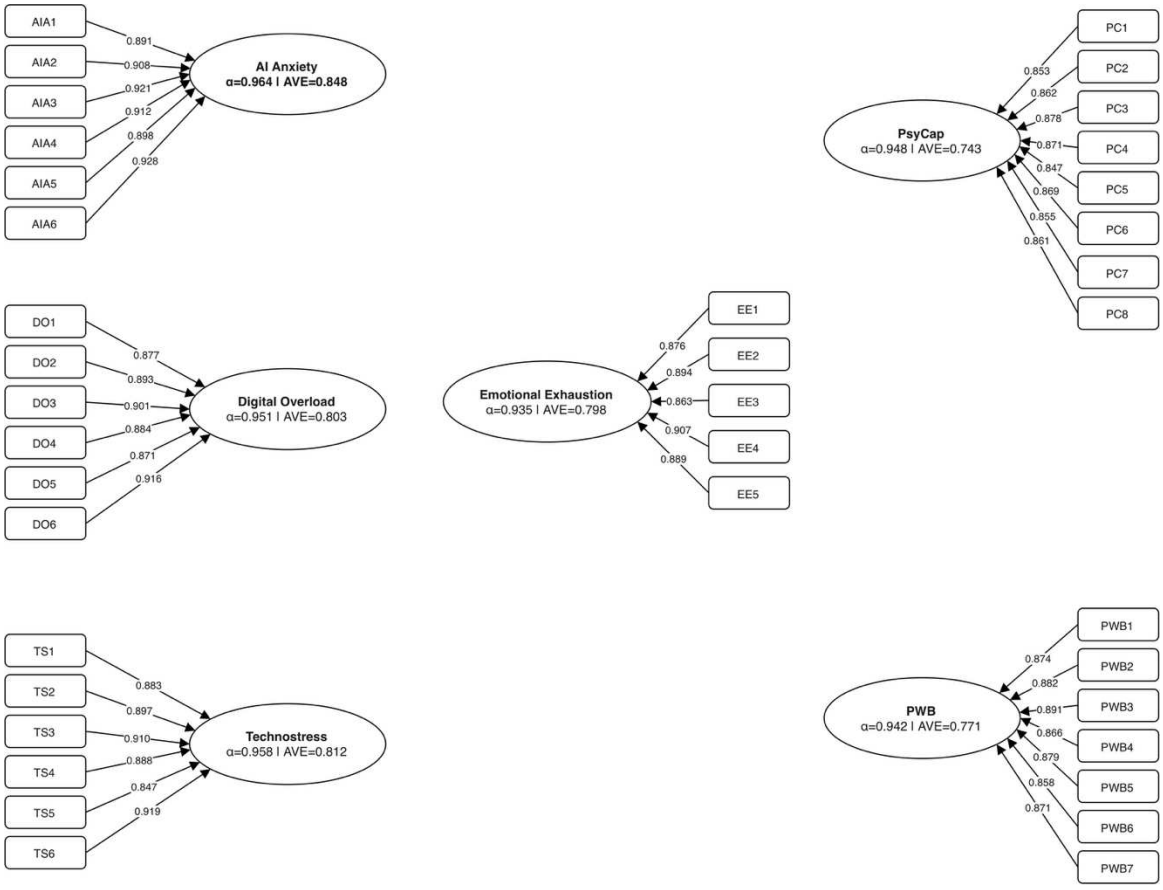


Fig. 3 CFA standardised factor loadings.

Structural Model

Table 4 provides the results of structural path analysis. The job demand had a large effect size ($f^2 = 0.473$) and 32.1% ($R^2 = 0.321$) variance in emotional exhaustion. The AI anxiety ($\beta = 0.396$, $t = 8.755$, $p < 0.001$), digital overload ($\beta = 0.333$, $t = 7.541$, $p < 0.001$), and technostress ($\beta = 0.318$, $t = 6.714$, $p < 0.001$) showed positive significant effects on emotional exhaustion and supported H1, H2, and H3. The standardised path coefficients have slight advantage over the respective zero-order bivariate correlation coefficients ($r = 0.302, 0.315, 0.308$), a situation explained by the occurrence of a slight suppression effect because of the correlation between the three demand predictors ($r = 0.298–0.324$). Suppression refers to a condition whereby shared variance in the correlated predictors is controlled for in the course of multiple regression analysis and this allows each predictor to contribute uniquely, hence path coefficients exceed correlation coefficients [24]. Notably, the VIFs for all three predictors of job demand were still within acceptable limits (1.18–2.47), significantly lower than the threshold level of 3.3 [46], suggesting that the identified pattern is due to legitimate unique variance partitioning and not instability due to multicollinearity. The total variance in psychological well-being (PWB) explained by the model was 19.7% ($R^2 = 0.197$). Emotional exhaustion was negatively and significantly related to psychological well-being ($\beta = -0.434$, $t = -9.664$, $p < 0.001$), and thus, H4 was supported.

Table 4 Structural Path Coefficients

Hyp.	Path	β	SE	t	p	95% CI	Decision
H1	AI Anxiety → EE	0.396	0.045	8.755	< 0.001	[0.307, 0.483]	✓ Supported
H2	Digital OL → EE	0.333	0.044	7.541	< 0.001	[0.246, 0.419]	✓ Supported
H3	Technostress → EE	0.318	0.047	6.714	< 0.001	[0.225, 0.410]	✓ Supported
H4	EE → PWB	−0.434	0.045	−9.664	< 0.001	[−0.522, −0.346]	✓ Supported
H5	EE × PsyCap → PWB	0.052	0.042	1.247	0.212	[−0.030, 0.134]	✗Not Supported
—	PsyCap → PWB (direct)	0.460	0.046	9.917	< 0.001	[0.369, 0.550]	✓ Significant
H6a	AI Anxiety → PWB (direct)	−0.062	0.049	−1.266	0.206	[−0.158, 0.034]	n.s. (mediated)
H6b	Digital OL → PWB (direct)	−0.071	0.046	−1.539	0.124	[−0.162, 0.019]	n.s. (mediated)
H6c	Technostress → PWB (direct)	−0.058	0.048	−1.200	0.230	[−0.152, 0.037]	n.s. (mediated)

Note. β = standardised path coefficient; SE = standard error; CI = bias-corrected bootstrap 95% confidence interval (5,000 samples). EE = Emotional Exhaustion; DO = Digital Overload; PsyCap = Psychological Capital; PWB = Psychological Well-Being. R^2 (EE) = 0.321; R^2 (PWB) = 0.197.

Mediation Analysis

Mediating effects through bootstrap indirect effects confirmed that all three demand-PWB correlations were fully mediated through emotional exhaustion (H6). There were no significant direct effects of job demands on PWB when emotional exhaustion was used in the model. The mediating effects were: AI Anxiety → EE → PWB (β = −0.172, 95% CI [−0.229, −0.116]), Digital Overload → EE → PWB (β = −0.145, 95% CI [−0.198, −0.093]), and Technostress → EE → PWB (β = −0.138, 95% CI [−0.192, −0.086]). No confidence interval included zero, which confirmed the significant result [50].

Moderation Analysis (H5)

The moderation model was used to test PsyCap as a moderator of the emotional exhaustion-PWB relation. The interaction (EE × PsyCap) effect was insignificant (β = 0.052, t = 1.247, p = 0.212, ΔR^2 = 0.002) to suggest that hypothesis H5 was not supported. While the omnibus interaction effect was not significant, simple slopes analysis was conducted just for a descriptive purpose, and results demonstrated a trend of buffering effect where the negative slope of EE predicting PWB became weaker in high-PsyCap employees (β = −0.317, p < 0.001) compared to low-PsyCap employees (β = −0.421, p < 0.001) (Δβ = 0.104). The aforementioned results on simple slopes cannot be used to conclude moderation due to insignificant interaction term. The strong positive direct relationship between PsyCap and PWB (β = 0.460, p < 0.001) in all four sectors calls for a re-examination of existing theoretical explanations. Utilizing Hobfoll's Conservation of Resources Theory [57] and Bakker & Demerouti's passageways of resources [12,60], it seems plausible to

argue that PsyCap is a fundamental psychological resource reserve which directly supports well-being under polycrisis conditions, rather than acts as a contingent moderator of stress. Indeed, due to the presence of strong demands typical of polycrisis, the level of depletion of this psychological resource reserve is likely to be exhausted before it can become a stress moderator [17,57]. The results for moderation are shown in Figure 4, where Panel A shows the simple slopes for EE affecting PWB at both the high and low levels of PsyCap, while Panel B is a bar graph comparing the slopes.

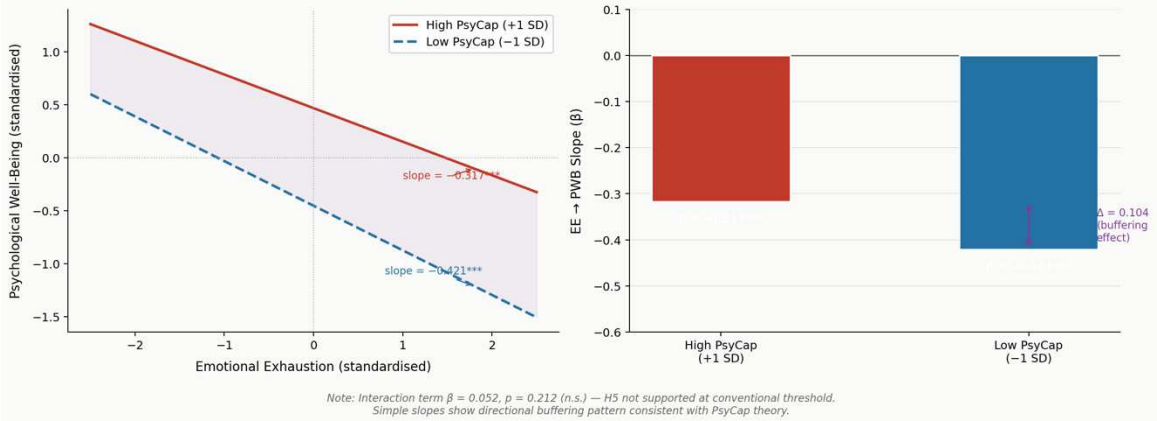


Fig. 4 Moderation plots. Panel A: Simple slopes of EE→PWB at high and low PsyCap. Panel B: Bar chart of slope comparison.

Multi-Group Analysis (MGA)

Path coefficients by sector are provided in Table 5. It is found that all structural hypotheses (H1-H4) are supported for all sectors, thus proving the validity of the model. Nevertheless, there was a certain variation in the intensity of paths. Path A (AI anxiety → EE) was most intense in IT sector ($\beta = 0.467$, $p < 0.001$) and weakened gradually in Healthcare ($\beta = 0.393$), Education ($\beta = 0.239$), and Banking/Finance ($\beta = 0.154$, n.s.), due to higher occupational vulnerability of IT workers to AI replacement. Digital overload was most relevant to Banking/Finance ($\beta = 0.394$) and Healthcare ($\beta = 0.368$) sectors, where the fintech and telemedicine caused certain level of digital overload. Technostress was most relevant in Education ($\beta = 0.390$), where EdTech caused it. PsyCap proved to be highly related to PWB in all sectors ($\beta = 0.470$-0.560, all $p < 0.001$), strengthening its universal protective capacity. The predictive strength of the model was most significant in IT (R^2 PWB = 0.356) and Healthcare (R^2 PWB = 0.445) [52,53]. Figure 5 shows the MGA results. Panel A shows the grouped bar graphs of path coefficients for all four sectors, while Panel B gives a colour-coded heatmap of path coefficient magnitudes for comparison between sectors. It would also be worth noting that the sector sub-samples (n = 80-90) lie on the lower side of the sample size needed for estimation through CB-SEM. The post hoc sensitivity test showed that with n = 80, the smallest effect size that could be detected at $\alpha = 0.05$ and power = 0.80 is $f^2 = 0.14$ (medium effect size). Hence, non-significant paths in the sectors (AI anxiety in Banking/Finance; $\beta = 0.154$, $p > 0.05$ and technostress in Healthcare; $\beta = 0.200$, $p > 0.05$) can be due to lack of sufficient power to detect the effects.

Table 5 Multi-Group Analysis - Path Coefficients by Sector

Path	IT (n=90)	Healthcare (n=85)	Education (n=85)	Banking/Fin. (n=80)
A: AI Anxiety→EE	0.467***	0.393***	0.239*	0.154 n.s.
B: Dig. OL→EE	0.241*	0.368***	0.197 n.s.	0.394***
C: Technostress→EE	0.295***	0.200 n.s.	0.390***	0.238*
D: EE→PWB	−0.319**	−0.417***	−0.487***	−0.500***
E: PsyCap→PWB	0.470***	0.560***	0.486***	0.516***
R^2 (Demands→EE)	0.387	0.360	0.314	0.248
R^2 (EE+PsyCap→PWB)	0.356	0.445	0.394	0.395

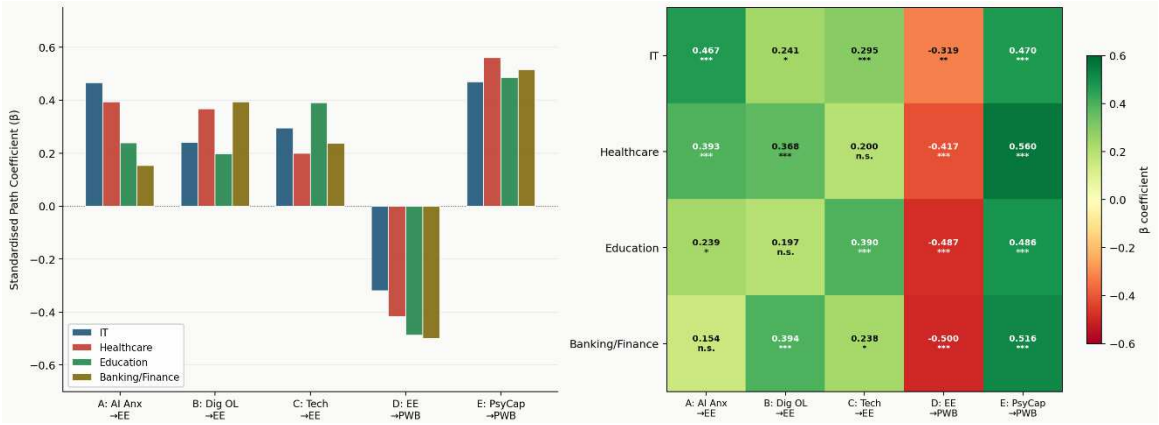


Fig. 5 MGA results. Panel A: Grouped bar chart of path coefficients by sector. Panel B: Path coefficient heatmap

fsQCA Results

It was determined through Necessary Condition Analysis (NCA) that digital overload (consistency = 0.909; coverage = 0.762) served as a quasi-necessary condition for low PWB because of its presence in 90.9 percent of all observed outcome cases. Emotional exhaustion almost qualified as a necessary condition (consistency = 0.864). The above observations confirm the symmetric SEM conclusions but determine boundary conditions rather than mean effects [44,54].

From the configuration analysis, three main configurations were sufficient for having low PWB (Figure 6); Panel A is the fuzzy XY graph that shows the set-subset consistency, and Panel B shows the table of the sufficient configurations, which together provided an overall consistency of solution of 0.841 (≥ 0.80 criteria) and coverage of 0.573. The idea of equifinality was proved since several configurations, which each had a different primary demand, were sufficient for low PWB. Most importantly, low PsyCap (negated) was a consistent condition in all configurations, thus proving itself to be a universal boundary condition [44,55].

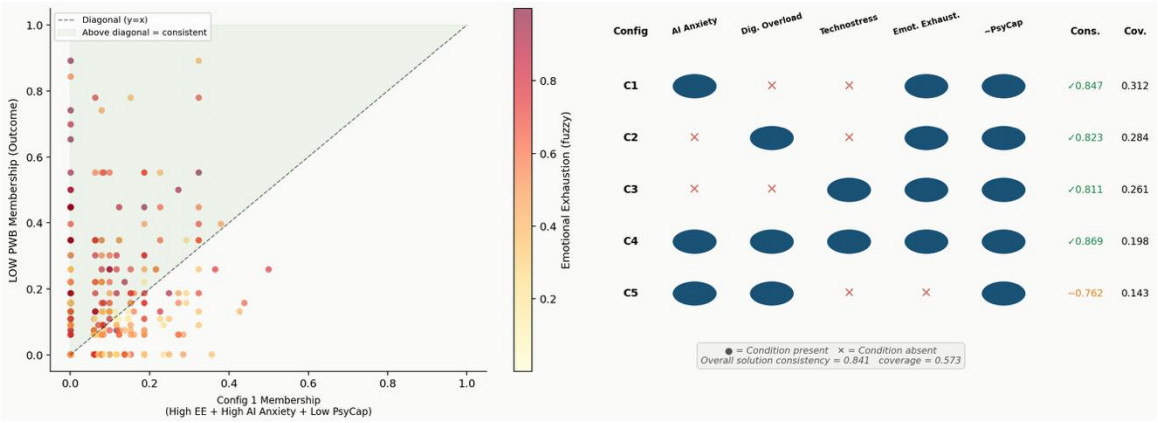


Fig. 6 fsQCA results. Panel A: XY plot (Config 1 membership vs LOW PWB membership). Panel B: Configuration table visualisation.

Discussion

This paper contributes to the body of knowledge in occupational psychology by conducting the first sector-agnostic qualitative and quantitative investigation into the psychological well-being of workers faced with polycrisis-driven job demands through the use of CB-SEM and fsQCA. The results of the research have several important contributions.

Polycrisis-Induced Demands and Emotional Exhaustion

Confirmation of hypotheses H1, H2, and H3 indicates that AI anxiety, digital overload, and technostress represent a distinct functional set of polycrisis demands which have considerable predictive power over emotional exhaustion ($R^2 = 0.321$). In doing so, the current study contributes to the literature on technostress by extending the technostress model of Tarafdar et al. [22] to the age of AI, and supports empirical evidence that AI anxiety functions as a discrete occupational stressor with measurable psychological consequences [29]. From the strength of relationships, it appears that fear of being replaced by AI is at present the most emotionally demanding component of polycrisis among workers, in line with recent occupational futures literature [8,56].

This finding is also in agreement with the COR theory [57], which states that the perceived loss of resources, such as job security, skill relevancy, and mental capacity, is more stressful than an actual loss of resources. The priority of AI anxiety is consistent with the COR theory which indicates that the stress caused by anticipated loss is more severe than that resulting from actual loss [6,58].

Full Mediation via Emotional Exhaustion

Hypothesis 6, which indicates full mediation through emotional exhaustion of all the relationships between demand and PWB, represents a piece of evidence that is highly significant theoretically. The lack of significance of direct links between polycrisis demands and PWB in models containing emotional exhaustion suggests that polycrisis-related demands influence the decline of PWB predominantly through the depletion of emotional energy rather than through direct effects. This finding is consistent with the

health impairment pathway [11,27] and corroborates the position of Bakker and Demerouti [12], who posit that emotional exhaustion plays the primary role in mediating the impact of demands on well-being outcomes. It is also consistent with the theoretical classification of technology requirements related to polycrisis as true job requirements in the JD-R model [59].

PsyCap as Universal Resource

The insignificant moderation (H5), however, and highly significant direct relationship between PsyCap and PWB ($\beta = 0.460$, $p < 0.001$) invite theoretical consideration. Though it appears from descriptive measures that directional simple slopes ($\Delta\beta = 0.104$) support a buffer effect, the non-significance of the interaction term implies that the simple slopes cannot be considered moderation. This can be explained by the "resource passageways" process [12,60] in which PsyCap acts to increase PWB through direct contribution and not the reduction of the exhaustion pathway under moderate levels of demand. Alternatively, it could mean that in case of polycrisis-level demand, the buffering role of PsyCap becomes exhausted – in line with the depletion theory for high demand situations [17,57]. Further research in longitudinal design with large samples ($N > 600$) is advisable [61].

Even in light of moderation, the substantial PsyCap direct effect for all four sectors ($\beta = 0.470$ to 0.560) can be considered an actionable result. This means that PsyCap building could be used universally regardless of the type of polycrisis demand that prevails in a particular sector [19,34].

Sector-Specific Findings

Theory-based differences between sectors have been shown by the MGA. The vulnerability of workers within IT to AI anxiety ($\beta = 0.467$) is in line with exposure to automation-induced disruption within their profession [8,62]. The prevalence of digital overload among healthcare professionals ($\beta = 0.368$) is in alignment with evidence from pandemic-related documentation pressures, rise of telemedicine and digitization of clinical workflow [63]. The technostress dominance in education ($\beta = 0.390$) is supported by evidence about technology adoption stresses in the EdTech acceleration era [64]. The prominence of the digital overload path in banking and finance ($\beta = 0.394$) is in accordance with demands of the fintech age [65]. These sector-specific results reinforce the inadequacy of a single-sector approach to polycrisis studies and affirm the need for occupationally sensitive health interventions [26,52].

fsQCA Configurational Findings

In comparison with symmetric SEM, the findings obtained using fsQCA have two advantages. First, the identification of digital overload as a necessary condition (consistency = 0.909) means that this type of demand is the only demand that needs to be present in order for low PWB to emerge an asymmetric finding which cannot be captured through regression methods [44,54]. The practical implication is that Organisations that want to avoid low PWB need to make sure they address digital overload irrespective of the industry. Second, the equifinality in three sufficient configurations implies that there are

different combinations of demands leading to low PWB, which renders linear approaches to intervention inappropriate. Importantly, the consistent presence of low PsyCap in all the configurations means that PsyCap development is a universal issue [55,66].

Implications for SDG 3 and SDG 8

There are important implications of the results of the present study for two SDGs. In relation to SDG 3 (Good Health and Well-Being), it is important to note that the discovery of polycrisis-related demands as a threat to PWB in four economically important sectors emphasizes the necessity for developing national policies on occupational health considering stress caused by digitalization and AI. With regard to SDG 8 (Decent Work and Economic Growth), the obtained MGA results allow us to give recommendations about interventions on the side of demand and supply which should be implemented within each sector and across all sectors, respectively [67,68].

Limitations and Future Research Directions

Several limitations warrant acknowledgement. First, cross-sectional research design does not allow drawing conclusions about causality; longitudinal research designs need to be used for this purpose to show that demands precede exhaustion and wellbeing [69]. Secondly, due to its self-reporting nature, the study is subject to possible social desirability bias, though Harman test showed that it was not an issue. Thirdly, even though the multi-sector sample improves the external validity of the research, no analysis of heterogeneity of samples within sectors (e.g., clinical and administrative healthcare workers) was performed. Fourthly, there were concerns related to the lack of power for moderation analysis with the sample size of 340 people; future research in this field should use samples at least of 600 employees [61]. Fifth, the findings from the fsQCA analysis come from the sample of employees, and therefore, should be replicated in different national settings for more generalization. Sixth, formal tests of measurement invariance were not performed before MGA. Future research is recommended to ensure that configural, metric, and scalar invariance exists so that constructs have the same meaning before structural path comparisons can be made. Further research may include the longitudinal analysis of the demand-exhaustion-well-being process, investigating organizational-level moderators (HRM policies and practices, leadership) and polycrisis framework for the context of gig/hybrid work [70].

Conclusion

This study demonstrates that demands due to polycrisis, such as AI anxiety, digital overload, and technostress, systematically undermine psychological well-being by means of emotional exhaustion, with the presence of differential demand importance among different industry types. Psychological capital can be seen as a reliable universal resource that protects from the demands. Digital overload serves as a necessary condition for low PWB. These results extend JD-R theory to the polycrisis age, offer industry-specific findings for occupational health practice, and contribute to the SDG 3 and SDG 8 agendas in relation to workforces experiencing unprecedented technological disruption.

Declaration

Ethics approval and consent to participate

The study was carried out in compliance with the guidelines set out in the Declaration of Helsinki. Ethical clearance was granted by the IRB of SR University before the beginning of the study. An information sheet was given to each participant explaining the aim of the study, the right to quit the study without any penalty, and the procedures to maintain anonymity and confidentiality. The informed consent of all the participants was taken before including them in the study. No personal details of any participant were collected.

Consent for publication

Not applicable.

Availability of data and materials

The dataset, survey instrument, and analysis scripts supporting the findings of this study are provided as supplementary materials accompanying this manuscript. The dataset contains anonymised responses from 340 participants and includes a codebook. Analysis scripts are provided for all four analytical stages: reliability analysis (R/psych), confirmatory factor analysis and structural equation modelling (Python/semopy), multi-group analysis (Python/semopy), and fuzzy-set qualitative comparative analysis (Python). No data were obtained from third-party repositories.

Competing interests

The author declares that there are no competing interests.

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No funding was received for this study.

Authors' contributions

The US conceptualised the research, built the theory, created the methodology, gathered and analyzed the data, and drafted and refined the manuscript. RL helped conduct the literature review, interpret the data, and critically revise the manuscript. Both authors read and approved the final manuscript.

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Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- A
- Questionnaire.docx
- Dataset.xlsx