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APPLICATION ARTICLE

Statistical characterization of managerial risk factors: a case of state-run hospitals in India

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Abstract

Public healthcare institutions are the crucial component in the social and economic development of a nation, particularly India. However, public hospitals in India confront multiple operational risk factors that compromise patient satisfaction. Although all the risk factors are essentially critical, the impact potential of any risk factor is ultimately determined by its ability to induce other risk factors. The current research derives motivation from these scenarios and investigates the characteristics of crucial operational risk factors experienced in the public healthcare sector in a South Indian state. Extensive questionnaire-based surveys were conducted among civilians and healthcare professionals in two phases, i.e., prior to the COVID-19 crisis and during the COVID-19 crisis, for identifying significant risk factors. The collected data is analysed using statistical techniques like exploratory factor analysis (EFA) and partial least squares based structural equation modelling (PLS-SEM) to characterise the inter-relationships between risk factors. The research discloses the translational effect of administrative/infrastructure constraints in public hospitals in compromising the operational performance indirectly through human-related issues rather than having a direct influence. More precisely, the presented model indicates that risk factors like the physical infrastructure limitations and shortage of staff will overburden the existing employees, resulting in human-related issues, including attitudinal issues of employees and community mistrusts and misbelieves. The results reveal seemingly resolvable budget allocation issues, but at the same time alarms the authorities to execute immediate countermeasures. Ultimately, this research seeks to empower public hospital administrators with interesting insights and managerial implications drawn from the statistical models.

Keywords Public hospitals · Operational risks · Exploratory factor analysis · EFA · Partial least squares based structural equation modelling · PLS-SEM · India

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1 Introduction

Reliable and accessible healthcare institutions are the basic need of humankind. It is important to ensure that health care delivery is safe, effective, patient-centered, timely, efficient, and equitable [15]. However, the global healthcare sector has dipped to a vortex of uncertainties at present primarily driven by COVID-19 pandemic [7, 12, 20]. The pandemic is still looming large, exposing the ill-equipped and resource deficit healthcare apparatus that many countries have, which otherwise would remain ignored or unnoticed [38]. In India, the unprecedented global stagnation and healthcare emergency induced by COVID-19 pandemic coupled with the after-effects of population explosion is straining public hospitals that are already grappling with other operational challenges. Commenced in early 2020, the COVID-19 pandemic continued riddling the healthcare system in India in 2021 and 2022 alike through what is generally termed as its second wave and third wave. An overstretched public healthcare institution, in turn, leads millions of citizens towards the mostly unregulated private healthcare entities [9]. This situation tends to push financially under-privileged and oppressed sections of society, who are in the majority, into long-term debt traps and financial insecurities. Furthermore, it is also essential to substitute the traditional rule-and-procedure driven management control exercised by public hospitals with well-designed performance management systems. However, most public healthcare institutions in India are still following the traditional system resulting in myriad operational issues. Hence, it is essential to address, analyze and mitigate the multi-faceted operational challenges that constrain public hospitals' performance.

These challenges are often termed as operational risk factors and include both infrastructural, human-related risk factors and even other resource constraints [52]. For instance, there are just 0.55 hospital beds per 1000 people in India, reflecting its feeble healthcare infrastructural facility [32]. An adequate supply of qualified employees is another essential aspect of healthcare systems. In reality, staff shortage is perhaps the most highlighted and discussed risk factor in the Indian healthcare settings. Apart from the conventional risk factors, new risk factors have emerged over the years due to the changing socio-political scenarios. One such risk factor is the spiking trust deficit that civilians have with public hospitals and healthcare professionals. Consequently, there have been repeated reports of incidents related to attacks and aggression against healthcare personnel by patients and their relatives as a manifestation of their dissatisfaction [35]. At the same time, the news reports on medical negligence issue have also surged [42, 57]. These circumstances starkly underline the need for identifying and characterizing the risk factors, including both conventional and recently evolved ones to ensure safer recovery and satisfaction of patients.

In the healthcare sector, all the risk factors are essentially critical. However, the impact potential of any risk factor is ultimately determined by its ability to induce other risk factors. For instance, physical infrastructure limitation can lead to overcrowding in hospitals that can further result in patient dissatisfaction. Besides this relation, it is already proved that staff shortages will also result in patient dissatisfaction [56]. Consequently, it is absolutely essential to investigate and validate the inter-relationships between the significant risk factors for ensuring seamless service delivery for safeguarding citizens' health [11]. Meanwhile, on the positive side, the COVID crisis is serving as a moment of reckoning and offers an opportunity to redefine the existing deficient healthcare policies. The situation persuades the authorities to synchronize capacity with demand and address other long-standing issues. It is reported that the Govt. of India is aiming to increase healthcare spending to 3% of the Gross Domestic Product (GDP) by 2022 for improving the infrastructure which is currently hovering around 1.5%, one of the lowest in the world [9]. Hence, it becomes imperative to prioritize the areas of improvement and carefully sequence reforms to derive maximum benefits from the additional investment. On this backdrop, the present research proposes a few research objectives (ROs) as illustrated in Fig. 1. The same objectives are as enumerated as follows:

RO 1 Identify significant operational risk factors in the public healthcare sector in the chosen Indian state through questionnaire-based surveys.

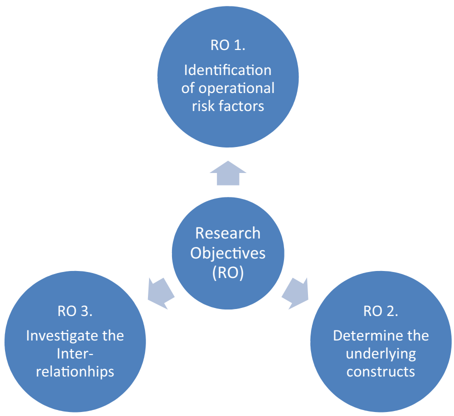
RO 2 Characterize the underlying constructs that reflects the risk factors to uncover the basic structure.

RO 3 Investigate the inter-relationships between the constructs (significant risk factors).

In addition to the civic agencies planning to make additional investment in the healthcare sector, the results obtained from this research will also benefit hospital administrators to redesign the service delivery process more patient-centric. More precisely, knowing the inter-relationships between the risk factors, the administrators will be able to map the positive ripple effect of mitigating one risk factor. This knowledge can assist in estimating the merits of each risk mitigation initiatives and its influence on multiple spheres.

The focus of this research is placed on 125 public hospitals having inpatient capability and operating in an Indian state. These hospitals belong to various categories such as Medical Colleges (MC), General Hospitals (GH), District Hospitals (DH), Taluk Hospitals (TH) and Taluk Headquarter Hospitals (THQH). These networks of

Fig. 1 Research objectives



public hospitals cater to the needs of 36 million residents in the state by delivering the most affordable health services. Among these 125 hospitals, only three hospitals have obtained National Accreditation Board for Hospitals and Healthcare Providers (NABH) accreditation, which is the major parameter that demonstrates the commitment to deliver quality care. Besides this evidence, multiple studies conducted earlier in the state also have disclosed various operational issues and challenges experienced by public hospitals in the state as well as in the country in general. These issues that warrants a slew of reforms range from infrastructure limitations in terms of beds per thousand people [32], lack of skilled medical professionals, fragmented health information system, weak governance, lack of accountability, hindrances from medical lobbies [45]. The primary reason for these issues is attributed to funding shortage [9]. Besides these independent and stand-alone studies, research that characterizes nearly all the significant risk factors is still missing in the literature. Accordingly, research that comprehensively maps the issues and challenges consumers' perspective, i.e. citizens of the state are vital in identifying the priority areas for development.

In this direction, a questionnaire-based survey is conducted among civilians and public healthcare professionals to identify the risk factors. After conducting the reliability and validity analysis, the data is subjected to one-sample *t*-tests with an assumed mean to shortlist the risk factors based on their statistical significance. Since there are no *prior* hypotheses about factors or patterns of measured variables reported in the healthcare literature so far, an exploratory factor analysis is conducted on these shortlisted risk factors to identify the underlying constructs (i.e., factors). The factors thus identified are employed to develop a structural equation model for establishing their inter-relationships and their causality with another construct, namely, 'Deteriorating operational performance of the hospitals'. The developed structural model is closely analyzed to derive meaningful inferences and thus assist in framing strategies for improving the standards of public hospitals.

The remainder of the paper is structured as follows: the recent research articles on the domain are reviewed in the following section. We subsequently discuss the data collection process and the statistical models developed in this study (Sect. 3), followed by the results, inferences and managerial implications. Finally, conclusions and avenues for further research are discussed in the last section.

2 Literature review

Patient satisfaction and engagement has always been considered as an important parameter for assessing the quality of healthcare institutions across the globe [3, 28]. Unlike other service sectors, the healthcare industry has to fulfill physical requirements along with the intellectual, emotional, cultural, and even spiritual needs of inpatients. In a developing nation like India, medical professionals also act as a rationer of services, while deciding how best to apportion the limited resources that he/she has at his disposal. The involvement of these multi-dimensional healthcare management aspects offers various research opportunities,

Table 1 Literature review

Article	Emphasis	Methodology	Major contributions
Thakur [49]	Healthcare waste management during Covid-19 pandemic	PESTEL analysis, TISM and MICMAC	Characterize the dimensions of sustainable healthcare waste management through PESTEL (political, economic, social, technological, environmental and legal) analysis
Motlatla and Maluleke [33]	Healthcare risk waste management	Survey based research	Revealed the knowledge of health professionals on healthcare risk waste management
Vishnu et al. [52]	Supply chain risk characterisation	Subjective methods like DEMATEL, ISM, PROMETHEE	Peripheral investigation of inter-relationships between risk factors experience in public hospitals in an Indian state
Ahalt et al. [1]	Overcrowding issue in emergency departments	Discrete-event simulation modeling with Arena	A comparative analysis of three crowding scores and suggest the best score that can be used as early warning signals to anticipate crowding
Bamfo and Dogbe [6]	Hospital selection	Empirical study along with binary logistic regression	A unique framework for comparing hospital is proposed that absorbs all major selection criteria including types of ailments and word-of-mouth
Thakur and Anbanandam [50]	Hospital waste management	ISM—MICMAC integrated approach	Discloses the barriers hindered in the healthcare waste management system in India
Pai and Chary [37]	Service quality	Qualitative study	A methodology for measuring patient perceived service quality is proposed
Kalaja et al. [27]	Service quality	Empirical case study based on SERVQUAL model	The case study on Durres public hospital elaborates the application of SERVQUAL model
Delcea and Alexandra [13]	General risk management	Grey systems theory	Relative importance of different risk factors in different perspectives are obtained
Kumar and Kumar [29]	Inventory management of folic acid tabs	System dynamics	A case study on the rural healthcare supply chain of folic acid tablets in India

Table 1 (continued)

Article	Emphasis	Methodology	Major contributions
Edozien [14]	Clinical Risks	Theoretical	A framework titled "RADICAL" is introduced for implementing, monitoring and reporting of risk management in healthcare institutions
Carlucci et al. [8]	Service quality aspects of outpatient services	Artificial neural networks	Identified the key service quality dimensions that decide the satisfaction levels of outpatients
VanVactor [51]	Collaborative communication	Empirical study	Five emerging themes were identified and a management model was developed for the enhancement of healthcare supply chain operations
Walston et al. [54]	Hospital atmosphere	Empirical study along with factor and regression analysis	Focused on three organizational dimensions that influence hospital patient safety climate i.e. Management support, Reporting system and Resource adequacy
Samuel et al. [47]	Inventory management	System dynamics	Visualization of bullwhip effect in healthcare inventory systems. Affect of capacity reduction and service delays are studied
Mustaffa and Potter [34]	Inventory management	Empirical study	Discloses issues with service levels of private healthcare sector in Malaysia
Alaloola and Albedaiwi [2]	Patient satisfaction	Empirical study	Identified critical factors that decide the patient satisfaction level at the King Abdulaziz Medical City, Riyadh, Saudi Arabia
Okoroh et al. [36]	Facilities risk management	Artificial neural networks based modeling	Identified nine potential risk factors in healthcare sector. The developed model would provide early warning for risk management
Iyer, and Bandyopadhyay [25]	Technology risks	Theoretical	A unique disaster recovery and business continuity model is proposed

notably in the operation management domain. The specific nuances of notable papers that offer far-reaching implications are reviewed in detail and presented in Table 1.

The widely researched topics in operations management include trust issues, service quality, operational flexibility, customer relationship management, demand management, inventory management, risk management, waste management, information-exchange related, misinformation, misalignment of interest between patients and companions, among others [7, 8, 13, 17, 20, 23, 25, 36, 37, 44, 49]. Furthermore, Kwon et al. [30] provide the strategic areas of healthcare supply chain for improving several aspects of service quality and simultaneously reducing cost. The areas proposed include understanding supply chain concepts, application of supply chain techniques and process improvement in healthcare institutions.

In addition to the already researched operational risk factors, the questionnaire-based survey conducted as part of this research reveals risk factors unique to the sector under investigation. Analyzing the characteristics of these additional risk factors, which has been largely ignored, appears to be crucial, especially in the Indian scenario.

From the literature review, it was evident that researchers working in the area of healthcare management have employed a wide variety of tools such as subjective models, simulation models, artificial neural networks, and other empirical techniques. However, most of the papers propose conceptual models compared to statistical models. It is regarded that statistical models can describe the system and validate the findings without placing unrealistic assumptions. Apart from these aspectes, the challenges laid out by the unprecedented COVID-19 crisis also merits introspection [40]. As described in the introduction section, in a developing nation like India, where multiple risk factors are present, the interplay between the individual risk factors is also a crucial and influencing characteristic. Even so, these regional-specific aspects barely got significant attention from the research community till date. Furthermore, literature on operations management has already highlighted the significance of inter-dependencies among the risk drivers that ultimately decide the impact potential [24, 39, 41, 53]. Accordingly, the objectives of the present research are not limited to identifying the significant risk factors. The paper also establishes the inter-relationships between the significant risk factors by employing statistical methods like the SEM. Moreover, most researches do not incorporate the perceptions of civilians or the patients who are the center pillar and the primary beneficiaries of civic-run healthcare systems.

As the first step in this research direction, Vishnu et al. [52] have previously reported an empirical study that discloses inter-relationships between significant risk factors experienced by public hospitals in an Indian state prior to the COVID crisis. The hypotheses investigated in this paper are fundamentally drawn from patterns of association observed from the subjective models presented in that work. Accordingly, the present statistical study provides conclusive evidence regarding the inter-relationships between the potential risk factors experienced in the public healthcare sector in the chosen Indian state. More to the point, the exploratory factor analysis conducted as a part of this research unravels underlying factors unique to the public healthcare sector upon which the risk factors can be grouped.

3 Identification of significant risk factors

3.1 Data collection

Risk factors are prevalent in all sectors, the healthcare industry is no exception, and the literature reflects likewise. A set of risk factors and hospital performance indicators are identified from the literature. These risk factors are listed to prepare the first draft of the questionnaire for conducting a survey among civilians who have leveraged the service of public hospitals in recent period. The questionnaire is structured into three sections. It begins with an introductory note illustrating the purpose of the survey and captures the respondents' demographic details. The second section focuses on identifying significant risk factors while the third section is intended to distinguish the relative importance of hospital performance indicators perceived by the respondents. These indicators are borrowed from the seminal paper by Chiu et al. [10] and as per the hospital management guidelines issued by National Accreditation Board for Hospitals and Healthcare Providers (NABH)—a constituent board of Quality Council of India.

A pilot survey was conducted among hospital employees (including hospital administrators, superintendents, practicing doctors and nurses) and civilians to ensure that the questionnaire was conceived uniformly and further to ensure face validity. Altogether, 122 responses were collected from hospital employees as a part of this pilot survey. The average experience of these 122 respondents was 15.17 years. Interestingly, more potential risk factors were disclosed in the pilot phase. These risk factors, mostly institutional risk factors, are included in the revised version of the questionnaire. The questionnaire is modified to include 29 potential risk factors and seven hospital performance indicators. Significance of each item in the questionnaire is rated on a Likert scale. A five-point Likert scale is employed for conducting the civilian survey since the surveyed respondents was not exhibiting enough discriminating power to rate the significance of risk factors on a seven-point scale.

The questionnaire-based survey is conducted in two phases (1) Prior to the COVID crisis and (2) During the COVID crisis. First phase survey was done during the period of June 2017 till March 2018. We approached 554 civilians representing the population with the survey questionnaire. The questionnaire was administered by leveraging both online and offline methods. The survey fetched 437 responses with a response rate of 78.88%. A few respondents were approached through personal contacts and the rest of the potential respondents were identified and approached through referrals (snowballing) provided by the already responded civilians. This is the reason for obtaining a relatively good response rate. The individual responses were later screened to filter out the biased and unreliable responses that finally led to 385 samples. In order to ensure the sample is a true representation of the population, proportional samples are collected in terms of population of each district and gender proportion in the state. The results provide the civilian perspective towards the public hospitals.

The same questionnaire employed in first phase of the research is deployed for the second phase survey. The second phase survey was conducted during the period of May 2021 and September 2021. Every effort was taken to collect data from the same respondents who participated in the first phase of the survey for making a direct comparison of results. However, many respondents were untraceable forcing the investigators to collect data from additional civilians. Nonetheless, both the surveys had 123 respondents in common. The survey was repeated to check whether the recent COVID driven circumstances have made any differences in perspectives among the public towards hospital risk factors and also to identify any additional risk factors that evolved particularly as a result of COVID-19 pandemic.

3.2 Preliminary data analysis

The obtained data were initially analyzed using the descriptive and inferential statistics. Firstly, the responses obtained from both the surveys were checked for internal consistency using the Cronbach's α test with IBM SPSS software. The Cronbach's α value was found to be 0.725 for the first phase and 0.813 for the second phase. The tests confirm the reliability, and thus the data were found acceptable for further statistical exploration.

A *t*-test is conducted on each risk factor independently by assuming normality and with a confidence level set at 95% to check the statistical significance of each risk factor. The test value is fixed on the numerical value corresponding to 'neutral' preference, i.e., value 3. Hence, the risk factor will be considered statistically significant only if the risk factor's mean value exhibits any positive statistical deviation (i.e., p-value < 0.05). The details of the statistically significant risk factors along with the descriptive statistics and the *p*-value from the one-sample *t*-test results are listed in Table 2.

Ultimately, the analysis of civilian survey data obtained in the first phase reveals 13 significant risk factors. The respondents' reprimands the presence of critical risk factors such as medical negligence issues, clinical risks, the conduct of unhygienic medical procedures, mediocre tools and medicines, unqualified medical staff, delays in critical supplies like medical oxygen, patient discrimination, power failures, accidents, among others. This scenario reflects that the patients are safer in public hospitals and does not confront any direct risk factors that compromise their safer recovery. As reported in Vishnu et al. [52], a similar survey was conducted among the hospital administrators indicating eight risk factors only. Unlike the civilians, hospital employees refute the significance of risk factors like corruption issues, employee attitudinal issues, labor strikes and absenteeism. Interestingly, civilians survey was found comprehensive since all the eight risk factors identified significant in the administrator's survey were found statistically significant in the civilian survey, including employee health issues.

Most interestingly, the same 13 risk factors were found statistically significant in the second phase as well. A two-sample *t*-test is conducted corresponding to each risk factor for checking the differences in the mean values obtained from the first phase and the second phase survey data (Table 2). As a result, the mean values of

Table 2 Significant risk drivers in healthcare industry

Risk driver code	Risk driver	Type	First phase survey (2017–2018)			Second phase survey (2021)			Mean difference with two sample *t*-test	
			Mean (A)	Standard deviation	p-value ($\alpha = 0.05$)	Mean (B)	Standard deviation	p-value ($\alpha = 0.05$)	Value = (B–A)	p-value ($\alpha = 0.05$)
R1	Staff shortage	Internal	4.11	1.306	.000	4.71	0.821	.000	0.60	**.000**
R2	Maintenance mismanagement	Internal	3.89	1.475	.000	3.93	1.661	.000	0.65	.723
R3	Physical infrastructure limitations (buildings, beds and instruments)	Internal	4.03	1.487	.000	4.76	0.793	.000	0.73	**.000**
R4	Waste management issues	Internal	3.17	1.339	.012	3.42	1.406	.000	0.25	**.011**
R5	Employee attitudinal issues	Internal	4.03	1.206	.000	4.11	1.115	.000	0.08	.339
R6	Absenteeism	Internal	3.35	1.314	.000	4.05	1.365	.000	0.70	**.000**
R7	Employee health issues	Internal	3.50	1.242	.000	4.33	0.742	.000	0.83	**.000**
R8	Labor strikes	Internal	3.58	1.561	.000	3.55	1.437	.000	−0.03	.782
R9	Corruption issues	Internal	3.60	1.123	.000	3.29	1.080	.000	−0.31	*.000*
R10	Political uncertainties (Affects in the form of fund allocation delays, staff transfers, change of rules and regulations, recruitment delays, etc.)	External	3.91	1.451	.000	3.77	1.344	.000	0.14	.165
R11	Monsoon time epidemic disease or pandemics	External	4.08	1.304	.000	4.41	1.292	.000	0.33	**.000**
R12	Community mistrusts/disbeliefs	External	3.84	1.080	.000	3.23	1.003	.000	−0.61	*.000*
R13	Public strikes	External	3.25	1.456	.001	3.18	1.286	.006	−0.07	.479

Bold values indicate a statistically significant p-value eight risk factors obtained in the second phase survey are considerably different from the previous exercise values, i.e. the first phase survey. Additional statistical analyses carried out with the data obtained from the civilian survey, i.e. the characteristics of 13 risk factors, are investigated in the following sections. The inferences drawn from the results are summarized in the last part of this paper.

3.3 Model development

This section describes the statistical models developed to investigate the inter-relationships between the significant risk factors hypothesized from the integrated DEMATEL-ISM model results presented in our previous research [52]. Exploratory Factor Analysis (EFA) is deployed to identify the underlying factors that define the significant risk factors and Partial Least Squares-Structural Equation Modelling (PLS-SEM) is developed to test the validity of the inter-relationships between the extracted factors. The computational procedure described in Appendix-I is followed in this study.

3.4 Exploratory factor analysis

The survey data are subjected to exploratory factor analysis. Principal Component Analysis (PCA) is employed for extracting the factors. Direct Oblimin (Oblimin and Kaizer normalization) technique is used for rotation since significant factor correlation (= 0.384) was visible. The rotation converged in six iterations

Table 3 Pattern matrix and structure matrix

Risk driver code	Risk driver	Pattern matrix		Structure matrix	
		Factor		Factor	
		F1	F2	F1	F2
R1	Staff shortage	−0.008	0.965	−0.379	0.968
R2	Maintenance mismanagement	0.097	0.979	−0.280	0.942
R3	Physical infrastructure limitations	−0.018	0.964	−0.388	0.970
R4	Waste management issues	−0.041	0.847	−0.367	0.863
R5	Employee attitudinal issues	0.929	0.068	0.903	−0.289
R6	Absenteeism	0.789	−0.159	0.850	−0.462
R7	Labor strikes	0.903	−0.102	0.943	−0.450
R8	Corruption issues	0.872	−0.070	0.899	−0.405
R9	Employee health issues	0.949	0.133	0.898	−0.232
R10	Monsoon complications	0.003	0.951	−0.363	0.950
R11	Political uncertainties	−0.103	0.902	−0.449	0.942
R12	Community mistrusts	0.886	0.111	0.843	−0.229
R13	Public strikes	0.798	−0.182	0.868	−0.489

resulting in two factors. The pattern matrix and structure matrix are delineated in Table 3. Pattern matrix holds the loadings. Each row in this matrix is essentially a regression equation. The structure matrix holds the correlation between the variables and the factors.

The results obtained from the analysis indicate the presence of two underlying factors based on which the risk factors can be classified. The inferences, i.e., the factors extracted from the survey data are given below:

Factor 1: Human Related Constraints and Issues (HRCI)

Number of items under the factor = 7 and includes the following risk factors: (1) Employee Attitudinal Issues, (2) Absenteeism, (3) Labor Strikes, (4) Corruption Issues, (5) Health issues with Employees, (6) Community Mistrusts/Disbeliefs and (7) Public Strikes.

Factor 2: Hospital Administrative/Infrastructure Constraints and Issues (HACI)

Number of items under the factor = 6 and includes the following risk factors: (1) Shortage of Staffs, (2) Maintenance Mismanagement, (3) Physical Infrastructure Limitations, (4) Waste Management Issues, (5) Monsoon Time Epidemic Disease or Pandemics and (6) Political Uncertainties.

An evident pattern is observed in the above classification. It can be observed that the risk drivers allocated under Factor 1 are human-related, and hence, this factor is named as Human Related Constraints and Issues (HRCI). The risk drivers under Factor 2 are generally related to various infrastructure and administrative challenges, and accordingly, this factor is named as Hospital Administrative/Infrastructure Constraints and Issues (HACI). This categorization will help to implement specific policy interventions for uplifting the standards of current public hospitals. More to the point, it can be statistically stated that variations in the 13 observed variables mainly reflect the variations in these two unobserved (underlying) factors.

3.5 Partial least squares-structural equation modelling

Partial Least Squares-Structural Equation Modelling (PLS-SEM) is a class of multivariate statistical technique for validating the causal relationship between several variables and/or constructs. PLS-SEM is employed since the data obtained from the survey are not strictly normally distributed. Also, PLS-SEM is found more suitable for exploratory research and theory building in conjunction with EFA. The reflective modelling procedure is followed since individual risk factors are also found dependent apart from the factors.

The hypotheses formulated for the model are as follows:

H_1 HACI have direct positive influence with HRCI.

H_2 HACI have direct positive influence with DOP (Deteriorating Operational Performance of Hospitals, extracted from the third section of the questionnaire).

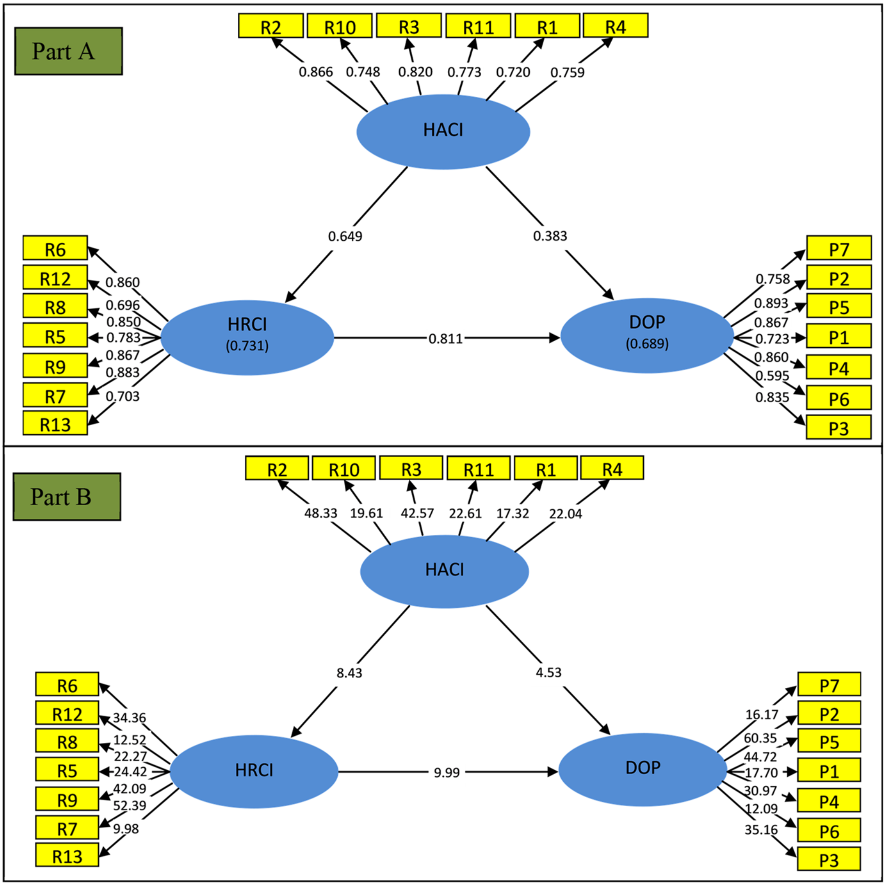


Fig. 2 The structural equation model

Table 4 Reliability, convergent validity and discriminant validity of constructs

Construct	Reliability and convergent validity				Discriminant validity		
	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)	DOP	HACI	HRCI
DOP	0.900	0.915	0.923	0.634	**0.796**		
HACI	0.874	0.891	0.904	0.612	0.381	**0.783**	
HRCI	0.911	0.919	0.929	0.655	0.330	0.411	**0.809**

DOP deteriorating hospital performance, *HACI* hospital administrative/infrastructure constraints and issues, *HRCI* human related constraints and issues

Bold values indicate the diagonal values

Table 5 Discriminant validity: items

Item code	Item	DOP	HACI	HRCI
R1	Staff shortage	0.242	**0.720**	0.269
R2	Maintenance mismanagement	0.352	**0.866**	0.354
R3	Physical infrastructure limitations	0.386	**0.820**	0.405
R4	Waste management issues	0.234	**0.759**	0.288
R5	Employee attitudinal issues	0.304	0.370	**0.783**
R6	Absenteeism	0.275	0.310	**0.860**
R7	Labor strikes	0.275	0.372	**0.883**
R8	Corruption issues	0.245	0.334	**0.850**
R9	Employee health issues	0.312	0.367	**0.867**
R10	Monsoon complications	0.244	**0.748**	0.312
R11	Political uncertainty	0.285	**0.773**	0.263
R12	Community mistrusts	0.173	0.317	**0.696**
R13	Public strikes	0.261	0.232	**0.703**
P1	Hospital image	**0.723**	0.362	0.214
P2	Hospital capacity utilization	**0.893**	0.378	0.297
P3	Timely delivery of service	**0.835**	0.315	0.257
P4	Overall patient satisfaction	**0.860**	0.305	0.322
P5	Hospital competitiveness	**0.867**	0.273	0.300
P6	Reduction in expenditure	**0.595**	0.226	0.178
P7	Average length of stay	**0.758**	0.229	0.246

DOP deteriorating hospital performance, *HACI* hospital administrative/infrastructure constraints and issues, *HRCI* human related constraints and issues

Bold values denote the highest value in the row and indicate the corresponding variable-factor mapping

H_3 HRCI have direct positive influence with DOP.

The methodology articulated in Appendix-I is followed to arrive in the following results illustrated in Fig. 2 and the model validation measures are provided in Tables 4 and 5.

3.6 Model fit and validation

Figure 2 (Part A) illustrates the PLS-SEM model indicating the indicator loadings corresponding to the outer model and the path coefficients associated with the inner model. Figure 2 (Part B) indicates the *t*-values corresponding to each relation. All the relations and loadings were found statistically significant with a 95% confidence level since the *t*-values are greater than 1.96. Statistically significant indicator loadings denote indicator reliability while internal consistency is validated by obtaining statistically significant path coefficients [22]. The values corresponding to Cronbach's alpha and composite reliability illustrated in Table 4 assure construct reliability as well as convergent validity.

The square root of AVE values of constructs (highlighted in green in Table 4) is found higher than the squared inter-construct correlation (as a measure of shared variance) confirming the discriminant validity of constructs. Also, it is found from Table 5 that all the indicator loadings are highest when the corresponding item is attributed to the perceived factor while the loadings to other factors are relatively smaller. This result clearly demonstrates the discriminant validity of the items. Since all the model fit parameters satisfy technical requirements for a sensible model, the model is found acceptable and fit for further interpretation. Accordingly, all the three hypotheses are statistically validated.

4 Inferences and discussion

The path coefficient associated with the relation between HACI and HRCI is estimated to be 0.690. This value indicates that administrative risk factors result in human-related risk factors, confirming the risk factors' inter-relationship. This relation, in turns, results in deteriorating operational performance of hospitals. The path coefficient value of 0.811 signifies this influence.

Albeit the path coefficient associated with the relation between HACI and DOP is relatively low, i.e., 0.383; however, at the same time, it is found statistically significant. In fact, Falk and Miller [16] in their seminal work on structural equation modelling, state that path coefficient with a value even less than 0.1 is acceptable and should be retained. The construct estimate values of 0.731 for HRCI and 0.689 for DOP confirm that a significant proportion of variance in the dependent constructs is well explained, and overall, the model is sound.

The observations indicate that both human-related risk factors and administrative risk factors result in deteriorating operational performance moderately. It can be inferred that administrative risk factors have a significant influence or will result in human-related risk factors that have a strong influence over the deteriorating operational performance of the hospitals under investigation. This characteristic denotes the impact potential or else the driving power of administrative risk factors in compromising operational performance. Recalling the DEMATEL results from Vishnu et al. [52], most of the risk factors that fell in the group 'causes' were administrative risk factors, and those fell in the 'receivers' group are mostly human-related risk factors. These results are in line with the observations from the ISM model were administrative risk factors are found to instigate human-related risk factors. Altogether, the SEM results validate the findings from the subjective models based on hybrid DEMATEL-ISM approach.

4.1 Managerial implications

Typical empirical researches conducted in social sciences and management is considered as cross-sectional studies. The relevance of the results obtained from such studies generally degrades with time. Ironically, the present paper unveils the robustness of empirical findings collected in two phases, conducted three years apart. While much has changed in the last two years, particularly due to COVID-19, much still remains the same. All the 13 risk factors found to be crucial in the first phase survey conducted during 2017–2018 continues to remain statistically significant till 2021. Though the results mark the absence of critical risk factors that directly sabotage patients' safer recovery, there are risk factors that compromise patient satisfaction and their hospital experience. This preliminary finding asserts that the public healthcare system has not transformed enough to become a patient-friendly institution over the years, i.e., from 2017 to 2021.

Relative to the first phase survey results, the mean values of eight risk factors are found significantly different in the second phase survey (Table 2). Among these eight risk factors, six risk factors (highlighted in red color) are found to be becoming more crucial since their mean value in the second phase survey is higher than its mean value estimated from the first phase survey. These risk factors include Staff Shortage, Physical Infrastructure Limitations, Waste Management Issues, Absenteeism, Employee Health Issues and Monsoon Time Epidemic Disease or Pandemics. This observation emphasizes the renewed thrust that the civilians place on the performance of public hospitals, especially on the premise of COVID-19 crisis. On the other side, mean values of two risk factors (highlighted in green color) estimated in the second phase survey are found lower than that estimated in the first phase survey. Accordingly, the risk factors, namely, Corruption Issues, Community Mistrusts/Disbeliefs, are found to be less critical in the second phase survey than the first phase survey.

Ultimately, the present research asserts the presence of the risk factors that continue to impede the quality of service delivered by public hospitals in the chosen Indian state. This deterioration will also restrain patients from deriving complete satisfaction. In contrast, the statistical results reflect the perceptions that civilians maintain towards public hospitals. The EFA model proposes two underlying factors: Human Related Constraints and Issues (HRCI) and Hospital Administrative/Infrastructure Constraints and Issues (HACI) based on the features shared among the risk factors belonging to the respective factors. These directly unobservable factors provide more realistic means to classify the risk factors into two categories rather than reducing the risk factors to conventional classes like internal/external and disruptions/uncertainties categories.

In addition to the direct inferences drawn from the developed models, we also present few additional insights obtained during the course of research. These details are mainly acquired from the exposure earned during the conduct of the survey and also as result of close interactions with the different stakeholders in the public healthcare system. This additional information is considered essential from the implementation perspective and to assist hospital administrators in obtaining a complete understating of the current system/practices. These recommendations and implications for improving hospitals' performance shared by various stakeholders, including hospital administrators, practicing doctors and nurses, are described below by linking with the existing literature in the healthcare management field.

In most parts of the country, public hospitals have been underfunded and are not patronized by society's privileged class [9]. This fund shortage and operational inefficiencies are the root cause of all major risk factors. The presented model states that risk factors like the physical infrastructure limitations and shortage of staff will overburden the existing employees, resulting in human-related issues, including attitudinal issues of employees and community mistrusts and misbelieves. These sequences of inter-dependencies are the reasons behind the surging number of conflicts that arise between healthcare professionals and the general public. Undoubtedly the budgetary allocation for healthcare needs to be ramped up over time.

To reduce the dependency on public hospitals, the federal government must strengthen complementary facilities like primary health centers and popularize telemedicine systems. These facilities have already proved to be effective in providing healthcare access in remote areas. The government must also endorse alternate medicine systems such as Ayurveda, Yoga and Naturopathy, Unani, Siddha and Homoeopathy (AYUSH). Their established capacities are relatively underutilized compared to the allopathic system [43]. A higher level of awareness and governmental patronization is essential to make these medicinal systems and established facilities available to the common man at the last corner of the society for the benefit of the former and the healthcare system altogether [46]. The overcrowding issue in public hospitals can be minimized to a large extent if civilians start harnessing the alternatives mentioned above. Minimizing the overcrowding issue will curtail the physical infrastructural constraints that will have a positive ripple effect in mitigating other risk factors as observed from the developed model. Additionally, lean management principles and the six sigma approach can be practiced in public hospitals to eliminate waste management issues.

5 Conclusions

It is an indisputable fact that the performance of public hospitals in developing nations needs vital transformation. An improvement in the current healthcare facilities will create a positive domino effect not only on public health but also on numerous aspects of human development. Unlike the conventional manufacturing sector, a healthcare facility's performance is ultimately determined by the perception of the public who tap the services of such institutions that are mostly intangible. Currently, public hospitals in India focus so much on the functionality, that they associate the least importance to emotionality. A hospital should be a trust mark, and patients need to feel reassured. To realize this priority shift, the healthcare professionals should try to best understand the service seekers, reinstate trust and boost confidence. In this direction, the present paper has considered the public perception to identify and characterize operational risk factors experienced in the public healthcare sector in a chosen Indian state. The questionnaire-based survey conducted as a part of this research discloses risk factors unique to the sector under investigation. This group of risk factors encompasses the characteristics of the present healthcare system that influence the level of satisfaction derived from the public.

The exploratory factor analysis discloses that the civilians tend to classify risk factors among (1) *Human Related Constraints and Issues* and (2) *Hospital Administrative/Infrastructure Constraints and Issues*. The results obtained from the structural equation model underscores the significance of the human factor in determining patient experience in public hospitals. In fact, the statistical models developed as a part of this research unravels the translational effect of administrative/infrastructure constraints in public hospitals in compromising the operational performance indirectly through human-related issues rather than having a direct influence. This inference from the structural equation model is an exciting and unique observation in supply chain risk management literature. These observations will facilitate policy experts and hospital administrators to identify key priority areas for improving hospital efficiency. Moreover, the results fielded by the present research are expected to add to the chorus of articles that can act as a roadmap to initiate long-due structural reforms in the sector. In this direction, to enable resource constrained public hospitals to respond to pandemics like COVID-19, the existing infrastructure must be agile. For instance, each public hospital must be capable of quickly modifying at least of its ward to respond to health emergencies like pandemics, natural disasters, among others. Further research may encompass on developing this infrastructural and organizational flexibility for public hospitals. Indeed, such human-centric interventions will enhance hospital performance based on which fresh strategies can be minted to add impetus to service delivery.

It is important to note that the risk characterization models developed in this research are fundamentally conceptualized for the public healthcare sector in a chosen Indian state for consolidating its specificities and location realities. For instance, during the onset of the second wave of COVID that struck in early 2021, many states in India were running short of medical oxygen supply. This crippling shortage of life-saver gas wreaked havoc resulting in fatalities in many north Indian states and union territories. However, the public healthcare system in the state was comparatively in a safer position since they had surplus capacity. In fact, during the grave situation, the state government supplied the surplus medical oxygen to neighboring states in response to their distress call. This scenario reflects that the significance of risk factors may vary from region to region within India itself. Accordingly, the scope of the present research is limited to this territory under investigation. However, the generalized approach can be easily replicated in other regions and institutions without additional hardships. Finally, further research is required to test and validate whether *Human Related Constraints and Issues* play a mediating role in establishing the relation between the factors *Hospital Administrative/Infrastructure Constraints and Issues* and *Deteriorating Operational Performance of Hospitals*. For conducting this study, the covariance based structural equation model has to be developed and analyzed.

Appendix

Appendix I: Description of statistical analysis and modeling methods

This section provides a brief description of the statistical techniques employed in the research.

Exploratory factor analysis

Factor analysis is a class of statistical approach used to analyze the inter-relationships among a large number of variables in terms of their common underlying, but unobservable dimensions termed factors [48]. Basically, factor analysis is a data reduction technique that summarizes the information in several original variables into a smaller set of factors without losing essential information [21]. Suppose a set of variables within a particular group are highly correlated among themselves but have relatively insignificant correlations with variables outside this set. In that case, it is conceivable that the set of variables represents a single underlying construct or factor responsible for the observed correlations, thus allowing the formation and refinement of theory [26, 55].

There are two types of factor analysis, namely exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Broadly, EFA is used to explore the main dimensions to generate a theory, or model, whereas CFA is used to test a proposed theory. In EFA, the researcher has no expectations of the number or nature of the variables and as the title suggests, is exploratory [55]. Since the research on supply chain risk analysis in the public healthcare sector has no prior theory or models as benchmarks,the present research adopts EFA for analyzing the risk factors that are found significant in the undertaken survey. The standard EFA procedure delineated by Williams [55] is followed in the present research. The model is developed in IBM SPSS version 21.

Partial least squares-structural equation modelling

Structural equation modelling (SEM) first appeared in the marketing literature in the early 1980s (e.g. [4, 5, 18, 19], but later found application in a variety of fields including operations management, economics, political sciences, among others. Fundamentally, SEM is a family of statistical models that follows a confirmatory (i.e., hypothesis testing) approach that seeks to explain relationships among multiple variables. Typically, this technique is employed to investigate the causal effects between multiple variables represented by a series of structural (i.e., regression) equations. These equations portray all the relationships between constructs, i.e., the independent and dependent variables involved in the model. These constructs are similar to a factor in the factor analysis that is generally unobservable or latent factors defined by multiple observable variables. Hence, this technique is a synergy between multiple regression and factor analysis.

The hypothesized SEM involving various regression equations can then be statistically tested simultaneously. The test involves the entire system of variables to determine the extent to which the model is consistent with the data. A set of indicators or goodness-of-fit measures are employed to validate the hypothetical model. If the measurements are adequate, the model argues for the plausibility of postulated relations among variables; if it is inadequate, the tenability of such relations is rejected. Based on the computational aspects, there are numerous types of structural equation modelling methods in the literature. Most important types are covariance-based SEM, and partial least squares (PLS) based SEM.

Relatively, PLS-SEM is less restrictive and does not mandate the normality of data. Furthermore, PLS-SEM is most appropriate to deploy in conjunction with EFA, which is meant for exploratory research and theory building rather than testing an already established concept. Hence, in the present research, PLS-SEM is applied to validate the inter-relationships between significant risk factors experienced in the civic-run hospitals under investigation.

A structural equation model with latent constructs has two components named as measurement models (or outer model) and the structural model (or inner model). The measurement models include the unidirectional predictive relationships between each latent construct and its associated observed variables or indicators. The structural model delineates the relationships (paths) between the latent constructs. Hence, the basic PLS-SEM [31] is performed in two-stages. In the first stage, the latent constructs' scores are estimated via a four-step process, as shown below. The second stage calculates the final estimates of the outer weights and loadings as well as the structural model's path coefficients. The procedure reported by Hair et al. [22], is followed to develop the PLS-SEM.

After estimating the proposed model, the resulting solution should be checked for reliability and validity. The reliability measures include construct reliability (assessed using Cronbach's alpha, rho_A value) and composite reliability. The overall validity of the model depends on convergent validity of constructs using Average Variance Extracted (AVE) value, discriminant validity of constructs, and discriminant validity of variables/items. In the present research, a computer application known as SmartPLS version 3.2.8 is leveraged to build the model and to automatically compute the necessary estimates, reliability indicators and validity indicators.

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Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Ahalt, V., Argon, N.T., Ziya, S., Strickler, J., Mehrotra, A.: Comparison of emergency department crowding scores: a discrete-event simulation approach. Health Care Manag. Sci. **21**(1), 144–155 (2018)
2. Alaloola, N.A., Albedaiwi, W.A.: Patient satisfaction in a Riyadh Tertiary Care Centre. Int. J. Health Care Qual. Assur. **21**(7), 630–637 (2008)
3. Alidina, S., Martelli, P.F., Singer, S.J., Aveling, E.L.: Optimizing patient partnership in primary care improvement: a qualitative study. Health Care Manag. Rev. **46**(2), 123–134 (2021)
4. Bagozzi, R.P.: Structural equation models in marketing research: basic principles. Princ. Market. Res. **3**(1), 7–385 (1994)

5. Bagozzi, R.P., Yi, Y.: On the evaluation of structural equation models. J. Acad. Mark. Sci. **16**(1), 74–94 (1988)
6. Bamfo, B.A., Dogbe, C.K.: Factors influencing the choice of private and public hospitals: empirical evidence from Ghana. Int. J. Pharm. Healthc. Market. **11**(1), 80–96 (2017)
7. Bharsakade, R.S., Acharya, P., Ganapathy, L., Tiwari, M.K.: A lean approach to healthcare management using multi criteria decision making. OPSEARCH **58**(3), 610–635 (2021)
8. Carlucci, D., Renna, P., Schiuma, G.: Evaluating service quality dimensions as antecedents to outpatient satisfaction using back propagation neural network. Health Care Manag. Sci. **16**(1), 37–44 (2013)
9. Chetterje, P.: Gaps in India's preparedness for COVID-19 control. Lancet. Infect. Dis **20**(5), 544 (2020). https://doi.org/10.1016/S1473-3099(20)30300-5
10. Chiu, W.T., Yang, C.M., Lin, H.W., Chu, T.B.: Development and implementation of a nationwide health care quality indicator system in Taiwan. Int. J. Qual. Health Care **19**(1), 21–28 (2007)
11. Covert, H.H., Sherman, M., Le, D., Lichtveld, M.Y.: Environmental health risk relationships, responsibility, and sources of information among Vietnamese Americans in coastal Mississippi. Health Risk Soc. **22**(5–6), 362–376 (2020)
12. Das, A.K., Islam, N., Billah, M., Sarker, A.: COVID-19 pandemic and healthcare solid waste management strategy—a mini-review. Sci. Total Environ. (2021). https://doi.org/10.1016/j.scitotenv.2021.146220
13. Delcea, C., Alexandra, B.I.: Fostering risk management in healthcare units using grey systems theory. Grey Syst. Theory Appl. **6**(2), 216–232 (2016)
14. Edozien, L.C.: The RADICAL framework for implementing and monitoring healthcare risk management. Clin. Gov. Int. J. **18**(2), 165–175 (2013)
15. Engle, R.L., Mohr, D.C., Holmes, S.K., Seibert, M.N., Afable, M., Leyson, J., Meterko, M.: Evidence-based practice and patient-centered care: doing both well. Health Care Manag. Rev. **46**(3), 174–184 (2021)
16. Falk, R.F., Miller, N.B.: A Primer for Soft Modeling. University of Akron Press, Akron (1992)
17. Fersch, B., Schneider-Kamp, A., Breidahl, K.N.: Anxiety and trust in times of health crisis: how parents navigated health risks during the early phases of the COVID-19 pandemic in Denmark. Health Risk Soc. (2022). https://doi.org/10.1080/13698575.2022.2028743
18. Fornell, C., Bookstein, F.L.: Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. J. Mark. Res. **19**(4), 440–452 (1982)
19. Fornell, C., Larcker, D.F.: Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. **18**(1), 39–50 (1981)
20. Govindan, K., Mina, H., Alavi, B.: A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: a case study of coronavirus disease 2019 (COVID-19). Transp. Res. Part E Logist. Transp. Rev. **138**(1), 1–14 (2020)
21. Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., Tatham, R.L.: Multivariate Data Analysis, 6th edn. Pearson Education Inc, New Delhi (2012)
22. Hair, J.F., Ringle, C.M., Sarstedt, M.: PLS-SEM: indeed a silver bullet. J. Market. Theory Pract. **19**(2), 139–151 (2011)
23. Harikumar, P., Saleeshya, P.G.: A systems approach to mapping performance in Indian healthcare organizations. Int. J. Healthc. Manag. **14**(4), 1134–1147 (2021)
24. Hemant, J., Rajesh, R., Daultani, Y.: Causal modelling of the enablers of CPFR for building resilience in manufacturing supply chains. RAIRO Oper. Res. **56**(4), 2139–2158 (2022)
25. Iyer, R.K., Bandyopadhyay, K.: Managing technology risks in the healthcare sector: disaster recovery and business continuity planning. Disaster Prev. Manag. Int. J. **9**(4), 257–270 (2000)
26. Johnson, R.A., Wichern, D.W.: Applied Multivariate Statistical Analysis, 6th edn. Pearson Education Inc, New Delhi (2015)
27. Kalaja, R., Myshketa, R., Scalera, F.: Service quality assessment in health care sector: the case of Durres public hospital. Procedia Soc. Behav. Sci. **235**, 557–565 (2016)
28. Khayat, K., Salter, B.: Patient satisfaction surveys as a market research tool for general practices. Br. J. Gen. Pract. **44**(382), 215–219 (1994)
29. Kumar, D., Kumar, D.: Modelling rural healthcare supply chain in India using system dynamics. Procedia Eng. **97**, 2204–2212 (2014)
30. Kwon, I.W.G., Kim, S.H., Martin, D.G.: Healthcare supply chain management; strategic areas for quality and financial improvement. Technol. Forecast. Soc. Change **113**(1), 422–428 (2016)

31. Lohmöller, J.B.: Latent Variable Path Modeling with Partial Least Squares. Physica-Verlag, Heidelberg (1989)
32. Mehra, P.: COVID corrections: how the pandemic reveals the failures of India's growth model. ORF Issue Brief **363**, 1–15 (2020). (**ISBN: 978-93-90159-11-6**)
33. Motlatla, M., Maluleke, T.X.: Assessment of knowledge about healthcare risk waste management at a Tertiary Hospital in the Northern Cape Province, South Africa. Int. J. Environ. Res. Public Health **18**(2), 1–15 (2021)
34. Mustaffa, N.H., Potter, A.: Healthcare supply chain management in Malaysia: a case study. Supply Chain Manag. Int. J. **14**(3), 234–243 (2009)
35. Naik, B.S.: Is the society in India envious of its doctors? A doctor's perspective. APIK J. Intern. Med. **8**(4), 214–215 (2020)
36. Okoroh, M.I., Ilozor, B.D., Gombera, P.P.: Modelling of risk management in health care facilities. Facilities **24**(5/6), 197–210 (2006)
37. Pai, Y.P., Chary, S.T.: Measuring patient-perceived hospital service quality: a conceptual framework. Int. J. Health Care Qual. Assur. **29**(3), 300–323 (2016)
38. Pattnaik, M.: Healthcare management and COVID-19: data-driven bibliometric analytics. OPSEARCH (2022). https://doi.org/10.1007/s12597-022-00576-2
39. Pfohl, H.C., Gallus, P., Thomas, D.: Interpretive structural modeling of supply chain risks. Int. J. Phys. Distrib. Logist. Manag. **41**(9), 839–859 (2011)
40. Pournader, M., Kach, A., Talluri, S.: A review of the existing and emerging topics in the supply chain risk management literature. Decis. Sci. **51**(4), 867–919 (2020)
41. Pramod, V.R., Banwet, D.K.: ISM for the inhibitors of service supply chain: a case study in a safety health environment and risk consultancy service sector. Int. J. Logist. Econ. Glob. **2**(2), 151–175 (2010)
42. Rayamane, A.P., Nanandkar, S.D., Kundargi, P.A.: Profile of medical negligence cases in India. J. Indian Acad. Forensic Med. **38**(2), 144–148 (2016)
43. Rudra, S., Kalra, A., Kumar, A., Joe, W.: Utilization of alternative systems of medicine as health care services in India: evidence on AYUSH care from NSS 2014. PLoS ONE **12**(5), 1–20 (2017)
44. Saha, E., Ray, P.K.: Modelling and analysis of healthcare inventory management systems. OPSEARCH **56**, 1179–1198 (2019)
45. Sahoo, C., Mishra, H.B., Chawda, T.: Issues in India's Healthcare System. Indian J. Public Health Res. Dev. **11**(2), 594–599 (2020)
46. Samal, J., Dehury, R.K.: Utilization, preference, perception and characteristics of people adopting traditional and AYUSH systems of medicine in India: a systematic review. J. Complement. Integr. Med. (2018). https://doi.org/10.1515/jcim-2018-0020
47. Samuel, C., Gonapa, K., Chaudhary, P.K., Mishra, A.: Supply chain dynamics in healthcare services. Int. J. Health Care Qual. Assur. **23**(7), 631–642 (2010)
48. Tabachnick, B.G., Fidell, L.S.: Using Multivariate Statistics. Pearson Education Inc, Boston (2007)
49 Thakur, V.: Framework for PESTEL dimensions of sustainable healthcare waste management: learnings from COVID-19 outbreak. J. Clean. Prod. **287**, 125562 (2021). https://doi.org/10.1016/j.jclepro.2020.125562
50. Thakur, V., Anbanandam, R.: Healthcare waste management: an interpretive structural modeling approach. Int. J. Health Care Qual. Assur. **29**(5), 559–581 (2016)
51. VanVactor, J.D.: A case study of collaborative communications within healthcare logistics. Leadersh. Health Serv. **24**(1), 51–63 (2011)
52. Vishnu, C.R., Sridharan, R., Kumar, P.R., Kumar, V.R.: Analysis of the operational risk factors in public hospitals in an Indian state. Int. J. Health Care Qual. Assur. **33**(1), 67–88 (2019)
53. Vishnu, C.R., Sridharan, R., Kumar, P.R.: Supply chain risk inter-relationships and mitigation in Indian scenario: an ISM-AHP integrated approach. Int. J. Logist. Syst. Manag. **32**(3–4), 548–578 (2019)
54. Walston, S.L., Al-Omar, B.A., Al-Mutari, F.A.: Factors affecting the climate of hospital patient safety: a study of hospitals in Saudi Arabia. Int. J. Health Care Qual. Assur. **23**(1), 35–50 (2010)
55. Williams, B.: Exploratory factor analysis: a five-step guide for novices. J. Emerg. Prim. Health Care **8**(3), 1–13 (2010)
56. Winter, V., Schreyögg, J., Thiel, A.: Hospital staff shortages: Environmental and organizational determinants and implications for patient satisfaction. Health Policy **124**(4), 380–388 (2020)
57. Yadav, M., Rastogi, P.: A study of medical negligence cases decided by the district consumer courts of Delhi. J. Indian Acad. Forensic Med. **37**(1), 50–55 (2015)

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