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Development of a comprehensive stress assessment tool for Indian public sector employees

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Abstract

The study aims to develop a comprehensive stress assessment tool for Indian public sector employees, considering unique stressors, cultural factors, and organizational characteristics. The study employed a deductive approach, cross-sectional design, and mixed-method study based on comprehension of extant stress management theories, to explore the factors contributing to employee stress. The study found that technological disruptions, austerity measures, blame games, multitasking, and work–life balance are significant factors of assessing employee stress. The findings of the study fill the gaps in extant literature and extends support to the job demand control and support model. The findings make practical contributions in assisting practitioners and policymakers to design suitable intervention programs to reduce employee stress and enhance employee productivity. The unique contribution of the study is, first of its kind in the Indian public sector context, that the tool has the potential to assess employee stress effectively at workplace and practitioners can derive benefits of the stress assessment tool.

Keywords Employee stress, Technological disruptions, Austerity measures, Blame game, Multitasking, Work–life balance

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Graphical abstract

Introduction

A startling 78% of workers in organizations experience anxiety and burnout due to stress, which the World Health Organization frequently refers to as the "Health Epidemic of the twenty first century." The financial ramifications are also worrying because, according to Deloitte's Mental Health Survey in 2022, workplace stress costs the organized sector $14 billion yearly.

The motivation behind the study

Existing research has highlighted the substantial contributions of high job demands, lack of control, and limited social support to increased employee stress levels [22, 27]. These stressors have detrimental effects, including reduced job performance, heightened absenteeism, and increased turnover rates. The COVID-19 pandemic has further exacerbated stress levels, with remote work, isolation, and uncertainty adding to employees' psychological burdens. To mitigate the impact of stress on employee well-being and organizational outcomes, organizations felt it essential to implement proactive stress management strategies and comprehensive employee stress assessment tools.

The rationale of the study

Indian Public Sector Undertakings (PSUs) face distinctive challenges that exacerbate employee stress and hinder organizational performance. This study aims to address the pressing issue of stress-related absenteeism (21%), turnover rates (6.8%), and productivity losses (equivalent to 36.94 lakh man-days lost in the last three years) within Indian PSUs, as highlighted in the 2023 Annual Report

by the Department of Public Enterprises, Government. of India. Despite the implementation of cutting-edge stress intervention programs such as Employee Satisfaction Survey, Employee Counselling Program, Systematic Appraisal, Referral, and Treatment, the absence of appropriate employee stress assessment tools has impeded effective stress management. These reports make it imperative to devise a stress assessment tool tailored to Indian PSUs work environments for enhancing employee performance and well-being.

Significance of the study

The relevance and significance of understanding and researching employee stress lie in its potential positive impact on employees and organizations. By improving employee mental health, organizations can enhance their performance, reducing healthcare costs, increased employee engagement, and higher job satisfaction. This study is grounded in the epistemological premise of contextual embeddedness, acknowledging the profound influence of specific circumstances on stressors and contributing factors in the Indian PSUs.

Research gaps

Traditional stress assessment tools exhibit gaps that necessitate a deeper understanding of the cumulative effects of multiple stressors and the unique experiences of individuals facing intersecting stressors. Considering potential cultural differences, it is crucial to evaluate long-term health outcomes and the applicability of stress theories and stress measurement tools based on them across cultures. Furthermore, exploring the dynamic nature of stress and the underlying mechanisms affecting stress adaptation over time can enhance our understanding of stress theories. Notably, existing stress assessment frameworks have primarily been designed for Western contexts, warranting further research into their suitability for various cultural contexts, industries, and occupations. The present study addresses these gaps and controversies in the field.

Research questions

The study formulated the following research questions:

RQ1: What key factors contribute to stress in Indian PSU employees?
RQ2: Which dimensions of contextual factors are most influential in assessing employee stress in Indian PSU employees?
RQ3: Do the interlinked factors integrate into a conceptual framework of employee stress assessment in Indian PSUs?

Research objectives

To address the research questions, this study aims to achieve the following objectives:

1. To assess the prevalence of employee stress within Indian PSUs.
2. To identify the key contributing factors of employee stress in Indian PSUs.
3. To establish the validity and reliability of the assessment tool through psychometric testing.
4. To evaluate the practical utility and relevance of the stress assessment tool within the Indian PSUs context.

Research hypotheses

Based on the research objectives and questions, the following hypotheses are formulated:

H0: The employee stress assessment tool does not comprehensively assess employees' stress levels in Indian PSUs.
H1: The employee stress assessment tool comprehensively assesses employees' stress levels in Indian PSUs.

Methodology

The research methodology comprises a cross-sectional study incorporating various approaches and iterative investigations. Qualitative and quantitative data will be collected through interviews and surveys from a targeted group of Indian PSUs employees, with a sample size of 520 participants.

Contributions of the study

The study's contributions compared to existing work are to refine and expand the Job Demand Control and Support (JDCS) theory of stress by incorporating stressors such as technological disruptions, austerity measures, blame games, multitasking, and work–life balance. The ultimate goal is to underscore the practical potential of the stress assessment tool in enhancing employee well-being and performance. Identifying high-stress departments and job roles will enable organizations to prioritize resources and implement evidence-based stress management programs. This study is expected to provide valuable insights and directions for future research in this critical field. The study's unique contribution is, first of its kind in the Indian PSUs context, that the tool can assess employee stress effectively at

the workplace and derive benefits from the study for stress management programs.

Theoretical framework

The JDCS theory guiding this study is favored for developing an employee stress assessment tool due to its holistic framework and empirical backing. The JDCS incorporates job demands, control, and support factors, offering a comprehensive understanding of workplace stressors. Its practical relevance makes it adaptable to various work settings and modern trends. The theory's balance between job-related demands, individual control, and social support aligns with the complexity of contemporary workplaces.

Structure of the paper

This research paper is structured as follows: "Review of literature" section reviews stress measurement literature and its relevance in Indian PSUs. In "Data and methodology" section outlines the data and research methodology for developing the stress assessment tool. In "Discussions" section discusses the tool's results on the psychometric evaluation of the tool, its reliability, and validity and summarizes the paper's findings, implications, and recommendations for future research. We conclude the study in "Conclusions" section.

Review of literature

The literature review provides an extensive overview of stress theories, frameworks, and assessment scales, mainly focusing on their applicability to Indian PSUs and concurrently highlighting the insufficiencies inherent in current stress assessment models.

The Indian PSUs work settings

The Indian PSUs are characterized by a unique work environment marked by substantial bureaucracy, hierarchical structures, and diverse operations across energy, manufacturing, and infrastructure sectors. Given the country's rapid technological advancements, economic reforms, and growing competition, these organizations face mounting challenges. Consequently, the need for an Employee Stress Assessment Scale arises. Technological disruptions pose significant stress as employees grapple with rapid changes. Austerity measures, driven by financial constraints, can increase workloads and job insecurity. Blame Gaming and Multitasking in a high-pressure environment exacerbate stress. Furthermore, managing work–life balance amid these pressures becomes essential for employee well-being and organizational effectiveness.

In times of economic instability, Indian PSUs often emphasize efficiency, creativity, and quality, which can inadvertently intensify the pressure and stress experienced by employees. The heightened stress carries diverse ramifications, ranging from increased turnover intention and overtime pay to diminished productivity and absenteeism. In light of these multifaceted repercussions, it becomes imperative to understand the stress comprehensively to manage it effectively in the Indian PSUs.

Different approaches to measure employee stress

The approaches to measuring employee stress differ, with a focus on specific environmental, organizational, and relational factors. Some approaches involve the development of direct measures that link stress experienced in the workplace with job design conditions; others involve the implementation of subjective measures that contain constructs related to a theoretical framework like, Job Demand Resources model and Effort–Reward Imbalance (ERI) model. Still, other approaches involve the development of general measures of workplace stress that do not necessarily link to some specific source of stress or organizational determinants, but instead focus principally on measuring the manifestations of stress (e.g., burnout, physiological responses, workaholism, conflicts, mobbing, etc.). This has produced a natural proliferation of workplace stress measures, ranging from straightforward measures of workplace stress to complex scales containing many subscales and many organizational determinants of stress (e.g., workload, demands, environmental and working conditions, role/task/job characteristics, managerial support, shifts, etc.), along with institutional evidence.

Theoretical bases of developing employee stress assessment tools

Numerous stress theories have made the foundation for developing employee stress assessment scales. Hans Selye's stress theory [26] advocated for an equilibrium between four stress dimensions to optimize eustress, underscoring the importance of harmonizing hyper- and hypo-stress. Selye's endorsement of physiological, psychological, and engineering stress theories, particularly emphasizing interactions between employees and their work environments, advances major theoretical frameworks for developing employee stress measurement scales. The Transactional Model of Stress and Coping by Richard Lazarus and Susan Folkman posits that stress results from the interaction between individuals and their environment. Scales based on this theory assess an individual's appraisal of stressors and their coping strategies. The Demand-Control Model (Job Strain Model) by Karasek and Theorell focuses on job-related stress and suggests that stress occurs when job demands are high and an individual's control over their work is low. Assessment

tools based on this model measure job demands, control, and job strain. Similarly, the ERI Model by Johannes Siegrist suggests that stress results from an imbalance between high effort expended at work and the low reward received in return. Scales based on this model assess effort, reward, and their perceived imbalance.

The Psychosocial Safety Climate Theory emphasizes the role of the organizational environment in stress prevention. Scales based on this theory measure an organization's commitment to creating a safe and supportive work environment. According to Arnold Bakker and Evangelia Demerouti's Job Demands-Resources Model, stress and well-being are influenced by job demands and resources. The balance between the demands of the job and the resources available to employees is measured using assessment scales based on this theory. The Urs Nater and Phil Evans' Cognitive Activation Theory of Stress focuses on the cognitive mechanisms involved in stress reactions.

Existing employee stress assessment tools

The various approaches taken to measure stress are reflected in the landscape of employee stress assessment models. To measure workplace stress levels, the Occupational Stress Indicator (OSI) is frequently used [4, 30]. However, it has received criticism for its flaws, such as a failure to address all stressors, a lack of focus on organizational support, and an inability to adequately capture the complexities of the contemporary workplace. To increase its usefulness, the OSI should be updated to include aspects of austerity measures, such as increased workload brought on by resource constraints and monetary uncertainty. On the other hand, measuring and controlling workplace stress is frequently done using the HSE Management Standards Indicator Tool. Although it uses a standardized approach that is user-friendly, its subjectivity, scope, and interpretational challenges obstruct its full effectiveness [5, 34]. The effectiveness of the scale can be enhanced by addressing the invasion of technology and work pressure from technology.

The Occupational Stress Questionnaire is a credible self-report tool for assessing occupational stress across various dimensions. However, it is not equipped to address challenges like technological disruptions and austerity measures. Furthermore, its susceptibility to self-report bias, lack of objectivity, and interpretational difficulties coupled with limited contextual information, like lack of flexibility, extended working hours, relationship issues affecting work life and constrains its applicability [2]. The Job Stress Survey assists in benchmarking stress levels. However, it primarily relies on subjective experiences, thus limiting the holistic assessment of job stress [28]. The scale overlooks the impact of fear of blame, avoidance of responsibility, and lack of focus due to blame game on employee stress. The Job Content Questionnaire (JCQ) offers valuable insights into psychological job requirements, social support, skill discretion, and decision authority [35]. Nonetheless, it may need to address distinct job characteristics, limiting its comprehensive assessment. To make the Job Content Questionnaire more relevant, one should consider expanding it to incorporate factors related to multitasking, such as the frequency of multitasking, extra workload, reduced resources, and their impact on job demands. The National Institute of Occupational Safety and Health work-related stress questionnaire, encompassing various aspects of work-related stress, enables comprehensive evaluations. However, the questionnaire's efficacy would be augmented by incorporating objective physiological indicators. This scale can capture stress arising out of job insecurity from technology, cost of living adjustments from austerity measures, and lack of flexibility from work–life imbalances.

The ERI model addresses psychosocial stress and quantifies stress dimensions, although self-report biases could influence response accuracy [2]. To ensure it remains effective in contemporary workplaces, the ERI model should integrate dimensions related to blame gaming, including aspects of workplace culture and the fear of blame. This scale remains silent on stress caused by the burden of technology, financial uncertainties, and unhealthy work environments. The widely used Perceived Stress Scale (PSS) is designed to gauge stress's unpredictability, uncontrollability, and overload aspects [8]. However, a notable limitation of the PSS is its relative neglect of contemporary life experiences and emerging stressors like technological advancements. To comprehensively assess stress in today's workplaces, there is a need to incorporate factors related to technological disruptions, such as exposure to technology and coping with technological changes, constantly increasing work demands affecting physical health, and time constraints due to multitasking, into the scale.

However, limitations emerge as contemporary life experiences and emerging stressors like technological advancements are overlooked. While the Depression Anxiety Stress Scales assess depression, anxiety, and stress, their accuracy and predictive capabilities are questioned. The Perceived Stress Questionnaire assesses cognitive and emotional reactions but neglects objective stressors and coping mechanisms, introducing biases [10]. Stressors like time-off issues, obsoleteness from technology, and exposure to technology can improve the scale. Sheldon Cohen's Perceived Stress Scale (CPSS) focuses on individuals' perceptions of stress frequency and capacity to handle stressors. However, it

may undervalue the positive effects of specific stressors, constraining its perspectives like task prioritization, teamwork, collaborative elements, and technology training. The Job Stress Scale (JSS) comprehensively evaluates job stress dimensions, yet it needs to distinguish between stress sources [32]. These measurement scales are frequently employed, and their utilization depends on contextual variables. However, their strengths and limitations limit their applicability within the diverse organizational settings of Indian PSUs.

Mitigating stress can boost employee performance through conflict management, training, counseling, and optimizing job roles [1]. Stress assessment, factor identification, and workload optimization can enhance employee well-being and performance [27]. The interplay between job conflict, stress, and employee satisfaction underscores the significance of job satisfaction [21]. Similarly, a study using the Tool to Assess and classify Work Stress-16 identified factors like effort and reward, organizational support, job security, and interpersonal relationships as indicative of stress. The TASS-16 could have been more effective by adding blame gaming and work–life balance elements.

The literature gaps

This literature review identifies critical research gaps in existing employee stress measurement scales, such as the OSI, HSE Management Standards Indicator Tool, and PSS. These gaps pertain to contemporary stressors like technological disruptions, austerity measures, blame gaming, multitasking, and work–life balance. To enhance these scales' effectiveness, they should be integrated into the overarching theory of Job Demand Control and Support theory to include dimensions related to these factors. This would enable a more comprehensive assessment of employee stress in today's workplaces, facilitating more targeted stress management strategies and better employee well-being.

Filling the research gaps

The study aims to fill identified research gaps by developing a novel employee stress assessment scale that comprehensively incorporates technological disruptions, austerity measures, blame gaming, multitasking, and work–life balance. Theoretical foundations will involve extensive literature review and expert consultations to ensure a robust conceptual framework. Practical development will involve data collection from diverse workplaces, ensuring real-world relevance. The resulting scale will bridge existing gaps and offer a holistic evaluation of contemporary stressors, providing valuable insights for organizations to enhance employee well-being and productivity.

Data and methodology

The study aims to create a stress assessment tool for Indian PSUs. An overview of the study design, participant selection, data collection techniques, and statistical analysis techniques used in the study are provided in this section.

Assessing and measuring employee stress is crucial for managing workplace well-being. To answer the research questions, researchers can employ several methods of data collection, including self-report questionnaires, job stress surveys, physiological measures, observational methods, interviews and focus groups, workplace assessments, and tracking absenteeism and turnover rates. We preferred a self-reporting questionnaire for developing an employee stress assessment tool due to its cost-effectiveness, scalability, and respondent anonymity. It allows for efficient data collection, ensuring accurate and diverse responses. Additionally, it is flexible, enabling quick reach to a vast pool of participants, making it an ideal choice for a comprehensive stress assessment tool.

Study assumptions

The various assumptions made to answer the research questions and test hypotheses are:

1. Construct validity and reliability will be ensured through pilot testing the items for scale development.
2. A sample size of 520 will be a representative sample of the study population.
3. Data collection through self-reporting questionnaire will enhance the tool's accuracy.
4. We assumed there were no confounding variables.

Study design

This research adopts a deductive, quantitative, cross-sectional, and descriptive approach to examine the prevalence, distribution, and associations of employee stress, to test the hypotheses, and to find answers to the research questions. This design aligns with the study's objectives, allowing for systematic stress measurement across a diverse sample.

Selection and operationalization of employee stress constructs

The selection of variables for developing an employee stress assessment model, including Technological Disruptions, Austerity Measures, Blame Gaming, Multitasking, and Work-Life Balance, is grounded in the existing literature. Numerous studies have widely recognized these factors as critical contributors to workplace stress. The existing body of research highlights their impact on employees' psychological and emotional

well-being, job satisfaction, and overall performance. Authors such as La Torre et al. [16], Carillo et al. [6], Klandermans and Van Stekelenburg [15], Roulet and Pichler [23], Dinh et al. [11] and Mutiara et al. [18] have extensively explored these variables in various organizational contexts, providing empirical evidence of their significance in inducing workplace stress. Hence, the selection of these variables is informed by a well-established foundation in the literature.

Abstract concepts are translated into observable variables to measure employee stress. The stress constructs include technological disruptions, austerity measures, blame games, multitasking, and work–life balance. Technological disruption refers to the radical changes caused by new technology, altering business processes and employee behavior, leading to stress. Austerity measures involve cost-cutting actions employers take due to financial turbulence, impacting employee well-being. Blame gaming deflects blame in response to allegations, inducing stress. Multitasking involves the concurrent execution of tasks, straining employees. Work–life balance measures the prioritization of individual and organizational activities in employees' lives.

Participants

The target population consists of Indian PSUs employees exhibiting potential sources of stress symptoms like anxiety, burnout, absenteeism, deteriorating health, and dissatisfaction, which can impact organizational performance. With 98 central Indian PSUs, the population is 0.24 million as of April 2023, and the study participants will be representative to assess employee stress levels.

Sampling method

Stratified random sampling is preferred for developing an employee stress assessment tool because it ensures a representative sample by dividing the population into meaningful strata. This approach helps capture diverse perspectives, making the tool more robust and applicable across various demographic groups within the organization. The sample is stratified on the basis of location and nature of industries. A random sample is drawn from Indian PSUs, like Bharat Heavy Electricals Limited, Oil and Natural Gas Corporation, National Thermal Power Corporation, and Coal India Limited.

Sample size determination

The sample size decided for preliminary items development is 30 employees, and for the main data analysis, the sample size is based on the 1:5 item-to-sample ratio for exploratory factor analysis (EFA) and adheres to the Rule of 500, ensuring statistical robustness. This results in 250 respondents for 40 questions on five factors, each containing eight questions. We arrived at the sample size of $N = 520$, and the rationale behind selecting such a sample is to enhance the generalizability of the findings.

Preliminary items development

A pool of potential stress assessment items capturing various stress dimensions is generated. The preliminary items selected to capture employee stress comprised 48 items in the context of technological disruptions, austerity measures, blame gaming, multitasking, and work–life balance on a 5-point Likert scale. Opinions from experts, including HR managers, HR professors, psychologists, and employees, were sought to review the items based on content and relevance. We dropped eight items based on their suggestions on inappropriateness. A preliminary stress assessment tool is administered to a small sample of 28 employees in Indian PSUs. Psychometric properties such as test–retest reliability (>0.70), internal consistency (>0.75), and item-total correlations are evaluated and confirmed. The tool is refined based on feedback and psychometric evaluation to ensure content validity and cultural appropriateness.

Development of the questionnaire

A questionnaire is used for data collection due to its cost-effectiveness, scalability, respondent anonymity, data accuracy, quick reach, and flexibility for respondents. A 5-point Likert scale ranging from strongly disagree to strongly agree is employed for 40 items, providing a better understanding for respondents compared to longer scales. The midpoint rating is included to maintain response effectiveness. The ordinal data from the instrument are treated as continuous data for adequate conceptualization, statistical analysis, and interpretation.

Data collection

Both primary and secondary data sources are utilized. Primary data are collected through the distribution of 520 questionnaires to respondents electronically via mail between January 2023 and May 2023. Efforts are made to convince respondents of the study's importance via telephone to reduce non-response bias. Time lags between measurements are proposed to minimize method-specific biases. Respondents are assured of anonymity and confidentiality to encourage honest and unbiased responses. Randomization of question order helps minimize systematic biases affecting specific employees. Data are thoroughly checked for cleanliness, missing values, outliers, and data entry errors. Missing values for six responses are replaced with the mean imputation of the particular item.

Statistical analysis

Descriptive statistics are used to analyze the data set. JASP (Jeffreys' Amazing Statistical Program) is employed for exploratory and confirmatory data analysis, providing American Psychological Association-styled results, plots, and tables for journals. EFA is used to identify underlying factors and dimensions of employee stress. Confirmatory factor analysis (CFA) validates the factor structure identified in the EFA stage. EFA examines dimensionality and factor loadings, while CFA confirms the measurement model's validity and improves tool accuracy. Researchers successfully used the EFA and CFA approaches to develop stress measurement scales recently [33, 37]. The decision criteria consider factors with at least three observed indicators and factor loadings of 0.5 or more. Factor correlation matrices assess the instrument's convergent and discriminant validity. CFA is utilized to test whether the hypothesized factor structure (i.e., the structure of the assessment tool) fits the observed data well. Cohen's d is employed to determine the effect size for establishing the practical utility of the tool. EFA and CFA use the same dataset for consistency, model validation, model-fit assessment, sample size consideration, and resource savings. This ensures consistent data structure, identifying potential latent constructs and formally testing hypothesized factor structures. Model fit will be evaluated through fit indices like Chi-squared values, RMSA, Tucker–Lewis Index (TLI), and Goodness-of-Fit Index (GFI).

Statistical validation process

To validate each stress construct, Kaiser–Meyer–Olkin (KMO) values, Bartlett's tests of sphericity, factor analysis variance, and construct reliability are calculated. Dual loading of items into factors is checked to ensure accurate measurement of the specific construct. Convergent and discriminant validity are assessed using hypothesis testing at a significance level of $\alpha = 0.05$, considering Type-I and Type-II errors. Common method variance (CMV) is mitigated by data from different sources (e.g., self-reports and supervisor reports), using reverse-scored items, altering the order of items, ensuring respondent anonymity, and employing CFA to assess CMV impact on the measurement model and controlling for it during data analysis.

Ethical considerations

Informed consent is obtained from all participants during data collection, ensuring confidentiality and anonymity to protect personal data and responses.

Data (results)

After administration of the pilot form of the stress assessment tool to a small sample consisting of 28 employees working in the Indian PSUs, we assessed the tool's psychometric properties and obtained Cronbach's alpha value at 0.82. The test–retest reliability score after administration of tool after one month resulted in a correlation coefficient of 0.78. Based on the results of the pilot testing, the refined tool resulted in a total of 40 items, as given in Table 1. The eight rejected items were ambiguous and lacked conceptual clarity. Out of the 520 questionnaires sent to the respondents, ($N = 508$) completed questionnaires with 12 incomplete forms were received. The responses led to a total response rate of 97.69%. The respondents' demographic profiles in Table 2 indicated

Table 1 Refined tool items. *Source*: Authors

Stress dimensions	Code variables assessing employee stress
Technological disruptions (TD)	TD 1-Exposure to technology TD 2-Invasion of technology TD 3-Coping with technology TD 4-Obsoleteness from technology TD 5-Work pressure from technology TD 6-Burden from technology TD 7-Training for technology TD 8-Job Insecurity from technology
Austerity measures (AM)	AM 1-Budgetary changes AM 2-Uncertainties AM 3-Extra workload AM 4-Reduced benefits AM 5-Reduced resources AM 6-Unhealthy work environment AM 7-Costs of living adjustments AM 8-Lack of financial State
Blame game (BG)	BG 1-Work culture BG 2-Lack of focus BG 3-Victimization BG 4-Teamwork BG.5-Fear of blame BG 6-Avoidance form responsibility BG 7-Collaboration BG 8-Job satisfaction
Multitasking (MT)	MT 1-Frequency of multitasking MT 2-Adjusting to changing work MT 3-Lack of focus MT 4-Time constraints MT 5-Quality of work MT 6-Reduced productivity MT 7-Task prioritization MT 8-Constant demands
Work–life balance (WB)	WB 1-Healthy worklife WB 2-Personal life interference WB 3-Lack of flexibility WB 4-Physical health WB 5-Extended working hours WB 6-Relationship issues WB 7-Lack of support WB 8-Time off issues

Table 2 Demographic profiles of the respondents ($N=508$). *Source*: Authors

Details	No. of employees	%	Details	No. of employees	%
Category employees			Education		
Workers	452	89	ITI	418	81
Supervisors	44	9	Diploma	68	13
Executives	12	2	Graduates	15	3
			Post graduates	07	1
Gender			Experience		
Male	486	96	5–10 years	494	97
Female	22	4	10–15 years	14	3

Table 3 Descriptive statistics ($N=508$)

Variables	Mean	SD	Skewness	Kurtosis
Technological disruptions (TD)	2.926	1.29	0.116	−1.056
Austerity measures (AM)	3.099	1.144	−0.109	−0.526
Blame game (BG)	3.093	1.235	−0.047	−0.901
Multitasking (MT)	3.132	1.128	−0.147	−0.622
Work–life balance (WB)	2.983	1.255	−0.091	−0.945
Avg	3.040	–	–	–

that most of the employees surveyed are in the worker category (89%), male-dominated, and ITI holder employees (81%).

Descriptive results

Table 3 displays descriptive statistics for variables in the study based on responses from 508 participants. Mean scores reveal participants' average stress perceptions: technological disruptions (2.926), austerity measures (3.099), blame game (3.093), multitasking (3.132), and work–life balance (2.983).

Table 5 Bartlett's test results. *Source*: Authors

Degree of freedom (df)	*p* value at significance level (*α*) 0.05
780.000	< .001

EFA results

The KMO values are found between 0.921 and 0.944, and Bartlett's test of sphericity is < .001 , as given in Tables 4 and 5. The result of the scree plot as given in Fig. 1, the Scree Plot Source: EFA Analysis, demonstrated that a maximum of five factors could be extracted from the data set to explain maximum variance just before the elbow line.

Eight variables, Table 6, i.e., exposure to technology, invasion of technology, coping with technology, obsoleteness, work pressure, burden, training, job insecurity, and from technology, are loaded into Factor 1. The construct is labeled Technological Disruptions, measuring the technical aspect of employee stress on the job. All the variables are loaded into the technological disruption construct with factor loading ranging between 0.819 and 0.892. On Factor 2, the eight loaded variables are budgetary changes, uncertainties, extra workload, reduced benefits, reduced resources, unhealthy work environment, costs of living adjustments, and lack of clarity on financial state ranging between 0.785 and 0.839, and the factor is labeled as Austerity Measures. Factor 3 encompassed variables like work culture, lack of focus, victimization, teamwork, fear of blame, avoidance of responsibility, collaboration, job satisfaction, numbering eight, loaded into Factor 3 with factor loadings between 0.767 and 0.845, and is labeled as Blame Gaming. Factor 4 has eight indicators: frequency of multitasking, adjusting to changing

Table 4 KMO test results. *Source: Authors*

Items	MSA	Items	MSA	Items	MSA	Items	MSA	Items	MSA
TD1	0.944	AM1	0.935	BG1	0.936	MT1	0.936	WB1	0.926
TD2	0.918	AM2	0.934	BG2	0.929	MT2	0.917	WB2	0.941
TD3	0.933	AM3	0.940	BG3	0.926	MT3	0.926	WB3	0.930
TD4	0.918	AM4	0.942	BG4	0.938	MT4	0.907	WB4	0.926
TD5	0.925	AM5	0.933	BG5	0.935	MT5	0.922	WB5	0.929
TD6	0.931	AM6	0.927	BG6	0.922	MT6	0.929	WB6	0.928
TD7	0.938	AM7	0.942	BG7	0.936	MT7	0.921	WB7	0.917
TD8	0.947	AM8	0.933	BG8	0.917	MT8	0.932	WB8	0.922
Average	0.931	Average	0.935	Average	0.929	Average	0.923	Average	0.927
								Overall MSA	0.930

TD technological disruptions, *AM* austerity measures, *BG* blame game, *MT* multitasking, *WB* work–life balance

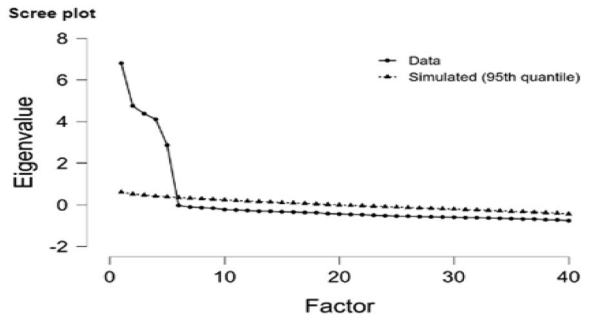

Fig. 1 The scree plot. *Source*: EFA Analysis

work, lack of focus, time constraints, quality of work, reduced productivity, task prioritization, and constant demands. The factor is labeled as Multitasking. The factor loading ranges between 0.772 and 0.839. The last factor, 5, is loaded with eight observed indicators like healthy work life, personal life interference, lack of flexibility, physical health, extended working hours, relationship issues, lack of support, and time-off issues, and is labeled as work–life balance. It measures the life events aspect of employee stress.

Validity and reliability results

From the factor loading in Table 6, it is seen that all the respective variables loaded into the concerned factors above 0.500 (Max 0.892 and Min 0.767). The variables are correlated among themselves in the respective factors. The average extracted variance (AVE) is above 0.5, and composite reliability (CR) is above 0.7. Individual variables' unique variance was found to be between 0.213 and 0.416. The correlation among the factors is close to zero. All the factors explain, Table 7, above 60% of the variance (62.25–70.19%). The cumulative variance explained by all factors is 66% (0.668).

CFA results

The fit indices' outputs help us evaluate how well the hypothesized model signifies the observed data. The factor model in Table 11 with 730 degrees of freedom has a Chi-squared value of 1228.023. GFI and Standardized Root Mean Square Residual (SRMR) are considered absolute fit indices. The GFI value is 0.891. The SRMR value is 0.034. As CMV can bias data analysis by creating false internal consistency and causing incorrect judgments, we were proactive in the design stage. The model-fit indices are presented in Tables 8 and 11. The Cronbach's alpha values in Table 9 exceed 0.70 for all the factors. The Chi-squared value (employee stressed/not stressed) at p (0.001) < α (0.05). The factor correlation and model-fit indices are presented in Tables 10 and 11, respectively.

Cohen's d is calculated as follows

d = Mean of responses on Refined Instrument − Mean of Responses in pilot testing/pooled standard deviation = 3.04–2.32/1.02 = 0.0.71.

Discussion

Our study examined dimensions of employee stress in Indian PSUs. The generated pool of 40 potential items resulted in the most relevant and reliable items for inclusion in the scale, demonstrating good face validity and comprehensibility. The tool's psychometric properties (Cronbach's alpha = 0.82) exhibited good internal consistency. The test–retest reliability with a correlation coefficient of 0.78 reflected that there are no issues with item performance, response patterns, or scale structure. The resulting 508 questionnaires with 12 incomplete forms received responses led to a total response rate of 97.69%. The 12 incomplete questionnaires were due to the transfer of employees in the data collection period.

The respondents' demographic profiles show that stress is prevalent at all levels of employees in these PSUs. The significant aspect of the demographics establishes that the experienced workforce (97%) between five and ten years plays a pivotal role in acting as catalysts for improved employee performance through strategic interventions in reducing operational stress. The standard deviations indicate variability around means. Skewness values close to zero suggest relatively symmetrical distributions. Kurtosis values show distributions with lighter tails. The data portray participants' stress levels across dimensions, with moderate variability and generally symmetric distributions.

EFA implications

The KMO values and Bartlett's test of sphericity showed an excellent factorability of the employees' responses [7]. The five factors extracted from the data set explain maximum variance. Exposure to technology (0.892), invasion of technology (0.874), and burden from technology (0.865) have significant positive loadings, which describe the most prominent indicators of employee stress arising from technological disruptions. The implications of the responses are that techno-overload, invasion, complexity, fear and anxiety, and uncertainty may be the major issues causing employee stress with the rapid advancement of technology in the workforce. Techno-burden would have resulted from the barrage of work-related emails, text messages, app notifications, and other sources. Techno-invasion leads to an unhealthy extension of work hours beyond the regular workday. Coping with technology may be triggered by new work management systems that require re-learning new skills and understanding complex concepts. Insecurity might be produced due

Table 6 Factor loadings. *Source*: Authors

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Unique variance
TD1	0.892					0.213
TD2	0.874					0.253
TD3	0.844					0.286
TD4	0.819					0.327
TD5	0.822					0.310
TD6	0.865					0.230
TD7	0.840					0.293
TD8	0.850					0.275
AM1		0.813				0.335
AM2		0.807				0.350
AM3		0.814				0.331
AM4		0.813				0.336
AM5		0.822				0.326
AM6		0.839				0.295
AM7		0.785				0.370
AM8		0.792				0.375
BG1			0.821			0.318
BG2			0.809			0.338
BG3			0.819			0.292
BG4			0.804			0.347
BG5			0.845			0.397
BG6			0.767			0.377
BG7			0.791			0.374
BG8			0.785			0.331
MT1				0.822		0.332
MT2				0.818		0.351
MT3				0.839		0.311
MT4				0.802		0.361
MT5				0.772		0.284
MT6				0.787		0.416
MT7				0.783		0.373
MT8				0.826		0.345
WB1					0.807	0.325
WB2					0.791	0.369
WB3					0.818	0.323
WB4					0.779	0.379
WB5					0.784	0.357
WB6					0.814	0.347
WB7					0.803	0.361
WB8					0.808	0.354

The applied rotation method is varimax. *TD* technological disruptions, *AM* austerity measures, *BG* blame game, *MT* multitasking, *WB* work–life balance

to losing jobs to technology-driven tools. Uncertainty results from frequent tech upgrades that can overwhelm workers, increasing their stress levels. These findings are supported by the findings of other research scholars [6, 16].

Uncertain work environment (0.839), reduced resources (0.822), and extra workload (0.814) are the most significant indicators of the stress involving austerity measures. The data revealed that executives and policymakers working in these PSUs affected austerity measures in the last five to six years, which could be the leading cause of employee dissatisfaction. These measures included stoppage of overtime payments, night allowances, and recruitment freezes. Health provision

Table 7 Factor characteristics. *Source*: Authors

% of variance explained	Sum squared loadings	Proportion of variance explained	Cumulative variance explained	Cronbach's alpha	Average variance explained (AVE)
70.19	5.834	0.146	0.146	0.95	0.754
65	5.282	0.132	0.278	0.93	0.761
64.36	5.225	0.131	0.409	0.93	0.768
62.25	5.214	0.130	0.539	0.93	0.781
63.71	5.175	0.129	0.668	0.93	0.745

Table 8 Chi-squared tests. *Source*: Authors

Test type	Model	Chi-square (X^2)	Degree of Freedom (df)	*p* value (α = 0.05)
EFA	Model	1005.336	590	< .001
CFA	Baseline model	16,450.248	780	< .001
CFA	Factor model	1228.023	730	< .001

Table 9 KMO, Bartlett's test, reliability and variance explained. *Source*: Authors

Constructs	KMO	Bartlett	Cronbach's alpha	% variance explained
Technological disruptions	0.929	0	0.95	70.19
Austerity measures	0.935	0	0.93	65
Blame game	0.929	0	0.93	64.36
Multitasking	0.923	0	0.93	62.25
Work–life balance	0.926	0	0.93	63.71

Table 10 Factor correlations. *Source*: Authors

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	1	0	− 0.012	0.011	0.006
Factor 2	0	1	0.006	0.004	0.004
Factor 3	− 0.012	− 0.006	1	0.005	0.002
Factor 4	0.011	0.004	0.005	1	0.005
Factor 5	0.006	0.004	0.002	0.005	1

cutbacks affect participants most as they have limited finances, creating unhealthy work environments. Extra workload affected stress among participants, as there were recruitment freezes. Reduced benefits resulted in a struggle to adjust to the cost of living. Additionally, a lack of clarity on the organization's financial state led to employee stress. Empirical evidence further sustains these findings [15]. These measures induced employee stress.

The Blame Game factor reveals that fear of blame (0.845) and victimization (0.819) are strong measures of employee stress. The blame game creates an unstable, toxic work environment, leading to tension and stress, as responded by the participants. It can also lead to scapegoating, which is often counterproductive. Employees resort to blame games to escape responsibility and protect their reputations. The blame game leads to distrust in relationships and diverts valuable attention and resources from solving the original problem. Over time, organizational cultures of resentment and negativity may cause suffering and inhibit creativity and innovation. Our study's findings are reinforced by works in similar research works [23].

Table 11 Model-fit indices. *Source*: Authors

Root mean square error of approximation (RMSEA)	0.037	Comparative Fit Index (CFI)	0.968
Standardized root mean square residual (SRMR)	0.034	Goodness of Fit Index (GFI)	0.891
Expected cross validation Index (ECVI)	2.772	Tucker–Lewis Index (TLI)	0.966
Bentler–Bonett normed fit Index (NFI)	0.925	Relative noncentrality Index (RNI)	0.968
McDonald Fit Index (MFI)	0.598	Bollen's relative fit Index (RFI)	0.920

Lack of focus (0.839) and constant job demands (0.826) influence the stress level of the employees the most, from multitasking factor. The respondents expressed that multitasking has become increasingly popular due to the use of electronic gadgets. However, it could have been more efficient and would lead to missed deadlines and shoddy work. Multitasking in the short term is very stressful, makes people feel worthless, and in the long period, it can pose a severe threat to health. In the long run, stress from multitasking becomes more precarious, as studies have established that work stress may lead to insomnia, stomach concerns, and headaches. Chronic job stress may result in long-term problems, including depression, heart disease, and back pain. Multitasking is dangerous and counterproductive, leading to a lack of focus and quality of work, reduced productivity, and adjustment to changing work. Our findings are strengthened by the works of other researchers [3].

The work–life balance factor is explained by lack of flexibility (0.818) and relationship issues (0.814) the most, and extended working hours (0.784) and physical health (0.779) the least. These findings of our study are complemented by similar works [11, 18]. Hence, the findings answered the research question (RQ1).

Validity and reliability test implications

The factor loading establishes that the correlated variables among themselves indicate convergent validity. The requisites for convergent validity were satisfied as the average extracted variance (AVE) is above 0.5, and composite reliability (CR) is above 0.7 [7]. The variables are not cross-loaded to other factors, establishing divergent validity. Individual variables' unique variance was found to be between 0.213 and 0.416. The correlation among the factors is close to zero, proving the stress assessment model's discriminant validity. Hence, it is validated that the indicators measure each of the constructs of employee stress [25]. All the factors explain above 60% of the variance, and the cumulative variance explained by all factors is above 60% ascertains that the model is a good fit [14]. The Technological Disruptions construct is the most significant measure of employee stress, and work–life balance is the least among the constructs. A Cohen's d value of 0.71 is considered to have practical significance, meaning that the observed difference is not only statistically significant but also meaningful in real-world terms [36].

As CMV can bias data analysis by creating false internal consistency and causing incorrect judgments, we were proactive in the design stage. Collecting information on dependent variables from different sources, altering item order, and framing reverse-scored questions helped us reduce CMV. The model has a perfect model fit with a Chi-squared value of less than 0.001, a TLI value of 0.966, and the root-mean-square error of Approximation (RMSEA) value of 0.037 [13]. Additionally, Cronbach's alpha values exceed 0.70 for all the factors, proving that the instrument used in the study is reliable [7]. The Chi-squared value (employee stressed/not stressed) at p $(0.001) < \alpha$ (0.05) rejects the null hypothesis as we have found evidence to support the claim that the employee stress assessment tool accurately measures stress levels in the Indian PSUs. The p value shows a reduced type I error. The type-II error is offset by the increased sample size ($n = 508$). Hence, the alternate hypothesis is accepted [19].

The factor correlation index assesses the correlation between the latent factors in the model that demonstrate the relationships between the underlying constructs. High factor correlations may indicate that the latent factors are related, potentially suggesting overlap or redundancy in the constructs being measured. On the other hand, low-factor correlations indicate that the factors are relatively distinct. The low-factor correlation matrix establishes that the factors are relatively independent. The GFI and SRMR index confirm our model-fit claim [13].

CFA implications

The fit indices' outputs help us evaluate how well the hypothesized model signifies the observed data. The factor model in Table 11 with 730 degrees of freedom has a Chi-squared value of 1228.023. GFI and SRMR are considered absolute fit indices, meaning that they assess the absolute fit of the model to the data without comparing it to a null or baseline model. The GFI value in Table 11 is 0.891, indicating variance explained by the population covariance. It confirms an excellent fit model. SRMR indicates a good fit between the model and the data. A low SRMR value suggests that the model's implied covariance matrix closely matches the observed covariance matrix, indicating a good data representation. The value is 0.034. These findings answer our research question (RQ3): All factors integrate into the model to assess employee stress.

The conceptual model

The model proposed by the researcher to examine and assess employee stress based on observed empirical results is represented here. In Figure 2, the Conceptual Model Source; Authors The stress assessment model mentioned above has been proposed based on the empirical evidence collected from the PSUs under study. The model demonstrates that technological disruptions, austerity measures, blame games, multitasking, and

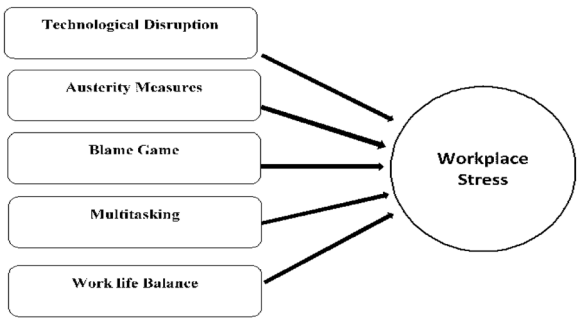

Fig. 2 The conceptual model. *Source*; Authors

work–life balance reasonably measure employee stress. This answered our research question (RQ2).

Hypotheses testing

The normed fit index, Table 11, value is 0.925, and the TLI is another incremental fit index that compares the proposed model with the null model. Whose values range from 0 to 1, with values at 0.966, indicating better fit. The CFI value of 0.968 compares how well the target model fits, whose value should be above 0.90. The RMSEA is an absolute fit index that measures how well the model fits the covariance matrix. RMSEA values range from 0 to 1, with lower values indicating a better fit. The RMSEA, in this case, is 0.037, indicating a good fit.

Since the model-fit indices in comparison with null model (where all stress assessment items are unrelated) are within an acceptable range (e.g., CFI and TLI close to 1, RMSEA close to 0.05), we can conclude that the stress assessment tool shows an excellent fit to the data. Therefore, we reject the null hypothesis and advocate the alternative hypothesis (H1) that the tool accurately assesses stress levels in the Indian PSUs. The factor correlation matrix in Table 10 demonstrates no collinearity among the factors ensuring the instrument's discriminant validity and satisfying the study's objectives.

To sum up, the factors gave back enough cumulative variances above 60%, regarded as a good fit for the data [14]. All the factors showed high reliability (> 0.80 each) in the measuring instrument, establishing a validated questionnaire. The sampling adequacy requirement of KMO measure and the Bartlett test of sphericity met the required standards, indicating that the sample was sufficient and the data fit for factor analysis. The composite reliability (CR) is above 0.7, and the average extracted variance (AVE) is above 0.5. Thus, the prerequisite for convergent validity was met [7]. Cohen's *d* suggests that the refined tool could be helpful for HR professionals and organizations in understanding and managing stress-related issues among employees.

Contributions to theories

The technological disruption factor contributes to the JDCS theory by highlighting the job demand. The rapid technological changes and the need to constantly learn new skills can increase job demands, potentially leading to stress. These responses may also relate to the lack of control over the pace of technological changes and the adequacy of training and support, contributing to the control and support aspects of the JDCS theory [12, 20]. The contributions of austerity measures as a factor of employee stress can be linked to the JDCS theory. Cost-cutting measures can lead to increased workloads, reduced resources, and uncertainty about job security, all aspects of job demands. The impact of budget reductions on benefits and the work environment can also affect the perceived level of control and support in the workplace [9, 24].

Blame game indicators are closely tied to the JDCS theory. A culture of blame can create stressful working conditions by affecting job control and support. When individuals fear being unfairly blamed, they may be less likely to take risks or suggest new ideas, impacting their control over their work environment and adding to stress levels. Items included in multitasking significantly contribute to the JDCS theory by focusing on job demands [23, 31]. The pressure to multitask and manage multiple tasks concurrently can increase stress levels. Additionally, the perceived lack of prioritization and planning in multitasking can impact the individual's sense of control over their workload [3]. Work–life balance items connect to the JDCS theory as well. Difficulty in maintaining a healthy work–life balance can lead to increased job demands, especially if work-related responsibilities interfere with personal life. The lack of flexibility in balancing work and personal commitments can impact the individual's perceived control over their time and contribute to stress [17].

In addition to the JDCS theory, the study also aligns with other employee stress theories, such as the Transactional Model of Stress and Coping, the ERI model, and the Social Support Theory. The tool provides insights into different stressors that employees face, which can be analyzed within these theories' frameworks to better understand the factors contributing to employee stress and potential strategies for intervention and support.

Contributions to practices and policies

The study makes contributions to real-world applications. The study helps identify high-stress-level departments or job roles, allowing organizations to prioritize resources and interventions in areas needing support and improvements. The tool's findings can guide the implementation of evidence-based stress management programs,

focusing on enhancing social support networks, providing stress-coping strategies, and fostering a positive work environment. For example, organizations can plan slow technology adoption to help employees adapt to new processes. A proper system of accountability can be fixed for non-performance without shifting blame. Organizations can handle multitasking through learning supervision, making a to-do list, or asking employees to take breaks. Policymakers and leaders can identify areas where work–life balance is compromised, leading to the development of policies and programs that promote flexible work arrangements and employee well-being.

Organizations can prioritize rapid technological advancements and efficiency without considering the impact on employees. High emphasis on technological disruptions can increase stress levels due to rapid changes and lack of support. On the other hand, low emphasis allows organizations to carefully assess the impact of technological changes by providing training, support, and resources to help employees adapt to new technologies and reduce stress [12]. Organizations facing financial challenges may implement strict austerity measures, leading to increased stress due to reduced benefits, job insecurity, and increased workload. On the other hand, organizations that prioritize employee well-being may minimize the negative impact of these measures by exploring alternative cost-saving strategies or providing additional support [23].

In a blame-oriented culture, leaders may focus on identifying and blaming individuals for mistakes, resulting in a stressful work environment. Discourage blame gaming and promoting a culture of accountability can create a more positive work environment with reduced stress levels. In fast-paced work environments, encouraging multitasking can increase productivity but can lead to employee burnout and stress. Executives who prioritize focus and provide necessary resources can reduce the adverse effects of multitasking and alleviate stress [23]. Organizations that value work–life balance prioritize policies and initiatives supporting employees' well-being and personal lives, reducing stress and increasing job satisfaction. Conversely, organizations that neglect work–life balance may create a stressful work environment that negatively impacts employee satisfaction and performance.

The stress assessment tool was developed using a diverse sample of employees from various departments and levels in the Indian PSUs. Its generalizability and contextual relevance were enhanced through rigorous validation and reliability testing. The tool aligns with established stress scales in the Indian context, such as the Occupational Stress Index and Employee Burnout Scale [29]. These studies confirm its generalizability and effectiveness in assessing stress levels, providing meaningful results, and supporting evidence-based decision-making in real-world contexts.

The stress assessment tool was developed using a large and diverse sample of employees from various departments, regions, and levels within the Indian PSUs, which increases its generalizability. The stress assessment tool enhances its contextual relevance and generalizability. The stress assessment tool underwent rigorous validation and reliability testing, strengthening its generalizability. The stress assessment tool aligns with and produces similar results to established stress scales used in the Indian context, and it enhances its generalizability. The study's findings are in line with the models on the Occupational Stress Index (OSI) (Work-Related Stress, Personal Stress, Physiological Stress) and Employee Burnout Scale (EBS) developed [29] to assess burnout levels (emotional exhaustion, depersonalization, and reduced personal accomplishment) among employees. Hence, the resulting stress assessment tool confirms its generalizability and will effectively assess stress levels, provide meaningful results, and support evidence-based decision-making in various real-world contexts.

Limitations

The potential sources of bias and constraints that may affect the generalizability of the findings could be measurement bias. We managed it through pilot testing of the questionnaire. Non-response bias was handled through follow-up reminders. The cultural differences in Indian PSUs may limit the tools' validity and relevance. Contextual factors like diverse bureaucratic processes, hierarchical structures, and fluctuating job demands may limit the study's findings. The size, industry focus, and organizational policies may limit the tool's validity to other sectors or industries.

Research directions

The stress assessment tool can be cross-validated in other organizations or industries to enhance its generalizability. Researchers may undertake a comparative study between private and public sector enterprises. We recommended that researchers pursue tool development employing longitudinal studies to track changes in employee stress over time, preferably bi-annually.

Conclusions

The research study highlights several key findings and their implications for understanding and managing employee stress in Indian PSUs. The study successfully developed a robust stress assessment tool comprising 40 items, demonstrating good face validity, comprehensibility, and strong psychometric properties, including reliability. This tool addresses a critical need for measuring stress levels in the unique context of Indian PSUs, providing a valuable resource for organizational management.

The research identified five major stress factors prevalent across all levels of employees in Indian PSUs: Technological Disruptions, Austerity Measures, Blame Gaming, Multitasking, and Work-Life Balance. These factors have practical implications for organizations aiming to improve workplace well-being. By utilizing the stress assessment tool, organizations can pinpoint specific areas where stress is most acute, enabling them to allocate resources strategically and implement targeted stress management interventions. As a result, fostering a positive organizational culture that prioritizes employee well-being becomes more attainable.

The study's contributions extend beyond practical applications to theoretical advancements. It refined and extended the established Job Demand-Control-Support (JDCS) framework, adapting it to the unique characteristics of Indian PSUs. Furthermore, the research findings may be limited by confounding factors like differences in organizational cultures across sample organizations and organizational practices that may influence stressors. Future research can be carried out on a longitudinal approach to enhance the study's generalizability.

Policy recommendations

Policy recommendations include implementing stress management programs, gradual budget cuts, fostering a blame-free culture, offering time management training, promoting flexible work arrangements, and conducting periodic employee surveys. Additionally, political factors may influence policy implementation, affecting employee stress levels and organizational responses.

Abbreviations

AVE	Average extracted variance
CFA	Confirmatory factor analysis
CMV	Common method variance
CR	Composite reliability
EFA	Exploratory factor analysis
ERI	Effort reward imbalance
GFI	Goodness-of-Fit Index
JCQ	Job Content Questionnaire
JDCS	Job demand control and support
KMO	Kaiser–Meyer–Olkin
OSI	Occupational stress indicator
PSS	Perceived Stress Scale
PSUs	Public sector undertakings
RMSEA	Root-mean-square error of approximation
RQ	Research question
SRMR	Standardized root-mean-square residual
TLI	Tucker–Lewis Index

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Adherence to transparency and openness (TOP) guidelines

We describe that all data, analysis code, and research materials are available at (https://osf.io/uqsvm/?view_only=51e0f4d795d54b1488e29b269e5227e5) for view only. Data were analyzed using JASP (Jeffreys' Amazing Statistical Program). This study's design and its analysis were not preregistered.

Author contributions

PK contributed to data collection, data analysis and report presentation. GN contributed to literature review, presentation and bibliography. All authors read and approved the final manuscript.

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Availability of data and materials

Data will be available on a reasonable request.

Declarations

Ethics approval and consent to participate

The study ensures that research participants can be confident that possible risks have been considered, minimized and deemed acceptable.

Informed consent

Participant's consent has been obtained voluntarily, without coercion.

Consent for publication

Not applicable.

Competing interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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