A Methodological Study of Key Factors Attributing to Rise in Demand of Emergency Medical Services in India

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<u>**Doctoral Track**</u>

A methodological study of key factors attributing to rise in Demand of Emergency Medical Services in India.

Key Words: Ambulance Services, Cluster Analysis, Indian States, Panel Regression.

Suggested Track(/s)

Health care operations/ Role of Big data in supply chain/ Logistics Operations

1. Summary

The increasingly rising of incidences of true and needful medical and health care related emergencies (more than 10 million of disabling injuries and 2 million deaths since 2001 in India) and of necessary emergency facilities deployment for non-urgent yet important healthcare conditions together with their ever increasing medical costs have been recognized as very severe and important problems as well as key reasons for undertaking this study. The demand for emergency services like that of ambulance services in India has been steadily rising over the years. Research in understanding the increase of demand of emergency services has not been up to the mark, as the type and nature of patients who have been transported by emergency services in India specifically 108, 102/104 ambulances and the severity of their illness who use the service genuinely has not been appropriately been taken into account. Unnecessary usage of ambulance can also become a social as well as an economic problem in India that has also been faced worldwide mainly in countries like Japan, USA etc. (Chihiro Kawakami & et al. July 2007)

The purpose of this research study is to understand the absolute needs of ambulance services as well as the ever-rising utilization curve of these services. The objectives included to determine how factors like accidents (fire, industrial, road as well as other traffic accidents), heart attacks, strokes, maternal institutional deliveries and other socio-economic factors like gender, age, population across various states affect the demand and utilization of ambulance services. Further this study can also account for inappropriate estimates of demand for unnecessary ambulance use produced by various factors inclusive of certain socio-economic factors.

2. Research Methodology

The study is based on the principles of multivariate statistical methods combined with time series methods, thus involving observations as well as analysis of various statistical variables. The key output variable (Y) in consideration is the ambulance demand and the independent variables (X i's) are fire accidents, heart attack, maternal institutional deliveries, strokes, industrial accidents, traffic accidents, population (male as well female considered separately). The data for these variables have been collected for each variable for all the available twenty-nine states in excel files from indiastat.com over a period from 2011-2015.

Cluster Analysis for the initial secondary data collected was the multivariate method that has been used to classify the states which has been classified on the basis of their total population. Initially five clusters were assigned based on their total population for the year 2015 i.e. 0-25000000, 25000000-5000000, 5000000-7500000, 7500000-10000000, 10000000 and above.

The Cluster K-Means method in Minitab 18 Software was used to group and classify twenty-nine states based on the different dependent variables into clusters that share common characteristics. This method is appropriate when initial sufficient information to make good starting cluster (as discussed above in previous paragraph) designations for the clusters. Cluster K-means uses a typical non-hierarchical procedure to group the different states. Therefore, in the clustering process, two states might be split into separate and independent clusters after they are joined together or two or more clusters can be joined together into a single cluster.

Once the clusters of the twenty-nine states have been identified, panel data regression has been performed for the various clusters identified as these data essentially are two dimensional data (typically these data are cross sectional along the states and they are longitudinal over the years).

A simple panel data regression model for our study is

$Y_{it} = a + b * X_{it} + E_{it}$

Y is considered as the dependent variable

X is considered as the independent variable

a, b are considered as the coefficients.

i and t are considered as the indices for individuals (29 states) and time (4 years)

E_{it} is considered as the error term which varies in a non -stochastic manner over i and t in fixed effects model whereas in random effects model, the error term varies stochastically over i or t.

There are three approaches which we have used with the panel data regression methodology. The methodologies along with major assumptions have been described below.

In pooled panels, there are no two sets of unique attributes of individuals that are within the measured set, and hence absence of universal and holistic effects across time. Pooled OLS can also be used to derive estimates that are not biased as well as consistent estimates of various parameters even when time constant attributes are not absent, but random effects are considered to be more efficient.

In fixed effects model, there are unique attributes of states that do not vary across time. These attributes may or may not have correlation with the dependent variables.

In random effects model there are unique, time constant attributes of individuals (in our study the various states) that are not at all correlated with the individual independent variables.

For testing whether pooled effects is preferred rather than random effects, the Lagrange Multiplier test has been used.

For testing whether fixed effects is preferred rather than random effects, the Wu-Haussman test has been used.

All the panel data regression models have been developed in R.

3. Analysis of Data and Findings

A cluster analysis performed in Minitab 18 based on the methodology outlined in the previous section with the eight different dependent variables yielded five clusters. These clusters are

Cluster 1- Eleven states (Jammu & Kashmir, Meghalaya, Mizoram, Sikkim, Tripura, Arunachal Pradesh, Goa, Himachal Pradesh, Nagaland, Manipur and Uttarakhand) were grouped under this cluster.

Cluster 2- Eight states (Assam, Bihar, Chhattisgarh, Haryana, Jharkhand, Odisha, Punjab and Telangana) were grouped in this cluster.

Cluster 3- Six states (Gujarat, Kerala, Karnataka, Madhya Pradesh, Rajasthan and Tamil-Nadu) were grouped in this cluster.

Cluster 4 – Two states (Andhra Pradesh & West Bengal) were grouped in this cluster.

Cluster 5- Two states (Uttar Pradesh and Maharashtra) were grouped in this cluster.

Cluster 6 – Cluster 4 And Cluster 5 were joined together for better results.

The dendogram obtained from cluster analysis of 29 states is given in Exhibit 1- Figure1 in the appendix. The cluster analysis has been presented in Exhibit 2- Figure 2 In the appendix

Next from the Lagrangian Multiplier tests, it has been found that for all the clusters, the p values are around less than or equal to 0.05 for all the five clusters. Hence, we go for either the results of the fixed or random effects model than the pooled effects model. A sample Lagrangian multiplier test result is given below.

Lagrange Multiplier Test - (Honda) for balanced panels

F Test For Random Effects

data: Y ~ X
normal = 1.5259, p-value = 0.06352
alternative hypothesis: significant effects

F test for individual effects

data: Y ~ X
F = 14.765, df1 = 10, df2 = 24, p-value = 5.85e-08
alternative hypothesis: significant effects

Now, to decide between the fixed or random effects model for each of the clusters, we run the Hausman test and check whether the p value is greater than the chi square value of 0.05. The overall results have been tabulated in Exhibit 3 – Table 1 in appendix and a sample Hausman test is included below.

A Sample Hausmann test

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data:  Y ~ X
chisq = 8.2248, df = 9, p-value = 0.5117
alternative hypothesis: one model is inconsistent
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We also see that the p value of the models (except for cluster 2) are quite low explaining the validity of choosing these models.

Having decided on whether to apply fixed or random effects model, we finally check the variables which affect the demand of ambulances. This is again obtained by checking the p-value for each variable against a t-value for each of the four clusters. (Variables having p-value less than 0.05 or near-by are significant)

4. Results and Discussion

The demand of ambulances in states of Manipur, Mizoram, Nagaland, Arunachal Pradesh, Goa, Himachal Pradesh, Jammu & Kashmir, Sikkim, Tripura and Uttarakhand are primarily affected by maternal health deliveries and heart attack. One of the possible reasons is that excluding

Goa, most of these states are in north east and northern region of India where the climate change is more relevant i.e. there is extremes of climate, and further the population also having more females than males is more susceptible to heart diseases and have greater maternal deliveries. This leads to more calling of emergency vehicles as the economy is also under development and people need emergency resources due to lack of their own resources to reach hospitals.

The eight states Assam, Bihar, Chhattisgarh, Haryana, Jharkhand, Odisha, Punjab and Telangana needs to be given a reconsideration and can be joined with other clusters as some of them are newly formed states.

For the remaining two models, we see that due to high degree of validity of these models, ambulances are in great demand in the six states of Gujarat, Kerala, Karnataka, Madhya Pradesh, Rajasthan and Tamil-Nadu mainly due to industrial accidents and road accidents. This can also be validated by the highly industrialized regions of most of the states except that of state of Kerala

For the final cluster of four states which has AP, Maharashtra, West Bengal and Uttar Pradesh, we see that most of the factors except that of stroke and heart attack affect the demand of ambulance. This can be explained by the fact that health in these states are predominantly fine due to the absence of extreme climates though the accidents have to be kept in control.

5. Conclusions and Recommendations

The study predominantly reveals that in most of the states the demand of ambulance exists and has been steadily on rise due to industrial, road, traffic as well as fire accidents apart from maternal health deliveries. This is common finding across economically developed as well as underdeveloped states in India. It must be viewed that the models developed in the study are unique to Emergency services of the Indian system. Favourable health policies need to address these issues by increasing the number of emergency resources as well as the response of these emergency response services. Since India is a diverse country with different cultures, the central government also has to come up with standard safety measures, policies to avoid traffic, industrial accidents etc. by working in close ties with the various state governments. There exists a definite need to perform as well as organize additional studies of other EMS systems so that we can comprehensively gain better and further our understanding as well as get better insights that can improve the regional emergency service systems as well as at the national level. Further research that can affect the demand as well as response of the emergency services can also be taken by considering other key factors like age of population, other emergencies like natural disasters etc.

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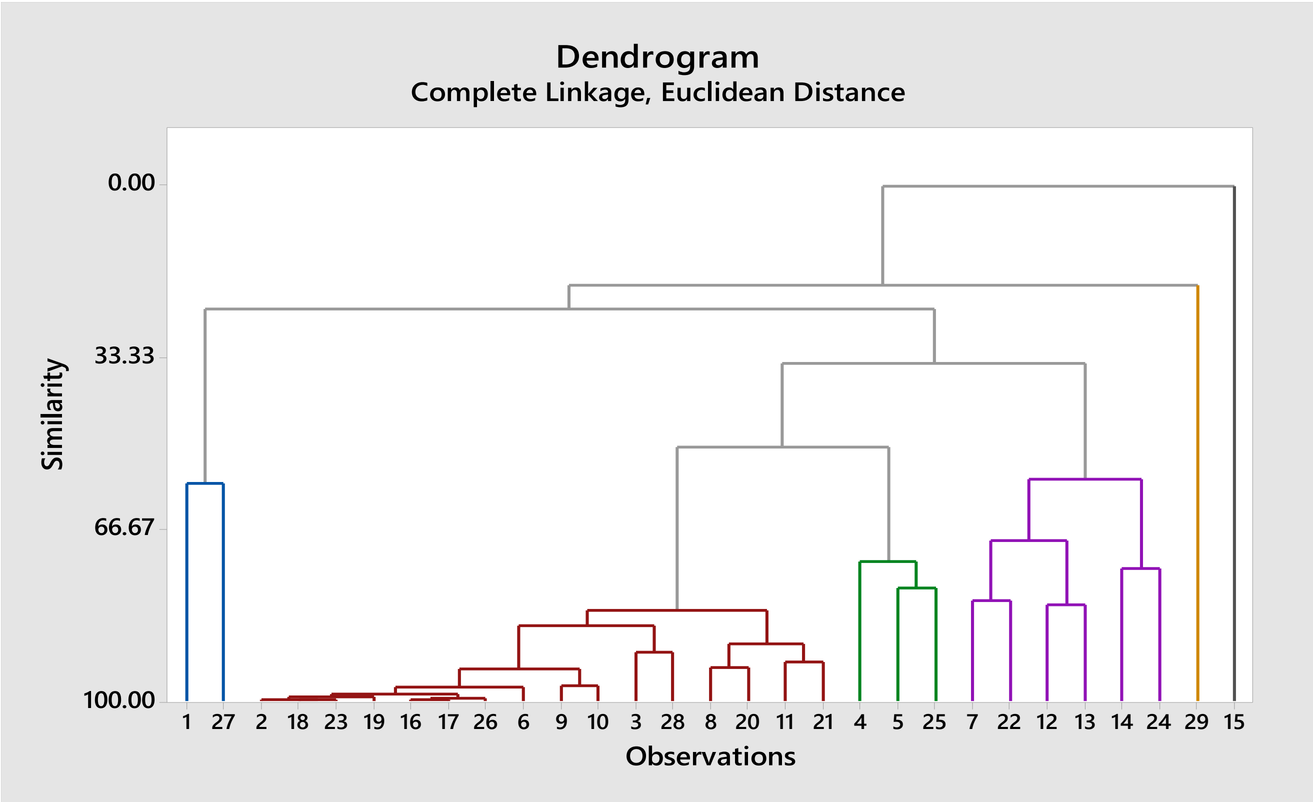
Appendix - EXHIBITS



Exhiit 1- Figure 1 : Dendogram of Cluster Analysis

Final Partition

Cluster	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	11	0.907	0.227	0.720
Cluster2	8	10.513	1.045	1.975
Cluster3	6	15.218	1.522	2.143
Cluster4	2	24.054	3.468	3.468
Cluster5	2	25.880	3.597	3.597

Cluster Centroids

Variable	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Grand centroid
Total Accidents	-0.7713	-0.3116	1.2778	0.0905	1.5647	0.0000
Fire Accidents	-0.6730	-0.2345	0.7687	-0.0792	2.4128	0.0000
Heart Attack	-0.4001	-0.2410	0.4333	-0.4100	2.2745	0.0000
Maternal Institutional Delivery	-0.8617	-0.0027	0.6575	0.3416	2.4365	0.0000
Stroke	-0.4440	0.0276	-0.3117	1.8598	1.4070	0.0000
Industrial Accidents	-0.2475	-0.2372	-0.0653	2.4845	0.0209	0.0000
Traffic Accidents	-0.7815	-0.3413	1.3618	0.4100	1.1680	0.0000
Total Pop	-0.7909	0.1557	0.2268	0.7772	2.2699	0.0000

Distances Between Cluster Centroids

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
Cluster1	0.0000	1.5746	3.8679	4.3811	7.0483
Cluster2	1.5746	0.0000	2.7338	3.4711	5.6146
Cluster3	3.8679	2.7338	0.0000	3.9199	4.0638
Cluster4	4.3811	3.4711	3.9199	0.0000	5.3904
Cluster5	7.0483	5.6146	4.0638	5.3904	0.0000

Exhibit 2- Figure 2 : Cluster Analysis

Cluster Number	P value	Model Selected	P value of model
Cluster 1	0.51772	Random Effects	Lower than 0.05
Cluster 2	2.2e-06	Fixed Effects	Higher
Cluster 3	2.2e-06	Fixed Effects	Lower than 0.05
Cluster 6	NA	Fixed Effects	Lower than 0.05

Exhibit 3 _ Table 1 : Hausmann Test Results