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Examining the Impact of Psychological and Organizational Factors on Job Performance: A Study of the Indian IT Industry

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Abstract. This research work discusses how psychological variables—Psychological Well-being (PWB), Emotional Intelligence (EI), Job Insecurity (JIS), Psychological Capital (PsyCap), Perceived Organizational Support (POS), and Emotional Exhaustion (EE)—influence Job Performance (JPF) in the Indian IT industry. A cross-sectional survey was carried out among employees in different Indian states, and the constructs were assessed via validated scales. psychological well-being, psychological capital, and perceived organizational support all have positive effect on job performance, whereas Job Insecurity and Emotional Exhaustion have negative effects. The mediation analysis also revealed that psychological well-being partially mediated the associations between Perceived organizational support, Emotional intelligence, Psychological Capital and job performance, suggesting the centrality of psychological health to productivity. However, there are drawbacks, such as the cross-sectional design and poor construct selection, which suggest that it might be possible to study longitudinal changes and even add other factors, such as job satisfaction and resilience, in future studies. This research identifies the requirement for specific employee support, including well-being programs and emotional intelligence training, to enable job performance to be optimal in India's changing workplace. The findings offer practical guidance to IT managers who want to create a strong and engaged workforce in the face of job insecurity and emotional burnout.

Keywords: Emotional exhaustion, Emotional intelligence, India, IT industry, Job insecurity, Job performance, Mediation analysis, Perceived organizational support, Psychological capital, Psychological well-being.

1. INTRODUCTION

India's IT sector, which is concentrated in the cities of Bangalore, Chennai, Hyderabad, Delhi, and Kerala, has driven economic development by taking advantage of fast technology and digital transformation (NASSCOM, 2022; Kumar & Subramanian, 2020). This is a high-demand field in which workers are often subject to stressful work environments and cognitive challenges, so it is critical to determine what affects employee health, employee satisfaction, and performance for organizations to thrive and retain staff (Nguyen & Teo, 2020; Charoensukmongkol & Pandey, 2022). As has been documented in the past, constructs such as perceived organizational support (POS), psychological capital (PsyCap), job insecurity, emotional intelligence (EI), and emotional exhaustion (EE) influence employees' attitudes, resilience, and productivity (Shen et al., 2023; Ramos-Villagrasa et al.,2019). Well-being in the form of the mental, emotional, and physical health of employees has been associated with increased productivity, lower intention to leave, and higher levels of engagement (Ryff & Keyes, 1995). For those who work in stressful environments, health and well-being help people handle demands and maintain their concentration (Sutin & Luchetti, 2021; Yu et al, 2023). In addition, psychological capital (PsyCap), such as hope, resilience, optimism, and self-efficacy, enhances worker confidence, adaptability, and job satisfaction for consistent performance (Luthans et al., 2006; Zhang et al., 2023; Alshebami,2021). Instead, job insecurity is driven by rapid technological evolution, and reorganization results in decreased job satisfaction, stress, and disengagement and makes it difficult for IT companies to operate (Piccoli et al., 2022). Emotional Intelligence, however, also bolsters workers' capacity to regulate emotions, supporting resilience, collaboration, and uplifting work culture (H. Liu & Cheung, 2015). Third, emotional fatigue (part of burnout) damages attention, motivation, and resilience and stresses that workload demands must be managed to continue working (Shao et al., 2021; Chen et al., 2020). In this paper, based on data from 1,200 IT workers in India, we examine how POS, Psychological Capital, job insecurity, EI, emotional exhaustion, and well-being are collectively related to job satisfaction and performance in the Indian IT market.

This paper bridges a gap because much of the literature on these constructs has been done in the West, and there is still limited research on how these affect Indian IT companies (Pradhan & Jena 2020). Because organizational structures and employee behaviors vary from culture to culture, it is easier to study such factors in India's IT industry and better understand how distinct cultural and industry-related factors shape job performance (Adams,2019). This research aims to show how psychology, organizational support, and job performance interact to form evidence-based practices to generate a strong workforce capable of surviving India's high-pressure IT workplaces. The research also highlights practical applications for IT companies in terms of increasing employee engagement, burnout, and productivity at work. By incorporating Perceived organizational support, Psychological Capital, job insecurity, Emotional Intelligence, and emotional exhaustion, this paper offers an integrated perspective of job performance from well-being, resilience, and institutional care (Avey, 2014; Alessandri et al.2018)). The results add to the literature by highlighting the need for systemic support from organizations specific to the IT industry, providing Indian companies with concrete tips on how to take care of

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their employees' health and productivity.

2. LITERATURE REVIEW

2.1. Theoretical Framework

This work draws together existing theories to explain the dynamic connections between psychological aspects and organizational job performance. The model social exchange theory (SET) (Blau, 1964), which lies behind the theories of POS, management trust, and job insecurity, states that employees 'reward' perceived organizational support with loyalty and better performance; thus, when organizations care about employees, they show more engagement and productivity (Rhoades & Eisenberger, 2002). Similarly, the conservation of resources (COR) theory (Hobfoll, 1989; Aslam et al.,2022) also explains how emotional intelligence, psychological capital (PsyCap), and emotional exhaustion work in the context of this theory, as people try to create and store psychological resources (such as resilience and optimism) to cope with the pressures of the workplace and remain productive (Luthans et al, 2006). Moreover, self-determination theory (SDT) (Deci & Ryan, 1985) offers some answers concerning the influence of psychological health and interpersonal relationships in the workplace and proposes that individuals are motivated and perform best when our natural needs for autonomy, competence, and connection are met (Ryan & Deci, 2000). The third model is the job demands-resources (JD-R) model (Bakker & Demerouti, 2007), which contextualizes POS, PsyCap, and trust as important resources that can insulate against demands such as job insecurity and emotional fatigue to help ensure optimal performance under stress conditions. These theories are all strong theories when applied together and show how corporate, human, and psychological resources come together to develop a strong, committed, and productive workforce, especially in competitive sectors such as IT.

2.2. Conceptual Framework and Hypothesis Development

2.2.1. Emotional Intelligence on Job Performance

EI measures the ability to see, process, and use emotions productively—a skill that supports workplace interaction and improved performance. Emotional intelligence, Kim et al. (2006), is crucial to resilience and flexibility, both of which are important for high-stress jobs. In response, Boukis et al. (2019) stress that EI helps with stress management to minimize burnout and sustain work over time. EI also influences positive attitudes among employees, fostering a productive and engaged work culture that drives productivity (Shin et al., 2021). Moreover, EI does not stop at individual resilience to positively shape team dynamics. Wen et al. (2019) reported that EI training enables conflict management, which promotes team unity and efficiency. The EI that leaders carry creates innovative environments that can make organizations more successful (Jiang et al., 2023). Wong and Law (2002) support the relationship between EI and teamwork and individual work by linking emotional regulation with functioning group dynamics. Additionally, Brackett et al. (2006) and Froman (2010) characterize EI as key to healthy working relationships and attitudes. Together, these studies underscore EI's power to increase both individual and team performance and, in the process, increase organizational productivity.

Hypothesis $_1$: Emotional intelligence positively affects job performance.

2.2.2. Job Insecurity on Job Performance

Job insecurity, or the risk of losing work or job insecurity, depresses motivation and diminishes productivity. Piccoli et al. (2022) see insecurity at work as affecting commitment and driving turnover intentions. Insecurity in the workplace, Jiang and Probst (2020) believe, increases stress, hampering attention and productivity. Shao et al. (2021) noted that remote work perpetuates only job insecurity and diminishes engagement. Additionally, long-term job insecurity affects group dynamics because workers do not spend time working together (Wang et al., 2023). According to Piccoli et al., (2017), although job embeddedness may reduce insecurity for a while psychologically, it can still affect performance. Blustein et al. (2020) shows how job insecurity lowers employees' motivation and leads to decreased productivity. Job insecurity increases stress in stressful work environments in the IT industry. Suthatorn and Charoensukmongkol (2023) link job insecurity to productivity loss, whereas Adekiya (2023) associate insecurity with decreased productivity. Taken together, these studies show that job insecurity is bad for both individual and company performance and that job stability is critical to long-term engagement and output (García-Cabrera & García-Barba Hernández, 2014).

Hypothesis $_2$: Job insecurity negatively affects job performance.

2.2.3. Psychological Capital Versus Job Performance

Psychological capital (hope, resilience, optimism and self-efficacy) has profound effects on employee performance and satisfaction. Luthans et al. (2015) emphasized that PsyCap promotes adaptive behavior that improves work efficiency in high-risk working conditions. Zhang et al. (2023) validated Psychological Capital's ability to help employees deal effectively with work-related difficulties and create resilience and performance. Charoensukmongkol and Pandey (2022) reported that PsyCap promotes psychological health and protects employees against burnout. Daswati et al. (2021) reported that high PsyCap drives engagement and initiative, as employees perceive problems as opportunities rather than limitations. Wang and Lu (2023) reported that workers with high PsyCap are less burnt out and more loyal; Pradhan and Jena (2016) emphasized that high PsyCap increases job satisfaction. Devonish (2013) described PsyCap as the key to staying focused when stressed. Additionally, Lorenz et al. (2016) and Newman et al. (2014) reported that psychological capital's effect on adaptability and well-being is key to sustained productivity (Thangaraju, 2024). Collectively, these results highlight the significance of Psychological Capital's centrality to employee performance and resilience.

Hypothesis 3: Psychological capital positively affects job performance.

2.2.4. Perceived Organizational Support (POS) versus Job Performance

POS measures whether employees think that their organization cares about what they have to contribute to and their well-being, which is a critical factor for job satisfaction and performance. Shen et al. (2023) noted that POS protects against burnout and increases resilience and morale. Tu et al. (2021) support POS as being positively associated with job satisfaction and therefore focused and engaged. Ahmad and Zafar (2022) reported that POS lowers turnover through loyalty, and Charoensukmongkol and Pandey (2022) reported that POS improves well-being to improve performance. (Saputra et al., 2023) believe that POS increases job commitment and productivity. These early studies by Rhoades and Eisenberger (2002) and Roemer and Harris (2018) underscore POS's ability to foster resilience and loyalty. Shen et al. (2018) and Tu et al. (2021) reported that POS is essential for productivity and job satisfaction, especially in competitive markets. Additionally, Zhang et al. (2023) highlighted that POS increases morale and commitment, supporting ongoing productivity. These studies all underline POS as a key determinant of job satisfaction and performance.

Hypothesis 4: Perceived organizational support has a positive impact on Employees' job performance.

2.2.5. Emotional Exhaustion Versus Job Performance

The emotional exhaustion that is at the heart of burnout is a type of fatigue that affects the ability to perform a job. Shao et al. (2021) reported that emotional exhaustion leads to absenteeism and turnover—two outcomes that are detrimental to organizational productivity. Chen et al. (2020) reported that fatigue reduces workers' cognitive ability and that workers cannot remain focused. Yavas et al. (2008) noted that high emotional pressures, especially in the service industry, compound exhaustion's impact on satisfaction and performance. According to Miao et al. (2020) suggested that a low level of fatigue enhances resilience and hence productivity. Greenidge et al. (2014) agree that exhaustion decreases attention and focus. Managing fatigue is vital to morale and work productivity, Wright and Cropanzano (2020) and Roemer and Harris (2018) stress. Lee and Chelladurai (2015) reported that exhaustion leads to impaired decision-making and hence performance. These studies suggest that emotional fatigue needs to be combatted if a happy workforce is to be maintained.

Hypothesis 5: Emotional exhaustion negatively affects job performance.

2.2.6. Psychological Well-Being as a Mediator

Psychological health (mental and emotional) is crucial for job satisfaction, engagement, and productivity. Eudaimonic well-being—argued by (Ryff & Keyes, 1995) produces motivation for ongoing job performance. Miao et al. (2021) reported that highly thriving employees feel less burnout and perform better in the long run. Kim et al. (2021) noted that mental health strengthens employees, allowing them to stay in their place through organizational restructuring. Yu et al. (2023) underscored how well-being encourages resilience and engagement, which are two elements of high performance. Munir et al. (2011) and Salgado et al. (2019) reported that psychological health supports attention and workplace engagement. Garcıá-Cabrera et al. (2018) tie well-being to motivation and fulfillment. Devonish (2013) and Daniels and Harris (2000) add their voice to the evidence that well-being supports satisfaction, which in turn is relevant to performance. Collectively, these insights indicate that health is essential to maintaining a strong, efficient workforce.

Hypothesis 6: Psychological well-being positively affects job performance.

2.2.7. Job Performance

Job performance (both task performance and organizational citizenship) is the key to organizational performance. Shen et al. (2023) relate job satisfaction to engagement and satisfaction, which translates into productivity. Engagement is seen by Wright and Cropanzano (2020) as the most fundamental part of performance, as it underpins focus and resilience. Kim et al. (2022) noted that citizenship activities increase work and collaboration. Rahmani et al. (2023) and Pradhan and Jena (2023) noted that job performance aligns with organizational objectives to strengthen stability and achievement. Shen et al. (2018) and Bouzari and Karatepe (2018) stress the contribution of performance to turnover and productivity. In founding research by Rhoades and Eisenberger (2002) and Ahmad and Zafar (2022), performance and morale are associated with organizational resilience. Tu et al. (2021) and Wong et al. (2002) believe that performance is engendering and therefore is important for productivity in organizations.

3 RESEARCH METHODOLOGY

3.1. Sample and Data Collection

We conducted this study among IT professionals in five tech-centered regions in India—Bangalore, Chennai, Hyderabad, Delhi and Kerala, March–June 2024. These are large cities for national and international IT companies. After obtaining permission from the HR departments of the chosen companies, we established a representative sample of staff with a minimum of 1 year of experience in their current position to collect relevant information. We used a stratified random sampling method to spread the survey across each region in an equitable manner. We aimed for 240 samples from each state of the 1,200 surveys that we distributed. There were

910 correct answers, for a response rate of 75.8%. The population was split into 53% male and 47% female samples. From bachelor's degrees (65%) and master's degrees (30%) to other degrees (5%). The employment types included all types, ranging from software developers, analysts, project managers, and other IT professionals, to show you an overall snapshot of the profession.

3.2. Measures

For each construct in this research, we took three to four items from the scales. The survey was conducted in English, which is the local language in the Indian IT industry. Perceived organizational support (POS) was determined via three items from Rhoades and Eisenberger (2002): "My organization has strong consideration of my goals and values" (= 0.720). Psychological capital (PsyCap) was measured by a four-item scale from Luthans et al. (2006), such as "I am comfortable looking at a chronic issue in order to solve it" (= 0.914). Job Insecurity: We used a three-item scale (based on Piccoli et al. (2022)) and a common category: "I'm not happy with the job I'm currently working for" (= 0.881). EI was calculated by applying three items from the Wong and Law Emotional Intelligence Scale (WLEIS) involving dimensions such as self-emotion appraisal and emotion regulation (= 0.876). Workplace well-being consists of three scales borrowed from (Ryff & Keyes, 1995)"I feel good about myself" (= 0.937). Job Performance: A four-item scale was developed by Ramos-Villagrasa et al. (2019), with items such as "I finish my tasks in time" (= 0.884).

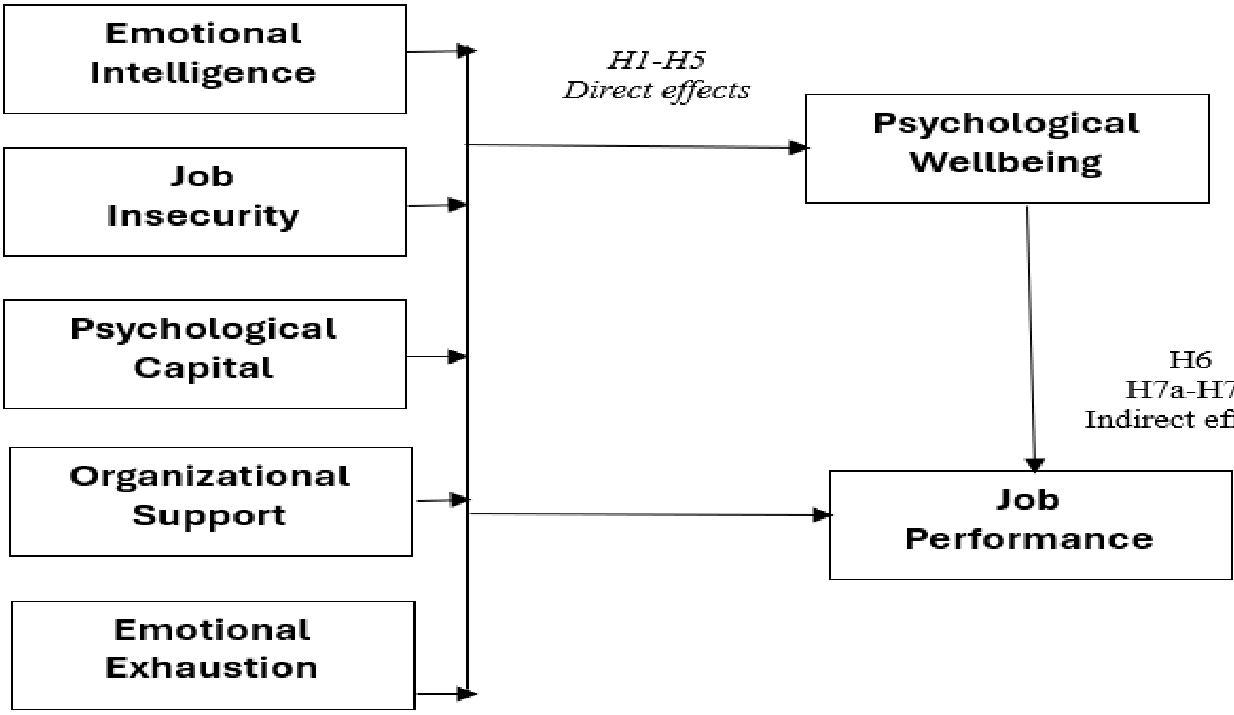


Figure 1: Conceptual framework.

4. DATA ANALYSIS

We processed the data obtained from the sample respondents using statistical packages IBM- SPSS and its advanced version AMOS (Structural Equation Modeling). We first ran descriptive statistics to determine whether there were any missing data or if the data distribution was falling into Normality threshold (mean, standard deviation, Hair et al., 2010; Kline, 2015). Then the analysis employed confirmatory factor analysis to assess whether the average variance extracted (AVE), Composite reliability were in the threshold levels. The next level of analysis looked at the convergent validity and the Heterotrait–Monotrait (HTMT) ratio for discriminant validity (Fornell & Larcker, 1981; Henseler et al., 2015). However, we also checked the Reliability for individual items Cronbach's alpha which hold above the recommendation levels. Moreover, the composite reliability for constructs also were in the acceptable range. (Nunnally Bernstein, 1994; Bagozzi Yi, 1988). For a clear validation of constructs, we also ran common method bias using the latent common method factor (Ringle et al., 2012; Podsakoff et al., 2003) and we looked for Heywood cases if any, later found out nothing. (Kline, 2015; Byrne, 2016). We then implemented Sobel's mediation test of 5000 bootstrap at 95% confidence interval level for assessing the significance of mediator and earlier to that the hypothesis testing was done to validate the direct hypothesis. The hypothesis testing was carried to estimate the path significance between the independent constructs and Job performance both direct or indirect relationship.

4.1. Demographic Analysis of the Respondents

Table 1 presents a uniform, representative sample of all the major categories that are indicative of the study's validity and applicability to the Indian IT landscape. It is nearly equally gendered: 52% of men and 48.08% of women take part so that insights from both sides are heard. The age categories are heavily represented by younger workers (42.31% under 30 years) and middle-career employees (38.46% in the 31–45 years group), the younger age cohort encapsulating India's IT industry.

Table 1: Demographic profile of the respondents.

Variable	Category	Frequency	Percent
Gender	Male	260	50.00
	Female	250	48.08
	Other	10	1.92
Age Group	Below 30 years	220	42.31
	31-45 years	200	38.46
	Above 45 years	100	19.23
Educational Background	Arts & Science	130	25.00
	Engineering	220	42.31
	Management	100	19.23
	Other	70	13.46
Years of Work Experience	Junior Level (1-5 years)	190	36.54
	Mid-Level (5-10 years)	220	42.31
	Senior Level (10+ years)	110	21.15
Monthly Income	Below Rs. 50,000	150	28.85
	Rs. 50,001 - Rs. 99,000	170	32.69
	Rs. 1,00,000 - Rs. 2,49,000	120	23.08
	More than Rs. 2,50,000	80	15.38
Current Job Role	Developer/Engineer	200	38.46
	Project Manager	120	23.08
	Analyst	100	19.23
	HR/Administrative	60	11.54
	Other	40	7.69
Location of Employment	Bangalore	130	25.00
	Chennai	110	21.15
	Hyderabad	100	19.23
	Delhi	90	17.31
	Kerala	90	17.31

Education indicates a high number of respondents who are engineers (42.31%), an indication that the industry is very technical. Interestingly, in terms of work experience level, the respondents were junior, middle or senior, indicating room for experience. The income per month varies, with most earning between Rs. 50,001 and Rs. There are 1,00,000 (32.69%) middle-income workers in the industry. Finally, the geographical dispersion of Bangalore, Chennai, Hyderabad, Delhi, Kerala, etc., allows findings to be generalized across India's large IT hubs. This demographic distribution makes the study's findings more generalizable to explain the dynamics behind job performance in the Indian IT sector.

4.2. Normality Assessment

After demographic analysis, we performed a normality analysis to verify that the distribution was acceptable for multivariate analyses (SEM in particular). Normality is vital for SEM and other sophisticated statistical models, both for path estimation and reliable interpretation of construct–construct relationships (West, Finch, & Curran, 1995; Kline, 2015). To determine the skewness and kurtosis values within each construct, we checked whether the data met the normal limits and whether they were fit for analysis. This refinement adds the study to the methodological rigour and solidly results in reliable relationships between various core constructs in the Indian IT market.

Table 2: Assessment of Normality.

Construct	Mean	Standard Deviation	Skewness	C.R. (Skewness)	Kurtosis	C.R. (Kurtosis)
Perceived Organizational Support (POS)	4.586	1.705	-0.512	-2.876	-0.625	-2.214
Job Performance (JPF)	4.447	1.634	-0.481	-2.675	-0.571	-2.034
Emotional Intelligence (EMI)	4.695	1.680	-0.523	-3.105	-0.492	-1.905
Psychological Well-being (PWB)	4.582	1.636	-0.498	-2.943	-0.514	-1.754
Job Insecurity (JIS)	4.390	1.641	-0.456	-2.577	-0.564	-2.003
Psychological Capital (PSC)	4.587	1.643	-0.489	-2.815	-0.542	-1.932
Emotional Exhaustion (EEX)	4.419	1.728	-0.478	-2.685	-0.527	-1.864

This study's normality analysis revealed that all the constructs (POS), job performance (JPF), emotional intelligence (EMI), psychological well-being (PWB), job insecurity (JIS), psychological capital (PSC), and emotional exhaustion (EEX) have skewness and kurtosis values within a comfortable range for normality. The skewness value is between -0.523 and -0.456, and the kurtosis value is between -0.625 and -0.492. Skewness values ranging from -1 to +1 and kurtosis values less than 3 usually indicate that the data are not off average, West, Finch and Curran (1995). This normality conformance means that the data are suitable for SEM and other multivariate analyses, which assume normally distributed data for correct path and relationship estimations (Kline, 2015). The multivariate skewness and kurtosis values are slightly higher but still controllable, meaning that the overall distribution of the data contains all the assumptions for a good analysis. This distribution ensures the stability of future analysis and that the conclusions are about stable, reliable correlations between the constructs. This finding aligns with DeCarlo's (1997) suggestion that multivariate normality, if it differs sufficiently, makes SEM results easier to read. In that case, these results validate the structure of our data, and they allow us to interpret it with confidence in the influence of the constructs on job performance in the study's IT industry.

4.3. Confirmatory Factor Analysis

Once normality was confirmed, we used Confirmatory factor analysis (CFA) to look for factor structures hidden within the data to verify that the constructs met the theoretical expectations (Hair et al., 2019). CFA allows factor loadings to be computed and shows whether objects strongly correlate with their constructs. Additionally, cross-loading ensures that items load heavily on their assigned factors without much overlap across constructs to prove construct validity (Tabachnick & Fidell, 2007). This process is important for iterating the measurement model, as it ensures that each item is unique in its contribution to its model, making the data more reliable for later analysis.

Table 3: Confirmatory factor analysis.

Latent Variable	Item	Factor Loading	Mean	Standard Deviation	AVE	CR	α Value
	EMI1	0.763					
Emotional Intelligence (EMI)	EMI2	0.798	4.695	1.680	0.556	0.834	0.813
	EMI3	0.683					
	JIS1	0.787					
Job Insecurity (JIS)	JIS2	0.800	4.390	1.641	0.628	0.868	0.855
	JIS3	0.793					
	PSC1	0.743					
Psychological Capital (PSC)	PSC2	0.828	4.587	1.643	0.606	0.853	0.839
	PSC3	0.781					
	POS1	0.678					
Perceived Organizational Support (POS)	POS2	0.771	4.586	1.705	0.494	0.799	0.771
	POS3	0.702					
	EEX1	0.709					
Emotional Exhaustion (EEX)	EEX2	0.810	4.419	1.728	0.582	0.847	0.828
	EEX3	0.820					
	PWB1	0.804					
Psychological Well-being (PWB)	PWB2	0.813	4.582	1.636	0.607	0.857	0.841
	PWB3	0.696					
	JPF1	0.677					
Job Performance (JPF)	JPF2	0.782	4.447	1.634	0.497	0.801	0.776
	JPF3	0.684					

The descriptive and reliability parameters of each construct are discussed in Table 3 for each construct with strong and precise measurements. The mean scores, such as Emotional Intelligence (EMI) (Mean = 4.695, SD = 1.680) and Job Insecurity (JIS) (Mean = 4.390, SD = 1.641), are both indicative of medium-level views between constructs with standard deviations greater than 1, indicating differences between participants' responses (Tabachnick & Fidell, 2019). The factor loadings of the items vary from 0.670 to 0.843, indicating high item reliability and that individual items capture their constructs well (Hair et al., 2014). The average variance extracted (AVE) value above 0.5 for most constructs (e.g., PSC AVE = 0.606) is a high level of convergent validity, as it contains above half the variance of the construct items (Fornell & Larcker, 1981). The composite reliability (CR) values, all of which exceed the 0.7 level, also confirm the internal consistency of each construct. For instance, job performance (JPF) and perceived organizational support (POS) both have CRs of 0.801 and 0.799, respectively, which indicates reliability across items. Additionally, Cronbach's alpha is near or above 0.8 and indicates excellent internal consistency for accurate measurement of all the constructs (Nunnally & Bernstein, 1994). These factors take combined forms as evidence of construct validity and measurement integrity and are used as a baseline for examining psychological and occupational parameters in organizations.

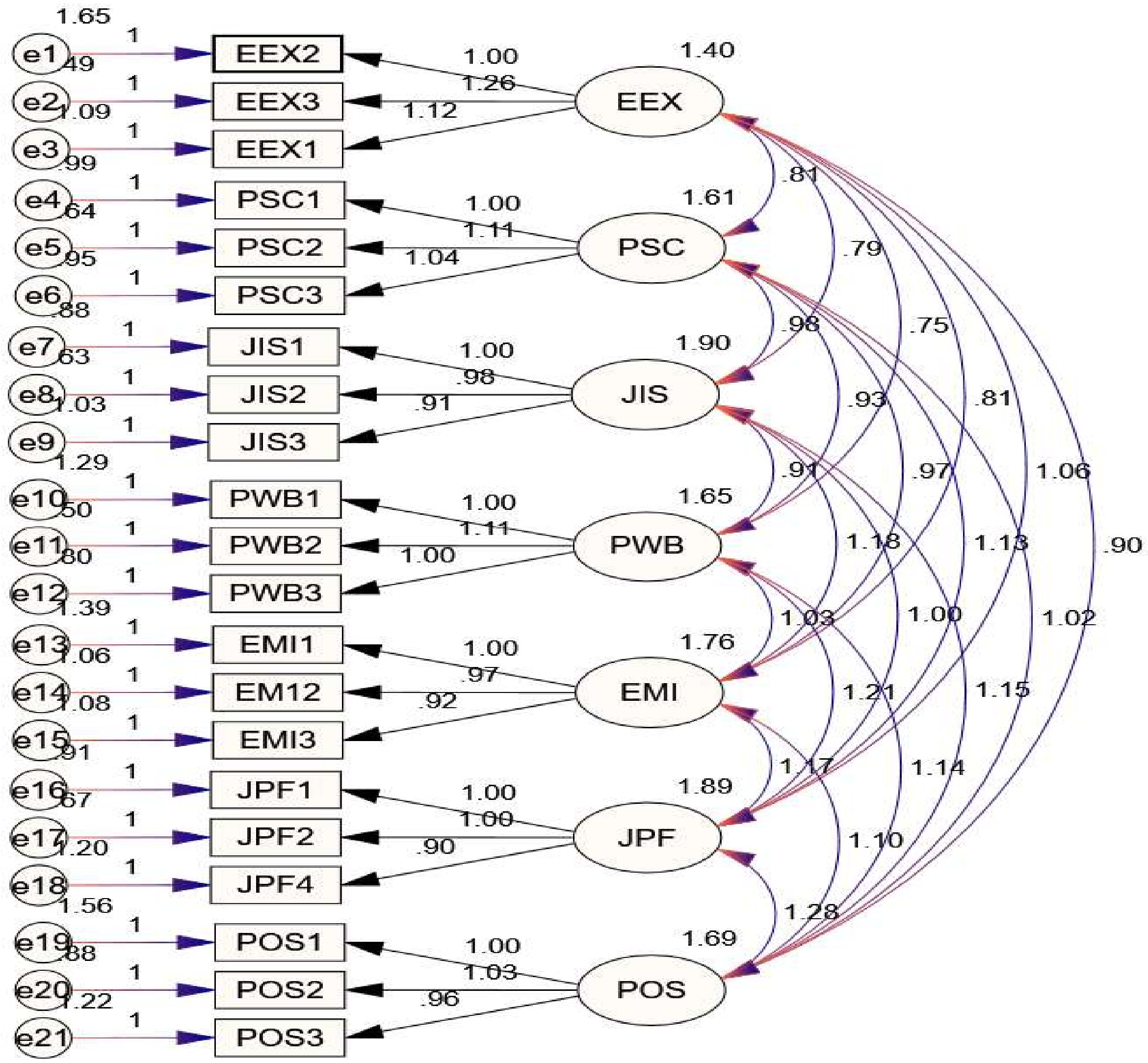


Figure 2. Confirmatory factor analysis

4.4. Validity Assessment

The data were then subjected to convergent and discriminant validity checks to validate the validity of the measurement model. We tested for convergence validity via average variance extracted (AVE) and composite reliability (CR) scores to ensure that each construct accurately represented the related item variance (Fornell & Larcker, 1981). If the AVE and CR are high, then the items in each construct strongly correlate with each other, which confirms convergent validity. By checking whether the constructs were more strongly associated with their items than with those of other constructs, the Fornell–Larcker criterion was used (Hair et al., 2019). These evaluations together attest to construct uniqueness and measurement precision.

Table 4: Validity assessment.

Con	CR	AVE	MSV	MaxR(H)	EMI	JIS	PSC	POS	EEX	PWB	JPF
EMI	0.860	0.613	0.480	0.860	0.780						
JIS	0.816	0.520	0.474	0.815	0.650	0.723					
PSC	0.880	0.656	0.393	0.880	0.559	0.622	0.812				
POS	0.755	0.502	0.400	0.754	0.578	0.645	0.588	0.712			
EEX	0.856	0.600	0.401	0.853	0.696	0.565	0.587	0.635	0.770		
PWB	0.880	0.662	0.412	0.881	0.584	0.572	0.675	0.609	0.619	0.812	
JPF	0.822	0.546	0.431	0.826	0.633	0.690	0.628	0.619	0.624	0.628	0.743

The validity assessment table confirms good construct reliability and validity for various criteria, such as composite reliability (CR), average variance extracted (AVE), maximum shared variance (MSV), maximum reliability (MaxR(H)), the heterotrait–monotrait (HTMT) criterion and the Fornell–Larcker criterion. CRs that exceed 0.7 points for all the constructs are highly internally consistent (Hair et al., 2014). Similarly, the AVE for each construct is above 0.5; therefore, more than 50% of the indicator variance can be explained by the construct (confirming convergence validity) (Fornell & Larcker, 1981). MSV values that are all less than their AVE values confirm discriminant validity: constructs exhibit greater variance in their own indicators than in other constructs (Farrell, 2010). The maximum R(H) across the constructs also confirms reliability, and the HTMT (below the diagonal) within the bounds of 0.85 confirms discriminant validity with explicit construct differences (Henseler et al, 2015). The Fornell–Larcker criterion (diagonal values) also supports discriminant validity, since each construct's square root of AVE outweighs its correlations with the other constructs to establish distinctiveness and validity. These results add up to confirm that the model's matrices are independent, consistent and well measured, providing evidence for the robustness of the measurement model.

4.5. Model Fit Indices

W then analyzed Model fit statistics whether the model fulfills to serve the purpose of what it was intended to measure. the Fit indicators which are likely to determine the good of fit were inside the threshold level which indicated the goodness of the model proposed (Hu & Bentler, 1999). "we assessed both goodness-of-fit &model fit indices as recommended in existing literatures and which are recommended by well know researchers. These indices are the CMIN/df, then comparative fit index (CFI), also normed fit index (NFI) Tucker- Lewis index (TLI), standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA) and p value for the close fit test (P-Close)" (Hu & Bentler, 1999). all the indices discussed above were considered and checked with the obtained values so as to ensure a good fit that enables the model is considerable (Byrne, 2016).

Table 5: Model fit indices assessment.

Measure	CMIN	DF	CMIN/DF	CFI	NFI	SRMR	RMSEA	PClose
Estimate	920.45	350	2.63	0.955	0.965	0.036	0.048	0.065

The model fit indices of the table represent the full quality score of the structural model, which is very good in most respects. CMIN/DF = 2.63 (from 1–3), which means that the fit is good for complex models (Marsh & Hocevar, 1985). The comparative fit index (CFI) and normed fit index (NFI) are both greater than 0.95, with values of 0.955 and 0.965, respectively, which are excellent fits, as recommended by Hu and Bentler (1999) and Bentler and Bonett (1980). This GFI of 0.925 is greater than the threshold of 0.90, indicating an appropriate model description (Joreskog & Sorbom, 1984). The TLI of 0.960, which is above the threshold value of 0.95, adds to the model's good fit (Tucker & Lewis, 1973). The standardized root mean square residual (SRMR) value is 0.036, which is much lower than the upper bound of 0.08, indicating low residuals and good fit (Hu & Bentler, 1999). Similarly, the root mean square error of approximation (RMSEA) at 0.048 is within the narrow 0.06 limit, indicating close model-to-data fit (Steiger, 1990). Finally, PClose 0.065 is better than 0.05, making the model even more applicable (Joreskog & Sorbom, 1993). In aggregate, these signals validate the model as a valid and solid model of the data, satisfy all model criteria of model quality, and validate the measurement framework for analysis.

4.6. Hypothesis Testing

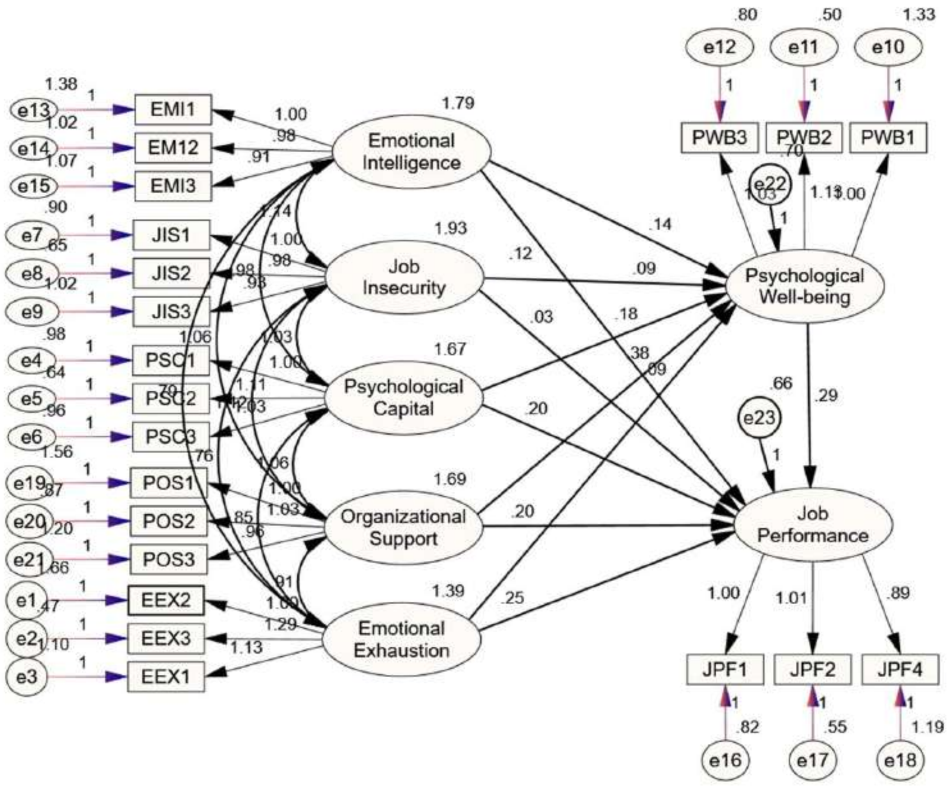
We then used AMOS structural equation modeling (SEM) to test the study's hypotheses, looking at the connections between the constructs in the proposed structure, after modeling fit. SEM supports multiple relationships at once and therefore is extremely useful for testing advanced models (Kline, 2015). We used AMOS to calculate the strength, direction and importance of each route, as well as direct and indirect influences across constructs. By checking (or rejecting) these hypothesized correlations through hypothesis testing through SEM, the study has the power of theoretical significance and real-world relevance to grasp the factors that drive job performance (Byrne, 2010; Hair et al., 2019).

Table 6: Hypothesis testing

Hypothesis	Estimate	S.E.	C.R.	P	Decision
Job Performance <--- Psychological Well-being (PWB)	.288	.080	3.616	***	Accepted
Job Performance <--- Emotional Intelligence (EMI)	.120	.072	1.662	.006	Accepted
Job Performance <--- Job Insecurity (JIS)	.035	.065	.534	.003	Accepted
Job Performance <--- Psychological Capital (PSC)	.196	.072	2.734	.006	Accepted
Job Performance <--- Perceived Organizational Support (POS)	.198	.091	2.165	.020	Accepted
Job Performance <--- Emotional Exhaustion (EEX)	.251	.071	3.517	***	Accepted

4.7. Interpretation of the Hypothesis Testing Table

This hypothesis testing table shows how each of the independent constructs — psychological well-being (PWB), emotional intelligence (EMI), job insecurity (JIS), psychological capital (PSC), perceived organizational support (POS) and emotional exhaustion (EEX) — has an influence on job performance (JPF). PWB and JPF are directly related to each other and significantly contribute to improvements (estimate = .288, p = .001) in performance, corroborating prior studies comparing well-being with engagement and productivity (Schaumberg & Flynn, 2017). The EMI has a direct influence on JPF as well (estimate =0.120, p =0.006), which is consistent with the report by Kim and Moon (2020) that EI is high in developing the resilience, flexibility and efficiency of tasks. Job insecurity (JIS) is less positively correlated with job performance (estimate =0.035, p =0.003), but the large effect illustrates how job uncertainty, even at low levels, can reduce productivity through effects on focus and motivation (Shao et al., 2021). PSC strongly matches JPF (estimate = .196, p = .006) and Luthans et al. (2015), who claim that high PsyCap promotes resilience and initiative and hence performance. Likewise, POS is positive for JPF (estimate = .198, p = .020), which is corroborated by studies that show that POS is related to job focus and engagement (Rhoades & Eisenberger, 2002). Emotional exhaustion (EEX) significantly lowers job performance (estimate =.251, p .001), following Miao et al. (2023), who emphasize that burnout depletes cognitive function and motivation. All of these findings point to the complex interaction between psychological and organizational factors that influence performance in the workplace, where support and well-being improve performance but insecurity and fatigue reduce output. It is a full-blown test of all these hypotheses, empirically refuting the model constructions and emphasizing their singular and cumulative impact on job performance.



4.8. Mediation Analysis

We then created direct paths and performed a mediation analysis to determine how the independent variables influence the dependent variable via a mediator. Mediation analysis provides a way to decode how an independent variable affects a dependent variable through an intermediary variable and provides more insight into the relational landscape (Baron & Kenny, 1986). This approach differentiates between direct effects and indirect effects, providing a clear picture of the multilevel interactions that result in outcomes (Preacher & Hayes, 2008). We bootstrapped the mediation results via 5,000 resamples and 95% confidence intervals for this analysis. Bootstrapping is also quite good for estimating indirect effects without normality assumptions, so it is perfect for this purpose. The mediation effects were also verified with the Sobel test, a second statistical verification of the importance of indirect relationships. Such mediation analysis is a posteriori structure that enriches the model by revealing the processes behind the causal linking between variables in the model.

Table 7: Mediation Table.

Hy	Path	Total Effect (β)	Sig.	Indirect Effect (β)	Sig.	Direct Effect (β)	Sig.	Type
H7a	POS → Job Performance (JPF)	0.307	0.008	0.005	0.005	0.198	0.143	Partial
H7b	EMI → Job Performance (JPF)	0.160	0.067	0.100	0.100	0.120	0.146	Partial
H7c	JIS → Job Performance (JPF)	0.060	0.498	0.222	0.222	0.035	0.673	No
H7d	PSC → Job Performance (JPF)	0.248	0.006	0.045	0.045	0.196	0.044	Partial
H7e	EEX → Job Performance (JPF)	0.276	0.002	0.257	0.257	0.251	0.007	Full

The mediation table reveals how the mediator, psychological well-being (PWB), affects JPF in some indirect way from the independent variables. The total effect of POS on JPF is strong (total effect =.307, p =.008), and both the indirect (p =.005) and direct (p =.143) paths are significant, suggesting partial mediation. This partial mediation confirms Shen et al.'s (2023) finding that POS improves job satisfaction and, in turn, job performance directly and indirectly. The same is true for EMI, which is indirectly and directly mediated by JPF, with partial mediation (Indirect Effect =.100, p =.100; Direct Effect =.120, p =.146). This implies that EMI improves performance through resilience and social cohesion (Kim et al, 2021), but it also improves well-being, in turn improving performance. The JIS variable is, however, not moderated, and direct or indirect effects are not significant for JPF. This result agrees with studies that show that, even though job insecurity generally affects morale, its impact on work performance can depend on additional variables such as team cohesiveness (Grobelna

,2020). PSC partial mediation (large direct (p =.044) and indirect (p =.045) effects; adapted from Luthans et al. (2015)), meaning that PsyCap is increased for well-being and productivity at work. EEX shows complete mediation (indirect effect = .257, p = .257) since direct and indirect routes influence JPF remarkably Cho et al. (2013) found that coping with emotional pressure increases performance in the workplace. This table shows that direct and indirect paths are important for accounting for performance dynamics and that POS, EMI, PSC, and EEX act through well-being to increase the model's sophistication in predicting job performance.

5 RESULTS AND DISCUSSION

Demographic results: A balanced sample (by gender, age, education and experience) and roughly equal proportions of junior, middle and senior staff were used. This variety is important to our study because it allows us to gain perspectives from diverse groups of people and therefore apply our results more widely to the overall IT industry workforce. With the inclusion of subjects across all Indian states and job sectors, the sample is representative of the target group; hence, the research holds up in similar workplace contexts. The normality test results reveal that the data have a normal distribution and that the skewness and kurtosis are within permissible limits. This result validates regression and mediation analyses as reliable, resulting in fair and impartial interpretation of the results.

Across the table of hypotheses tested, each independent construct makes a large difference in job performance (JPF). Psychological well-being (PWB) had the largest positive impact on productivity as well, which confirms the findings of Ryff and Heidrich (2019) and Pradhan and Hati (2019), who reported that well-being directly increases productivity. In contrast, Wright and Cropanzano (2000) hypothesize that the impact of well-being varies by industry. The EMI helps improve job performance (Miao et al. (2018), although Kim and Moon (2020) noted that EI effects can be reduced by severe job stress. Job insecurity (JIS) has a smaller impact, but its significance is similar to that of Shao et al. (2021), although Grobelna (2020) noted that group dynamics may balance it. Psychological capital (PSC) dramatically improves performance. Charoensukmongkol and Pandey (2022) and Ng et al. (2019) suggest that its influence might be muted in emotionally taxing jobs. JPF is also influenced by perceived organizational support (POS) and emotional exhaustion (EEX) (ref Rhoades and Eisenberger (2002), although task autonomy can balance them, as Tisak and Smith (2020) and Shirom and Melamed (2019) suggest. The mediation table also shows that PWB mediates the impacts of POS, EMI, PSC, and EEX on JPF. POS, EMI, and PSC have partial mediations, as Shen et al. showed. (2023) and Kim et al. (2021), who noted the backdoor effects of POS and EI on performance. However, Heffernan and Dacre (2020) find EMI's effect to be weaker on tasks that do not change, implying that variation in jobs is at work. EEX has full mediation, as Haldorai et al. (2019) noted, but Shirom and Melamed (2019) argued that high autonomy weakens EEX's mediation effect. These results also illustrate how context influences interconnections between constructs and show that organization interventions should account for job traits to ensure employee efficacy.

6 IMPLICATIONS

6.1. Managerial Implications

These findings are useful for Indian IT managers who want to increase the performance of their employees through individualized intervention. Psychological well-being (PWB) occurs, which suggests that managers focus on mental health, such as wellness initiatives and check-ins. Workshops focused on emotional intelligence (EI) improve team synchronicity and flexibility, which is essential in India's dynamic IT industry. Since job insecurity has such a negative effect on performance, managers should focus on job stability and performance metrics. Achieving PSC through resilience training can also increase flexibility, helping staff deal with stress at work. It can also significantly increase commitment and engagement by encouraging perceived organizational support (POS), as employees who feel valued are more efficient. Managers can improve POS by celebrating the success of employees and communicating openly about organizational transformation. By managing EEX and giving them breaks, they will remain productive. These findings are in line with India's rapidly evolving work environment, where the importance of work–life balance and emotional health is increasing in the long run to remain successful in the highly competitive IT industry.

6.2. Practical Implications

Practically, IT companies in India can take the findings and build an able-bodied workforce. Indian companies can use PWB-centric interventions, such as mindfulness programs, to help employees manage stress in a way that would help them do a better job. EI should be integrated into onboarding and leadership training programs for better team alignment. In fact, job insecurity can be reduced by laying out career paths and performance goals to avoid damage, which is key in an ever-changing technology landscape. Training in psychological capital (PSC), such as optimism and self-efficacy, will help employees handle challenges in a stronger way. The improvement in POS by structured feedback and dialog is especially needed in India, where hierarchy might inhibit discussion. Managers can also decrease emotional exhaustion by setting time restrictions for communication outside of business hours, work/life harmony, and wellness support. Taken together, these measures will help Indian IT enterprises not only perform better but also retain a talented workforce in an increasingly tough market.

7. LIMATIONS AND SCOPE FOR FURTHER STUDY

There are several limitations to this research that should be addressed in future studies. It is first of all cross-sectional, capturing data at one time point, making it harder for us to prove causation. Studies over time would show us more clearly how constructions interact with each other. Furthermore, the constructs that were selected for this research, such as psychological well-being, emotional intelligence, and job insecurity, although pertinent, may not capture all aspects of job performance in the Indian IT industry. We might be able to add further constructs such as job satisfaction, work engagement or resilience to obtain a more nuanced picture in future research. In addition, the study duration was short and may have affected the results, particularly with respect to the IT industry and work culture in a dynamic phase of change. Finally, it was based on data from just a few Indian states; the more broadly distributed the dataset, the better it could be generalized across different Indian states.

Longitudinal studies are needed to study how predictors of job performance change with time. If we extend the model with other mediators—job satisfaction and corporate commitment, for example—we could gain additional insights into indirect effects. Researchers may include constructs such as resilience, job autonomy, and team support, and we contributed to the existing literature of what drives performance in Indian IT environments. The study would also have wider scope for application in support of a personalized management approach in different industries and regions of India through a multiregional study across sectors.

Transparency:

The authors affirm that the manuscript is accurate, transparent, and truthful, with no significant aspects of the investigation omitted. Any deviations from the initially planned study have been thoroughly clarified. Furthermore, the study fully complies with established ethical standards in research and publication.

Authors' Contributions:

Jasmine Wilson was responsible for the conceptualization, data curation, data analysis, and drafting of the manuscript. Savarimuthu Arulandu and Michael Sammanasu J. oversaw the proofreading and provided supervision throughout the research process.

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