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Factors Affecting Covid-19 Critical Care Capacity: A Case Study of Lahore, Pakistan

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Abstract: *Covid-19 was declared a pandemic in 2020 and diffused everywhere in the world. Since then, many models have been created to study the diffusion of the disease. This paper is an attempt to predict the dispersion of COVID-19 and extract the prime factors of COVID-19 critical surge care capacity in Lahore. The primary data were collected using a questionnaire as a tool. The data were obtained from both public and private hospitals in Lahore. The implementation of factor analysis in the current study of the prime causes of COVID-19 surge capacity was analyzed to anticipate a reference for rudimentary research on COVID-19 and its prevention and management. It was analyzed through factor analysis that Patient Surge during the peak month of the pandemic caused employee burden, PPE unavailability and shortage, lack of testing supplies, bed and ventilator shortages, and an increase in cases with no hygiene and precautionary measures. These are the major factors that were responsible for the surge of disease in Lahore. It was identified that resolving these basic issues can bring improvements in future disease management, early preparation, and quick response to the pandemic outbreak to prevent human suffering and financial loss.*

Key Words: COVID-19, Surge Care Capacity, Factors Analysis, Patient Surge, Healthcare

Introduction

COVID-19 emerged as a major global concern, particularly affecting developing nations. Initially, on December 31, 2019, China's Hubei Provincial Health Commission reported a cluster of pneumonia cases of unknown origin. The first reports indicated 41 cases, including seven severe and one fatality (Kofi Ayittey et al., 2020). Later, on January 11, 2020, the initial count of 27 patients was revised (Chan et al., 2020). This infectious disease, officially named coronavirus disease 2019 (COVID-19) or SARS-CoV-2, prompted the World Health Organization (WHO) to declare it a Public Health Emergency of International Concern (PHEIC) on January 30, 2020. By March 11, 2020, with cases surging worldwide, WHO declared COVID-19 a pandemic. By July 11, 2020, over 12.5 million cases were reported in 188 countries, with over 560,000 fatalities (Klein et al., 2020).

Historically, hospitals have served as major hubs for medical care, and emergencies bring this fact to light. It is still up for debate whether pandemics qualify as disasters, but it is certain that they contribute to a rise in disease transmission. Worldwide, hospital and critical care systems are experiencing unprecedented stress due to the coronavirus illness. (Abir et al., 2020). Hospital capacity issues are caused by a sudden, erratic spike in patient demand that has an impact on vast populations around the world (Montano & Savitt, 2020) (Shahid et al., 2022). Hospitals must be equipped to deal with epidemics and pandemics, just like they would with any other type of crisis. The world is dealing with a pandemic caused by the coronavirus disease 2019, which has been characterized by illness, mortality, an economic downturn, and unstable healthcare systems. Medical healthcare is now inextricably linked to economic growth and governmental structures, as demonstrated by the fact that this health-related catastrophe has destroyed the economics of the globe as a whole. (Gul & Yucesan, 2021, Ducarme 2020).

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Asia's most populous and impoverished region is South Asia. Due to its low doctor-to-population ratio and underdeveloped health systems (Chalise, 2020), this region is particularly vulnerable to the epidemic (Babu et al., 2020). With a score of 35.5/100, Pakistan ranked third in the subject matter for Global Health Security. The poor grade emphasizes the country's lack of a response to emergencies and a preparedness system. Out of 195 countries, the country ranked 167th in terms of its performance on health indices. Pakistan recorded 930,511 cases since the outbreak began, among many other vulnerable countries (Shahid et al., 2022).

The primary approach for halting the pandemic's spread is hospital planning, which comprises the management of resources, capacity building, monitoring, and communications (Haghani et al., 2020). Numerous South Asian nations' hospitals' readiness for COVID-19 reveals gaps in their backup plans, PPE and isolation facilities (Babu et al., 2020). A saturating of the health system and testing approach is regarded as a sign of inadequate preparations and is caused by underestimations, inadequate planning, and a lack of communication. The absence of governmental standard operating procedures (SOPs) tends to strain the nation's already precarious healthcare system (Khalid & Ali, 2020).

The present paper makes an effort to forecast COVID-19 distribution and identify the key determinants of Lahore's essential surge care capability. Factor analysis was used to identify the key factors or dimensions that contribute to the spread and impact of the virus. The variables that measure the spread and impact of COVID-19 in the study area are based on the number of confirmed cases, deaths, recoveries, hospitalizations, and testing rates. A factor analysis is performed on these variables to identify the key factors that contribute to the spread and impact of COVID-19 in Lahore.

Objectives

This research makes two major additions to the preliminary studies: Firstly, it provides a methodological strategy for visualizing the spread of COVID-19 confirmed cases in the hospitals of Lahore. Secondly, it extracts the prime factors of COVID-19 surge care capacity in the study area. Through factor analysis, it was determined that the Patient Surge during the Pandemic's peak month resulted in increased workloads for employees, a shortage of PPE, a lack of testing materials, a shortage of beds and ventilators, and a rise in cases without proper hygiene and precautions. This study is useful because it provides policymakers with information that will help them increase the capacity and management of hospitals during the surge of disease.

Novelty Statement

This study stands out for its global perspective on the pandemic and its causes. COVID-19 is a newly found, highly contagious disease that has rapidly spread as a pandemic to at least 213 nations. COVID-19 is caused by the newly identified coronavirus SARS-CoV-2. COVID-19 transmission is complicated and swift, making disease control problematic (Wang & Alexander, 2020). In this research, the prime causes of Covid-19 were extracted by using statistical techniques. Through factor analysis (FA), a large number of variables are converted into a small number of factors (Khan, 2020). Correlated variables are merged with independent parameters in this strategy. The extracted variables identify the basic area of the cause of this widespread disease and help the decision-makers manage healthcare resources in an area.

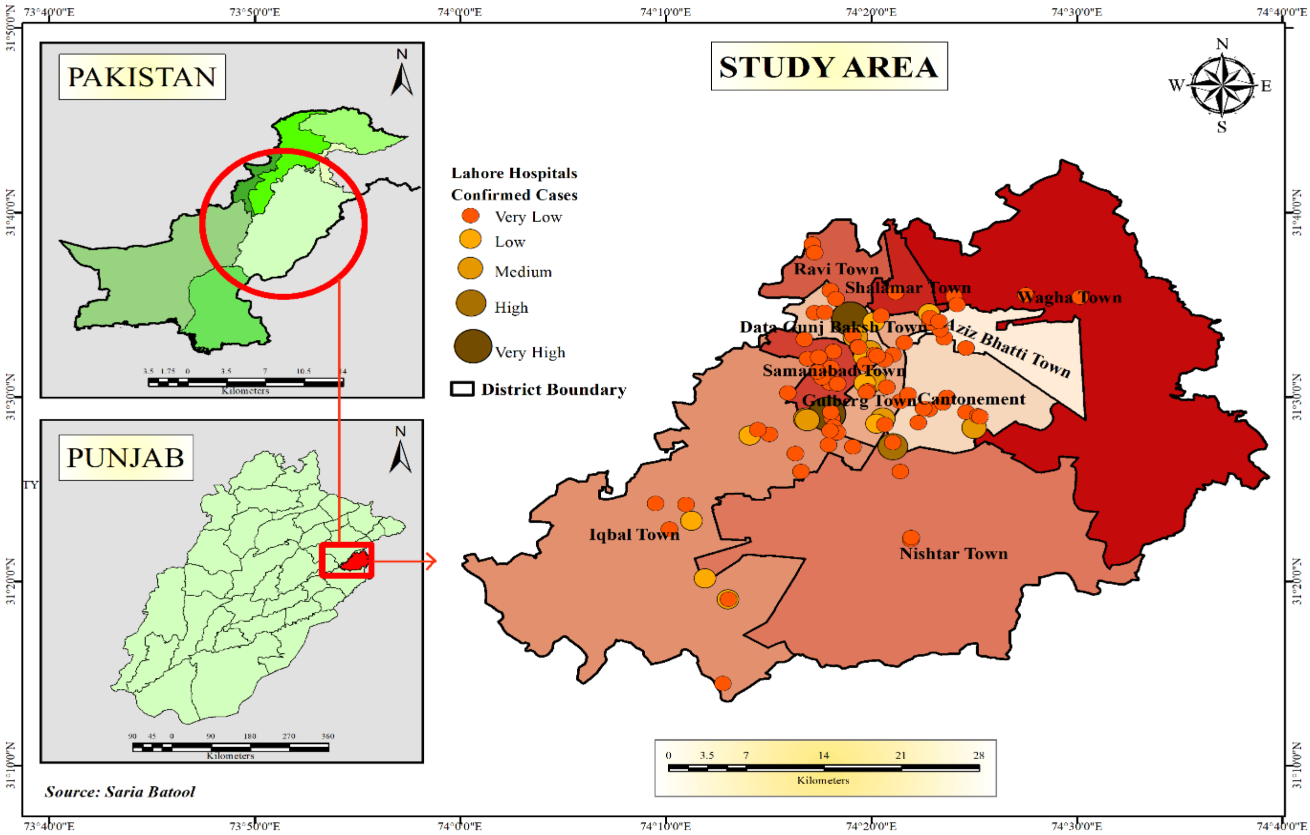
Material and Methods

Study Area

The study was carried out in Lahore's metropolitan area. A descriptive cross-sectional study was conducted in public hospitals run by the Specialized Health Care and Medical Education Department (SHC&ME) in Lahore (Nisar et al., 2022; Shahid et al., 2022). This research was conducted from May to July 2020 over a three-month period. Primary Data was collected from the public hospitals to obtain the desired results by meeting the research objectives. Figure 1 shows the hospital-wise confirmed cases in Lahore district.

Figure 1

Hospital-wise confirmed cases of Covid-19 in Lahore.



Data Analysis

The Statistical Package for Social Sciences (SPSS) IBM software was used to process, clean, and analyze the COVID-19 data after it had been compiled and tabulated in Microsoft Excel. To determine the availability of medical resources during the peak times of COVID-19, information related to ICUs, beds, and ventilators has been acquired from the Specialized Healthcare & Medical Education Department.

The questionnaire was created to collect information from significant public hospitals. A field survey was carried out in Services Hospital, Mayo Hospital, Sir Ganga Ram Hospital, Lahore General Hospital, Sheikhzyad Hospital, and Jinnah Hospital. Forty questions were prepared for this study, and the purpose of each question was to elicit opinions from both the general population and the medical personnel regarding the impact of the COVID-19 virus in Lahore and the accessibility of healthcare resources in public hospitals. Interviews with physicians, head nurses, nurses, patients, and staff were conducted. Numerous questions were posed to gather public views and opinions to meet the need for data collection. An interviewee's thoughts, behaviours, views, expectations, and background are thoroughly examined. As a result, 300 out of 400 questionnaires were completed, and this field survey yielded data.

Primary data from the survey were entered in SPSS, and the data's initial reliability was assessed. Factor analysis has been used to analyze the data because statements were on a five-point Likert scale (Arora et al., 2020). Analyses include the data reliability test, in which we analyze the level of Cronbach's alpha. Descriptive statistics in which mean and standard deviation are calculated, the Measure for Sampling Adequacy in Kaiser-Meyer-Olkin (KMO) and Bartlett's test, Total variance, communities, correlation matrices, scree plots, component matrices, and rotated component matrices were extracted in the study. After that, information was shown in the form of tables with factors, and the final principal factors were labelled as COVID-19's primary causing factors.

Factor Analysis (FA), a widely recognized multivariate statistical method, transforms specific dependent variables into distinct factors, with the original factors retaining crucial information from the initial dataset. Conversely, FA is utilized to reduce the dimensionality of large datasets by accounting for the minimal set of factors. The primary aim of factor analysis (FA) is to ascertain the degree of association between variables. For instance, variables within the same factor exhibit a strong correlation, while those in different factors exhibit a considerably weaker correlation. In numerous applications, the count of eigenvalues exceeding one in the correlation matrix is employed to determine the number of principal factors in FA.

The adequacy of Factor Analysis (FA) was assessed through the Kaiser-Meyer-Olkin (KMO) index. When the KMO exceeds 0.8, it affirms the precision of the FA (Mahmoudi et al., 2021). Factor Analysis treats all factors with equal importance and rectifies correlations among different variables by removing redundant ones, thereby alleviating this issue. To extract the principal factors from the Factor Analysis, a comprehensive elucidation of KMO, Bartlett's test of sphericity, communality, item statistics, total variance explained, scree plot, correlation matrix, component matrix, rotated component matrix, as well as the procedures for presenting factors and labelling them is provided.

Results and Discussions

Data Reliability

After manually inputting the data into SPSS, the initial task is to assess the data's reliability to determine its suitability for further analysis. This evaluation relies on Cronbach's alpha, the most commonly used metric for measuring reliability. A Cronbach's alpha exceeding 0.9 indicates a highly reliable questionnaire, while a value above 0.8 signifies good reliability. Additionally, if Cronbach's alpha surpasses 0.7, the questionnaire is considered to have an acceptable level of reliability. However, if it falls below 0.6, the questionnaire's reliability is deemed insufficient, and if it dips below 0.5, it is deemed unsuitable for use.

In Table 1, the reliability analysis's findings are displayed. The results demonstrate that Cronbach's Alpha is 0.980, demonstrating the high quality and dependability of the questionnaire data for further study.

Table 1

Reliability statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.980	.981	40

Source: Author

Descriptive Statistics

Summary statistics for a number of variables are shown by the descriptive approach. Table 2 shows a list of these variables. The standard deviation and mean both indicate how close the data is to the mean, and the data were limited to reduce inaccuracies. In the descriptive statistics, the total number of variables is 400, and the values of the mean and standard deviation of the variables are illustrated below.

Table 2

Descriptive statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Affected	400	1	5	3.52	1.421
Global threat	400	1	5	2.39	1.557
Respiratory droplet	400	1	5	2.19	1.415
Transmission	400	1	5	2.66	1.456
Symptoms	400	1	5	2.56	1.416
Cure	400	1	5	2.96	1.390
Severe Cases	399	1	5	2.63	1.372
Medical Mask	400	1	5	2.56	1.273
Measures	400	1	5	3.84	1.528
Isolation	400	1	5	2.42	1.468
Crowded Places	399	1	5	2.51	1.571

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Strict Measures	400	1	5	2.32	1.537
Beds capacity in ICU	400	1	5	2.50	1.420
Shortage of testing supplies.	400	1	5	2.48	1.358
Lack kits	400	1	5	2.72	1.459
Shortages of critical supplies	400	1	5	2.85	1.357
Condition of isolation wards	400	1	5	2.82	1.336
Hygiene measures	400	1	5	3.04	1.255
Sharp increases in prices.	400	1	5	2.62	1.271
Waits in test results	400	1	5	2.84	1.354
Lack of testing supplies	400	1	5	2.68	1.342
Protecting staff	400	1	5	2.66	1.292
PPE contribution shortage	400	1	5	2.57	1.239
PPE availability	400	1	5	3.03	1.127
Patient Surge	400	1	5	2.62	1.298
Staff exposure	400	1	5	2.44	1.318
Emotional troll	400	1	5	2.59	1.352
Discharge Patients	400	1	5	2.43	1.236
Non-touch devices	400	1	5	2.93	1.172
Cleaning Supplies	400	1	5	3.05	1.334
Smaller Hospitals	400	1	5	2.53	1.376
OPD closed	400	1	5	2.53	1.521
Worsen ventilator	400	1	5	2.48	1.321
Ventilator shortages	400	1	5	2.49	1.362
CDC guidance	400	1	5	3.03	1.392
Guidance from State	400	1	5	2.79	1.451
Workload	400	1	5	2.66	1.342
PPE reuse	400	1	5	3.21	1.114
Adequate staff	400	1	5	2.70	1.245
Employee burden	400	1	5	2.92	1.395

KMO and Bartlett's Test

Factor analysis is employed for multidirectional scales to identify underlying components or factors that account for correlations within a set of variables. In cases where the Kaiser-Mayer-Olkin (KMO) coefficient falls between 0.5 and 1 and the significance of Bartlett's test of Sphericity is less than 0.05, it is appropriate to conduct exploratory component analysis. In this particular study, Principal Components with Varimax Rotation was the chosen factor analysis method (Le et al., 2020). The results in Table 3 reveal a KMO value of 0.927, which falls within the acceptable range of 0.5 to 1, and Bartlett's Test statistic of 26132.940 with a significance level of 0.00 ($p < 0.05$), affirming the suitability of exploratory factor analysis for this study. In accordance with standard criteria, the KMO value should exceed 0.50, indicating adequate sampling adequacy. Additionally, Bartlett’s test of Sphericity demonstrates a highly significant relationship between the variables. With a p-value of 0.000, which is less than the alpha level, we reject the null hypothesis, suggesting that the correlation among variables is not indicative of an identity matrix.

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Table 3

KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.927
Bartlett's Test of Sphericity	Approx. Chi-Square	26132.940
	Df	780
	Sig.	.000

Communalities

The table below presents the commonalities for the variables, along with the proportion of variance in these variables that can be attributed to the extracted factors. In the first column of the commonality, you'll find the initial values of the correlation matrix, indicating the percentage of variation in each variable. High values suggest that the variable is well accounted for by the data, whereas low values indicate that the variable is inadequately represented and not thoroughly explained by the dataset.

The extraction value in commonalities must be greater than 0.5; values below 0.5 must be disregarded. The commonalities are shown in Table 4, where their beginning values are all 1, and their extraction values range from less than 1 to larger than 0.5. As a result, not a single entity is excluded because all commonalities have extraction values greater than 0.5.

Table 4

Different commonalities with extraction computed by principal Component Analysis

Communalities	Initial	Extraction
Affected	1.000	.831
Global threat	1.000	.884
Respiratory droplet	1.000	.899
Transmission	1.000	.810
Symptoms	1.000	.796
Cure	1.000	.868
Severe Cases	1.000	.852
Medical Mask	1.000	.778
Measures	1.000	.907
Isolation	1.000	.86
Crowded Places	1.000	.857
Strict Measures	1.000	.880
Strict Measures	1.000	.884
Beds capacity in ICU	1.000	.808
Shortage of testing supplies.	1.000	.862
Shortages of critical supplies	1.000	.836
Condition of isolation wards	1.000	.792
Hygiene measures	1.000	.842
Sharp increases in prices.	1.000	.852
Waits in test results	1.000	.855
Lack of testing supplies	1.000	.805
Protecting staff	1.000	.857
PPE contribution shortage	1.000	.877
PPE availability	1.000	.836
Patient Surge	1.000	.782
Staff exposure	1.000	.894
Emotional troll	1.000	.904
Discharge Patients	1.000	.809
Non-touch devices	1.000	.875
Cleaning Supplies	1.000	.867
Smaller Hospitals	1.000	.750
OPD closed	1.000	.884
Worsen ventilator	1.000	.875
Ventilator shortages	1.000	.835
CDC guidance	1.000	.863
Guidance from State	1.000	.871
Workload	1.000	.863
PPE reuse	1.000	.787

Communalities	Initial	Extraction
Adequate staff	1.000	.734
Employee burden	1.000	.814

Determination of Factors

Determination of factors on the bests of Latent Root Criterion

The latent root criterion is the most commonly employed method for determining the number of factors that warrant further examination. It involves removing eigenvalues (latent roots) that are less than one. It is advisable to refrain from incorporating variables that contribute less variation than any individual variable in the original dataset. While the latent root criterion is highly applicable in principal component analysis when all variance is encompassed, its suitability diminishes when all variance is considered in common factor analysis.

Total Variance Explained

Out of the total components, seven are deemed significant despite having no variation. Conversely, 33 components, while exhibiting variation, are not considered significant based on the total variance explained. Table 5 presents the extracted Sums of Squared Loadings for these seven variables, elucidating the comprehensive explanation of the data's overall variance. This analysis has identified seven prominent factors as the main drivers in the factor analysis.

Table 5

Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	23.928	59.821	59.821	23.928	59.821	59.821	11.22	28.048	28.048
2	2.515	6.287	66.11	2.515	6.287	66.108	5.978	14.945	42.992
3	2.006	5.016	71.124	2.006	5.016	71.124	4.724	11.811	54.803
4	1.803	4.508	75.632	1.803	4.508	75.632	4.574	11.435	66.238
5	1.338	3.346	78.977	1.338	3.346	78.977	2.885	7.212	73.450
6	1.079	2.697	81.674	1.079	2.697	81.674	2.475	6.187	79.637
7	1.070	2.674	84.348	1.070	2.674	84.348	1.884	4.711	84.348
8	.748	1.870	86.218						
9	.737	1.843	88.061						
10	.613	1.533	89.594						
11	.529	1.322	90.917						
12	.471	1.179	92.096						
13	.335	.838	92.934						
14	.318	.795	93.729						
15	.284	.709	94.438						
16	.257	.642	95.080						
17	.232	.580	95.660						
18	.213	.533	96.194						
19	.165	.412	96.606						
20	.147	.368	96.974						
21	.131	.329	97.303						
22	.128	.320	97.622						
23	.111	.276	97.899						
24	.096	.241	98.139						
25	.089	.222	98.362						
26	.086	.216	98.578						
27	.078	.194	98.772						
28	.071	.177	98.949						
29	.062	.155	99.104						
30	.058	.144	99.248						
31	.049	.122	99.370						
32	.045	.113	99.483						
33	.039	.098	99.580						

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
34	.035	.087	99.667						
35	.028	.070	99.737						
36	.028	.069	99.806						
37	.023	.056	99.862						
38	.021	.053	99.915						
39	.017	.043	99.958						
40	.017	.042	100.000						

Extraction Method: Principal Component Analysis.

Scree Plot

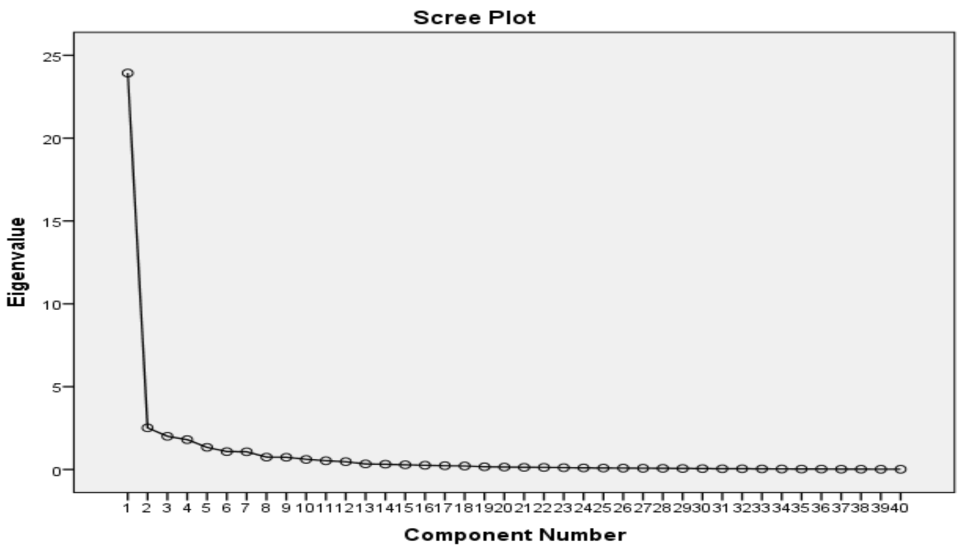
A scree plot presents the number of factors along the x-axis and their corresponding Eigenvalues along the y-axis. It visually illustrates that the Eigenvalue of the first component surpasses those of the subsequent components. This observation is pivotal in determining whether the variance accounted for by the initial Eigenvalues is substantial enough to warrant our focus while considering the remaining components as extraneous noise in this context (Ledesma et al., 2015). The plot consistently exhibits a descending trend.

The "elbow" of the plot, where the curve starts to level off, is crucial in determining the optimal number of components to be derived from the analysis. In this case, the curve initially descends sharply with the first component, then levels off. The point at which the curve starts to form a straight line signifies the maximum number of components that should be extracted. In this instance, the scree plot forms an elbow shape with seven factors. The initial seven significant factors on the Y-axis account for a larger portion of the variation, as evidenced by the steeper slope of the graph. Beyond these seven, the curve becomes more gradual, indicating that the remaining 33 factors have minimal impact on addressing the critical surge care capacity requirement.

The scree plot demonstrates variance in seven primary parameters because the Eigenvalue threshold was set at 1. If the threshold had been set at 0.5, more variables would have been included in the representation.

Figure 2

Scree plot



Component Matrix

Component matrices play a crucial role in the process of determining the appropriate number of factors for extraction. Table 6 displays a component matrix before any rotation. In this matrix, the factor loadings for each variable are shown, indicating the degree of association between variables.

Table 6
Component matrix

Variables	Component						
	1	2	3	4	5	6	7
Affected	.315	-.023	-.668	.197	.433	-.226	-.084
Global threat	.903	-.075	-.135	-.066	.193	-.052	.009
Respiratory droplet	.897	-.167	-.225	-.071	.010	.097	.030
Transmission	.737	-.378	-.084	-.165	-.109	.155	.233
Symptoms	.722	-.127	-.236	.179	-.314	-.177	.202
Cure	.734	.219	-.340	-.219	-.263	.119	.187
Severe Cases	.882	-.129	-.070	-.162	.130	.037	-.087
Medical Mask	.788	-.264	-.056	.246	.125	.088	.022
Measures	.022	.367	.112	.811	.312	.043	.033
Isolation	.895	-.050	-.051	-.062	.143	.182	.047
Crowded Places	.859	-.211	-.221	-.068	-.082	.095	.072
Strict Measures	.879	-.218	-.231	.046	-.011	.001	-.064
Strict Measures	.899	-.042	-.076	-.216	.047	-.113	.073
Beds capacity in ICU	.589	.081	.375	-.322	.399	-.148	.175
Shortage of testing supplies.	.863	-.160	.229	-.192	.043	.013	-.003
Shortages of critical supplies	.793	-.130	.402	-.081	.088	-.008	.121
Condition of isolation wards	.746	.147	.063	-.210	.037	.405	.004
Hygiene measures	.452	.591	.216	-.285	.212	.311	-.139
Sharp increases in prices.	.797	.239	-.049	-.191	.264	-.167	.148
Waits in test results	.678	.421	-.356	.048	-.019	.227	-.193
Lack of testing supplies	.688	.529	-.113	.069	-.136	.107	-.055
Protecting staff	.869	-.157	.091	.149	.152	.155	.022
PPE contribution shortage	.873	-.091	.216	.192	.037	.125	-.077
PPE availability	.792	.263	.096	.256	-.099	-.024	-.232
Patient Surge	.790	-.206	.287	-.006	.101	.111	-.106
Staff exposure	.916	-.099	-.090	-.152	-.044	-.105	.044
Emotional troll	.893	.026	.001	-.038	.045	-.318	.039
Discharge Patients	.847	.052	-.187	.090	-.174	-.024	-.122
Non-touch devices	.702	.029	.275	.017	-.535	-.077	-.114
Cleaning Supplies	.477	.336	.145	.242	-.214	.039	.633
Smaller Hospitals	.735	.370	.114	-.088	.083	-.167	.130
OPD closed	.885	-.211	-.194	.012	.005	-.040	-.128
Worsen ventilator	.808	.396	.013	.099	-.065	-.215	.069
Ventilator shortages	.853	.287	-.081	.064	-.001	-.116	.032
CDC guidance	.824	.216	.205	.070	-.159	-.082	-.242
Guidance from State	.794	-.064	.275	-.076	-.125	-.120	-.353
Workload	.878	-.145	-.029	.070	-.065	-.141	-.203
PPE reuse	.737	-.164	.316	.169	.037	-.297	.020
Adequate staff	.765	-.114	-.094	.214	-.015	.276	.064
Employee burden	.531	-.469	.251	.449	.037	.198	.090

Extraction Method: Principal Component Analysis (7 components extracted)

Rotated Component Matrix

The next step in achieving a more robust factor solution is the implementation of a rotation technique. In this process, smaller values are disregarded. The specific values chosen for suppressing our factor loadings are contingent on the sample size. All factors undergo this suppression, and among them, seven-play a crucial role in causing a significant surge during the Covid-19 pandemic. This rotation technique serves as a vital tool in interpreting the factors as it streamlines the factor structure, leading to a clearer understanding. To enhance our results, we employed Verma rotation. In Table 7, seven factors are extracted with a value greater than 0.5. After the extraction of variables, assign the names to the variables, such as F1, F2, F3, F4, F5, F6, and F7, and then combine similar factors in one label.

Table 7
Rotated component matrix

	Component						
	1	2	3	4	5	6	7
Global threat	.610						
Respiratory droplet	.707						
Transmission	.741						
Severe Cases	.637						
Mask	.764						
Isolation	.684						
Crowded Places	.704						
Strict Measures	.703						
Protecting staff	.764						
Patient Surge	.686						
OPD closed	.677						
Adequate staff	.720						
Employee burden	.808						
Non-touch devices		.746					
PPE availability		.628					
PPE contribution shortage		.711					
PPE reuse		.527					
CDC guidance		.694					
Guidance from State		.692					
Workload		.584					
Waits in test results			.739				
Lack of testing supplies			.672				
Shortage of kit supplies.			.631				
Beds capacity in ICU				.838			
Ventilator shortages				.536			
Shortages of critical supplies				.571			
Sharp increases in prices.				.617			
Smaller Hospitals				.543			
Affected					.879		
Symptoms						.503	
Cleaning Supplies						.820	
Measures							.932

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 13 iterations.

Presentation of Factors

The factors are outlined in Table 8, displaying their respective loadings along with the cumulative variances. Factor one encompasses a total of 14 parameters, which include Global threat, Respiratory droplet, Transmission, Severe Cases, Masks, Isolation, Crowded Places, Strict Measures, and Protecting staff. Factor 2 is made up of seven parameters, including Workload, Non-touch devices, Personal protective equipment availability, Personal protective equipment contribution shortage, Personal protective equipment reuse, CDC guidance, and State guidance. Factor 3 consists of three parameters: the duration of time it takes to receive test results, the scarcity of test materials, and the lack of kit supplies. Factor 4 consists of 5 parameters, including ICU bed capacity, shortages of ventilators, shortages of vital supplies, hike in prices, and smaller hospitals. Only one parameter, affected, is included in factor 5. Cleaning Supplies and Symptoms make up Factor 6. Taking Measures during COVID-19 is the sole parameter that makes up Factor 7.

Table 8

Presentation of factors

Factors and items	Factors Loadings	Explained Variance
F1		9.205
Global threat	.610	
Respiratory droplet	.707	
Transmission	.741	
Severe Cases	.637	
Mask	.764	
Isolation	.684	
Crowded Places	.704	
Strict Measures	.703	
Protecting staff	.764	
Patient Surge	.686	
OPD closed	.677	
Adequate staff	.720	
Employee burden	.808	
F2		4.582
Non-touch devices	.746	
PPE availability	.628	
PPE contribution shortage	.711	
PPE reuse	.527	
CDC guidance	.694	
Guidance from State	.692	
Workload	.584	
F3		2.042
Waits in test results	.739	
Lack of testing supplies	.672	
Shortage of kit supplies.	.631	
F4		3.105
Beds capacity in ICU	.838	
Ventilator shortages	.536	
Shortages of critical supplies	.571	
Sharp increases in prices.	.617	
Smaller Hospitals	.543	
F5		0.879
Affected	.879	
F6		1.323
Symptoms	.503	
Cleaning Supplies	.820	
F7		0.932
Measures	.932	

Labelling of Factors as Group

Table 9 presents a collection of variables grouped together, making substantial contributions to the surge of COVID-19 cases during the peak days. The first category of factors is represented by the key factor

"Patient Surge Causes Employee Burden," which encompasses Global threat, Respiratory droplets, Transmission, Severe Cases, Masks, Isolation, Crowded Places, Strict Measures, Protecting Staff, Patient Surge, OPD Closed, Adequate Staff, and Employee Burden, all indicated by one major component. In the second group of components, characterized by the significant component "PPE Unavailability and Shortage," we have non-touch devices, PPE availability, PPE contribution shortfall, PPE recycling, CDC guidelines, state instructions, and workload contributing to this factor. The significant issue, "Lack of testing supplies," is used to designate the third category of variables, which includes waiting for test results, a lack of testing materials, and a shortage of kit supplies. One key component, "Shortages of Beds and Ventilators," is used to designate the fourth category of issues, which includes the capacity of ICU beds, shortages of ventilators, sharp price rises, smaller hospitals, and shortages of critical supplies. The fifth-factor group is identified as Affected people, which is associated with an "Increased number of Cases". The significant factor "No Hygiene Measures" is used to indicate the sixth category of factors, which includes symptoms and cleaning supplies. "Precautionary Measures" designates the sixth group of factors and measures.

Table 9

Labelling of factors as groups

Factors	Group	Name of Group
F1	Global threat, Respiratory droplet Transmission, Severe Cases, Masks, Isolation, Crowded Places, Strict Measures, Protecting staff, Patient Surge, OPD closed, Adequate staff, Employee burden	Patient Surge leads to Employee burden.
F2	Non-touch devices, PPE availability, PPE contribution shortage, PPE reuse, CDC guidance, Guidance from State Workload	PPE unavailability and shortage
F3	Waits in test results, Lack of testing supplies, Shortage of kit supplies	Lack of testing supplies
F4	Beds capacity in ICU, Ventilator shortages, Sharp increases in prices, Smaller Hospitals, Shortages of critical supplies	Shortages of Beds and ventilators
F5	Affected	Increase the number of Cases
F6	Symptoms, Cleaning Supplies	No Hygiene Measures
F7	Measures	Precautionary Measures

The primary outcome of this factor analysis is the reduction of 40 variables down to seven significant factors. These factors are identified as follows:

1. Patient Surge causes Employee Burden
2. PPE Unavailability and Shortage
3. Lack of Testing Supplies
4. Shortages of Beds and Ventilators
5. Increase in Cases
6. No Hygiene Measures
7. Precautionary Measures

These seven factors encapsulate the key dimensions influencing the COVID-19 situation under study. Making decisions and managing diseases will be made easier. As a result, this type of study will help in preparing for early emergencies, combatting pandemic outbreaks, and planning for the foreseeable future.

Conclusion

Indeed, low- and middle-income countries face a critical challenge in dealing with both economic and health conditions. Their healthcare systems are often fragile, and the quality of healthcare services may be subpar. Effective management of all resources, including personnel, equipment, supplies, and knowledge, is imperative for pandemic preparedness. Public hospitals, in particular, grapple with resource shortages, a situation exacerbated during emergencies. A robust emergency plan that aims to alleviate the impact of a widespread virus must prioritize hospital preparedness. Consequently, evaluating organizational readiness becomes a pivotal aspect of this planning process, especially in the case of pandemics like COVID-19, which entail varying hospital requirements due to multiple waves of illness. The research showed that most public hospitals were not adequately prepared, characterized by persistent flaws in the administration of resources, logistics, and critical services, such as diagnostics and infection prevention and control, which compel the providers to devote extra attention to addressing any potential future reappearance of the pandemic.

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