Inter-district Disparities in Social Sector Activities: An Empirical Analysis for Himachal Pradesh State

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Abstract

In this paper, an attempt has been made to examine inter-district disparities in Himachal Pradesh state with respect to social sector activities. The study was based on secondary data compiled on as many as 35 indicators of social sector activities at five points in time (1999-2000, 2004-05, 2009-10, 2014-15 and 2018-19) for twelve districts of the state. With a view to nullify the effect of varying sizes of population and area among the districts, data on the indicators were suitably expressed on per capita (or per unit of area) basis and were, then, retransformed appropriately so as to ensure stabilisation with respect to both mean and variability. The resulting data set was then subject to *Exploratory Factor Analysis* (with *promax rotation*), duly followed by *Confirmatory Factor Analysis.* Finally, values of *Composite Index* were obtained so as to assess relative positioning of different districts with respect to their social sector development. As per the main findings, a totality of four *latent factors* were extracted which, taken together, were capable of explaining 74.6% of the total variance in the data set. Confirmatory factor analysis has pointed towards the appropriateness of the factors extracted. As per the computed values of composite index, Kullu, Kinnaur and Chamba happened to be laggard districts, thereby calling for the need to adopt suitable corrective measures in respect of such districts, so as to ensure balanced development of social sector activities in the state.

Key Words: Social sector Activities, Exploratory Factor Analysis, Confirmatory Factor Analysis, Promax Rotation, Latent Variables, Composite Index.

JEL Classification Codes: C8, I14, I21, I24

1. Introduction

Consolidation of social sector is most crucial for ensuring economic development at a rapid pace. Expansion of social infrastructure helps to remove the barriers of economic development and also helps in a better usage of resources. In fact, overall scenario of social sector activities (including education, health and social security) is widely recognised to be a useful indicator of welfare of inhabitants of a region.

In India, provision of most of the social sector activities is the responsibility of state governments. Wide disparities, if any, among different regions of the state can provide a useful policy input for the government to ensure balanced development. As per certain studies (like, those due to Pal, 1995; Singh, 1999; Sethi, 2000a, 2000b; Singh, 2000; Narain *et al.,* 2005*;* Ramaswamy, 2007; Sethi and Gill, 2007; Nayyar, 2008; Sethi and Pandhi, 2012, 2014; Sethi and Kumar, 2016; Barik, 2017), there have been wide inter-regional disparities with respect to economic characteristics, like per capita SDP, HDI, Investment, Rural Development, Consumption Expenditure on Health & Nutrition, *etc.* However, there seems to be an absence of a comprehensive empirical study on social sector development at district level in the context of Himachal Pradesh state. Therefore, an attempt has been made in this direction in the present paper.

The paper has been organized into four sections, including the current one. Database and methodology adopted in the paper have been outlined in Section 2. Main findings from the study have been presented in Section 3. And, finally, concluding remarks and policy implications drawn from the study have been given in Section 4.

2. Data and Analytics

The study was based on secondary data compiled on a totality of $p = 35$ indicators of social sector at five points in time (1999-2000, 2004-05, 2009-10, 2014-15 and 2018-19) for $m = 12$ districts of Himachal Pradesh state. The districts were: Bilaspur (BLSP), Chamba (CHMB), Hamirpur (HMRP), Kangra (KANG), Kinnaur (KINR), Kullu (KLLU), Lahaul & Spiti (LSPT), Mandi (MNDI), Shimla (SHML), Sirmaur (SIRM), Solan (SOLN) and Una (UNNA). The indicators considered have been given in Appendix 1. Data compilation was made primarily from various issues of Statistical Abstracts of the state, as also through official information procured from Economic and Statistical Office (ESO) of the Himachal Pradesh state at Shimla. Information was also compiled on geographical area and population of the districts at different points in time.

With a view to nullify the effect of varying sizes of population and area among the districts, data on the indicators were suitably re-expressed on per capita (or per unit of area) basis. Due attention was paid to re-express the indicators so that their higher values pointed towards betterment of social-sector activities. In order to ensure stabilisation of different indicators with respect to both mean and variability, these were *standardised* by subjecting them to the well-known transformation

$$Z_i = \frac{X_i - X_{Min}}{X_{Max} - X_{Min}}; i = 1, 2, ..., p \qquad \ldots (2.1)$$

The resulting data on the standardised indicators were subject to *Exploratory Factor Analysis* (EFA) duly followed by computations of the values of *Composite Index* so as to assess relative positioning of different districts with respect to their social sector development.

The basic model adopted for the EFA could be expressed as

$$\underline{Z} = \Lambda \underline{F} + \underline{\varepsilon} \qquad \ldots (2.2)$$

where $\underline{Z}$ is $p \times 1$ vector of the (standardised) indicators, $\Lambda = (\lambda_{ij})$ is $p \times m$ matrix of factor pattern coefficients (*i.e.,* loadings), $\underline{F}$ is $m \times 1$ vector of factors extracted, and $\underline{\varepsilon}$ is $p \times 1$ vector of error (or, uniqueness) terms (with zero mean), assumed to be unrelated among themselves and with the factors in $\underline{F}$. Here p (= 35) stands for the number of indicators and m for the number of factors extracted. We may mention, each indicator will have a factor loading associated with each factor. These loadings (varying generally between -1 and +1) are something like correlation coefficients, and are reflective of the connectivity between indicators and factors; larger the value, stronger will be the association between the observed variable (indicator) and the latent variable (factor). Due to orthogonalilty of factors, variance of the observed variables is expressible as

$$V(Z_i) = 1 = h_i^2 + \psi_i; \; i = 1, 2, \ldots, p \qquad \ldots (2.3)$$

where $h_i^2 \left(= \sum_{i=1}^{n} \lambda_{ij}^2\right)$ stands for *communality*, which denotes the extent of variance (=1) in the given observed measure Z_i, that stands explained by the common factors $F_1, F_2, \ldots, F_m$, and may be conceptually viewed something like *coefficient of multiple determination* (R^2) if Z_i were regressed upon the m factors extracted. The remaining extent of variance ($= \Psi_i$) in x_i is *uniqueness term.* In order to enhance the extent of variance explained by the factors in the observed variables, we have made use of oblique *promax rotation* of the axes. The number ‘m’ of factors extracted (through the) was decided through the *parallel analysis* performed on *eigen values* of the *principal components*.

Seeking the help of OECD (2008), and making use of the matrix of Λ of loadings, *composite index* for each of the districts was constructed through the following steps:

(i) For each of m factors extracted, the proportion of variance explained (say, pve_j) in the data set was computed as

$$pve_j = \frac{\sum_{i=1}^{p} \lambda_{ij}^2}{\text{trace(icm)}} \qquad \dots (2.4)$$

(ii) For the i[th] indicator, let the maximum loading (say, λ_i^*) is realized on a particular factor having a proportion of variance explained $= pve^*$ (say)

(iii) For this indicator, weight (W_i) was computed as

$$W_i = pve^* \times \lambda_i^* \qquad \dots (2.5)$$

(iv) And, finally, composite index (CMP_t) for the t[th] district was computed as

$$CMP_t = \frac{W_i \, Z_{ti}}{\sum_{i=1}^{p} W_i} \qquad \dots (2.6)$$

where Z_{ti} refers to the standardised value of the i[th] indicator in respect of t[th] district. Computed values of the composite index formed the basis for gauging relative positioning of the districts, jointly on the basis of the study variables, with respect to the level of social sector development.

An examination of the appropriateness of the factors extracted was subsequently made through *Confirmatory Factor Analysis* (CFA). Basically, according to Bollen (1989), CFA may be viewed as a conjunction of EFA and Regression (Path Analysis). The basic model adopted in CFA makes an augmentation in (2.2) by including a $p \times 1$ vector of intercept terms ($\underline{\tau}$):

$$\underline{Z} = \underline{\tau} + \Lambda \underline{F} + \_ \qquad \dots (2.7)$$

For EFA models, $\underline{\tau}$ is generally assumed to be $\underline{0}$, but with CFA this is not necessarily the case. Indeed, if we are interested in comparing latent variable means across groups, the model intercepts play an important role. As was true with EFA, in CFA as well, the model parameters were estimated using the variances and covariances of the observed variables. However, whereas in EFA, the focus was on deciding how many factors to extract and which type of rotation to use, with CFA these issues are not a concern. In CFA, we simply have a predetermined factor structure in mind and try to explore (through certain quantitative yardsticks) as to how adequately the model fits into the available data set. Following Finch and French (2015), some such yardsticks used were: (a) Root Mean Square Error of Approximation (RMSEA); (b) Comparative Fit Index (CFI); (c) Tucker–Lewis Index (TLI); and (d) Standardized Root Mean Square Residual (SRMR). Smaller the values (say ≤ 0.08) of each of RMSEA and SRMR , and larger the values (say ≥ 0.90) of each of CFI and TLI measures indicated adequacy of the fitted latent variables model.

For estimation purpose, we have used customised R-programmes, based on *psych, tsfa* and *lavaan* codes.

3. Main Findings

Main findings from the analysis have been discussed under the following sub-heads:

3.1. Exploratory Factor Analysis (EFA)

At the outset, an attempt was made to test whether the available panel dataset of the 35 standardised indicators followed a multivariate normal distribution or not. For that, we have applied Mardia's test (Table 3.1.1). As per the test, there existed highly significant departure from symmetry in the data set, though kurtosis was not an issue. Figure 3.1 provides a support to the prevalence of non-normality. We could thus say that strict multivariate

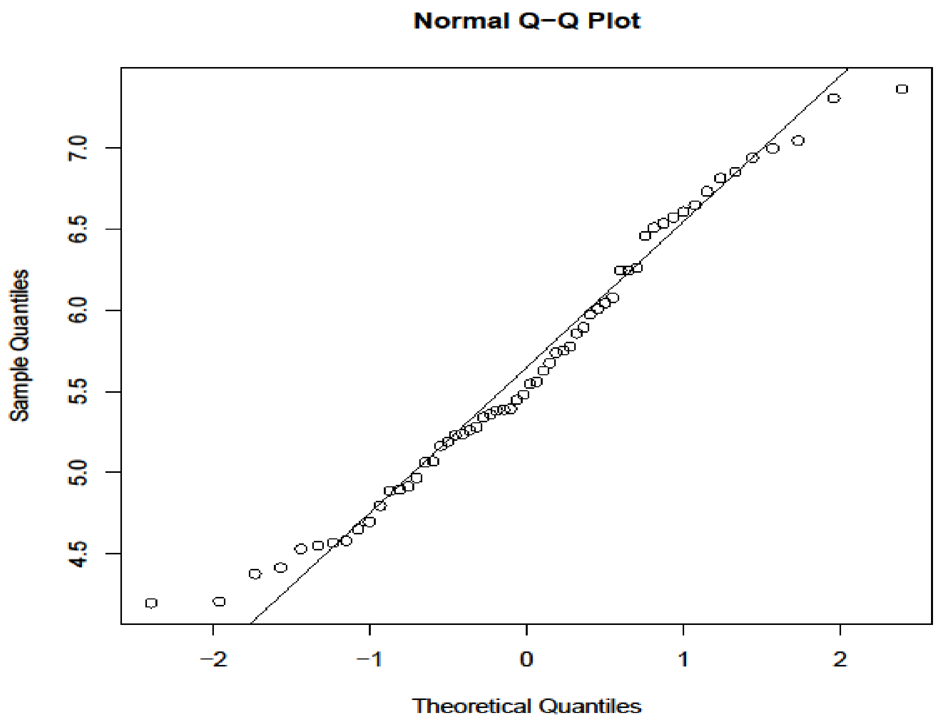
Table 3.1.1. Computations from Mardia's Test of Multivariate Normal Distribution (MND)

Quantity	Value of the Measure	p-Value	Remark
Skewness	7256.16	< 0.0001	***
Kurtosis	-0.94	0.3473	NS

*** Significant at 0.1% probability level; NS Non-Significant

normality in the data set was at doubt. Accordingly, we have avoided using the *maximum likelihood method of estimation* in the subsequent analyses, as the same is based on the assumption of strict normality. We have instead resorted to the application of more flexible (though relatively less efficient) *weighted least squares method of estimation.*

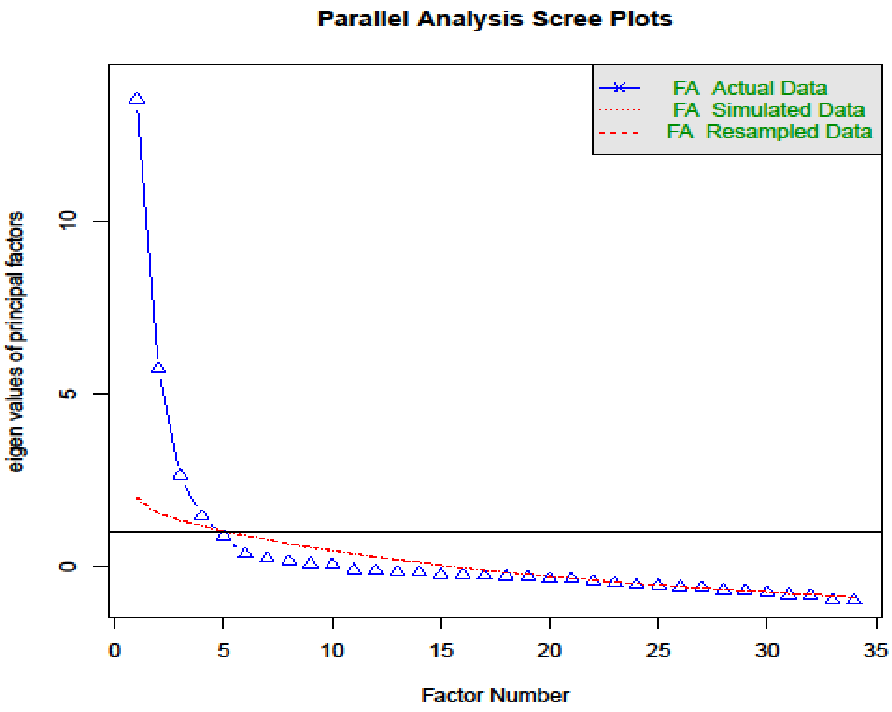
Figure 3.1



Next, the matrices of intercorrelation coefficients (ICM) and of their p-values were determined from the available panel dataset of the standardised indicators. However, in order to save space, we have not presented these matrices. *Parallel Analysis* was then performed on the ICM, so as to make an assessment of the likely number of factors to be extracted (Figure 3.2). As per the *scree plot* obtained through parallel analysis, the expected number of factors to be squeezed turned out to be *four.*

Through exploratory factor analysis, we obtained (apart from other statistics) communalities of different indicators. Since communality measures the extent of variance in the given indicator Z_i that stands explained jointly by the extracted factors; therefore, such a measure is desired to be sufficiently high in magnitude. In line with Osborne, *et al.* (2008), the threshold value of communalities was taken to be 0.4. In the present analysis, two of the indicators, *viz.,*

Figure 3.2



NANS and NDTR were observed to have relatively low values (= 0.187 and 0.302, respectively) of communalities and were, therefore, discarded from the data set. The EFA was re-performed with the curtailed set of 33 variables, providing us again with an extraction of four factors.

Results on loadings of the indicators and other useful measures *viz*., communality and uniqueness in respect of the extracted factors are given in Table 3.1.2. As per the table, each of the 33 indicators were observed to be associated with values of communality exceeding the threshold limit (of 0.4). The four factors taken together were capable of explaining 74.6 percent of the total variance present in the available data set (Table 3.1.3).

A further perusal of Table 3.1.2 provides a clear picture about the constitution of the four factors extracted. The first factor was constituted by as many as 12 indicators, *viz.,* NADS (Number of Ayurvedic Dispensaries per 100 sq km), NPLS (Number of Police Stations/ Police Posts per 100 sq km), NPHC (Number of PHC per 100 sq km), NPRS (Number of Primary Schools per 100 sq km), NFWC (Number of Family Welfare Centres per 100 sq km), NCHC (Number of CHC/RH per 100 sq km), NHSS (Number of High/ Hr Secondary Schools per 100 sq km), TSHS (Teacher-School Ratio in High/ Hr Secondary Schools),

Table 3.1.2. Factor Loadings of the Study Indicators and Other Useful Computations

Variable	FCT1	FCT2	FCT3	FCT4	Communality	Uniqueness

NADS	**0.938**	-0.068	0.102	0.025	0.972	0.028
NPLS	**0.937**	-0.008	0.085	-0.150	0.826	0.174
NPHC	**0.909**	-0.024	-0.145	-0.024	0.869	0.131
NPRS	**0.868**	-0.141	0.184	-0.043	0.913	0.087
NFWC	**0.850**	-0.096	0.100	0.089	0.88	0.120
NCHC	**0.823**	-0.011	-0.069	0.044	0.718	0.282
NHSS	**0.820**	-0.091	-0.173	0.226	0.944	0.056
TSHS	**0.775**	0.291	0.008	0.058	0.472	0.528
NAHS	**0.765**	0.030	-0.120	0.022	0.596	0.404
NGVC	**0.714**	-0.145	-0.359	-0.435	0.797	0.203
NMDS	**0.681**	-0.173	-0.019	0.207	0.748	0.252
NHSP	**0.664**	-0.194	0.010	0.077	0.654	0.346
PTHS	0.202	**0.938**	-0.151	-0.151	0.876	0.124
NUAP	-0.142	**0.914**	0.054	0.001	0.968	0.032
NADC	-0.129	**0.895**	0.033	0.034	0.914	0.086
NBAI	-0.094	**0.868**	0.056	-0.047	0.841	0.159
NCRM	0.185	**0.820**	0.283	0.022	0.495	0.505
PTPS	-0.006	**0.758**	-0.204	-0.052	0.723	0.277
NPTO	-0.297	**0.751**	0.147	0.014	0.847	0.153
NPTI	-0.221	**0.652**	0.031	0.006	0.613	0.387
PTMS	-0.026	**0.636**	-0.245	0.365	0.606	0.394
NBAY	0.010	**0.617**	-0.102	-0.024	0.424	0.576
EMSB	-0.132	-0.092	**0.863**	0.046	0.821	0.179
EPSG	-0.289	-0.083	**0.862**	-0.169	0.882	0.118
EPSB	-0.272	-0.116	**0.855**	-0.162	0.867	0.133
EMSG	-0.149	-0.011	**0.808**	0.106	0.714	0.286
TSPS	-0.053	0.014	**0.808**	0.026	0.659	0.341
NSTD	0.276	0.232	**0.760**	0.210	0.631	0.369
NDSP	0.442	0.148	**0.681**	-0.248	0.497	0.503
NBRR	0.161	-0.414	**0.451**	0.259	0.718	0.282
EHSB	0.125	-0.184	0.096	**0.787**	0.827	0.173
EHSG	0.144	-0.101	-0.095	**0.775**	0.717	0.283
TSMS	-0.002	0.148	-0.022	**0.767**	0.575	0.425

Table 3.1.3. Extent of Variance Explained by the Extracted Factors

Computation	FCT1	FCT2	FCT3	FCT4
SS of Loadings	9.301	7.306	5.358	2.64
Proportion of Variance Explained	0.282	0.221	0.162	0.08
Cumulative Variance Explained	0.282	0.503	0.666	0.746

NAHS (Number of Ayurvedic Hospitals per 100 sq km), NGVC (Number of Government Colleges per 100 sq km), NMDS (Number of Middle Schools per 100 sq km), and NHSP (Number of Hospitals per 100 sq km). The second factor was constituted by 10 indicators, *viz.,* PTHS (Pupil-Teacher Ratio in Secondary Schools), NUAP (Number of Unarmed Police Per Lakh of Population), NADC (Number of Ayurvedic Doctors per Lakh of Population), NBAI (Number of Beds per Lakh of Population Available in Allopathic Institutions), NCRM (Number of Crimes per Lakh of Population), PTPS (Pupil-Teacher Ratio in Primary Schools), NPTO (Number of Outdoor Patient Treated in All Allopathic Institutions per Institution), NPTI (Number of Indoor Patients Treated in All Allopathic Institutions per Institution), PTMS (Pupil-Teacher Ratio in Middle Schools) and NBAY (Number of Beds in Ayurvedic institution per Lakh of Population). Eight indictors, *viz.,* EMSB (Enrollment per Lakh of Population in Middle Schools – Boys), EPSG (Enrollment per Lakh of Population in Primary Schools – Girls), EPSB (Enrollment per Lakh of Population in Primary Schools – Boys), EMSG (Enrollment per Lakh of Population in Middle Schools – Girls), TSPS (Teacher-School Ratio in Primary Schools), NSTD (Number of Sterilisations Done per Lakh of Population), NDSP (Number of Dispensary in per 100 sq km) and NBRR (Number of Births Registered per 1000 Population) made up the third factor. And, the remaining three indicators, *viz.,* EHSB (Enrollment per Lakh of Population in High/ Hr Secondary Schools – Boys), EHSG (Enrollment per Lakh of Population in High/ Hr Secondary Schools – Girls) and TSMS (Teacher-School Ratio in Middle Schools) resulted in the formation of the fourth factor.

Except for just one indicator (*viz.,* TSHS), all the remaining 11 indicators of the first factor were in terms of 'Number of Set-ups per 100 sq km', thus signifying the intensity of physical infrastructure. Accordingly, the first latent factor was assigned the name of *Intensity of Physical Infrastructure* (INPI). As regards the second factor, a majority of the indicators were in terms of 'Number of Users per Lakh of Population/ per Institution'. Accordingly, we have assigned the name to the second latent factor as *Intensity of Service Users* (INSU). Similarly, in the light of a majority of the constituent indicators, we have named the third and the fourth latent factors as *Enrollment in Junior Classes* (ENJR) and *Enrollment in Senior Classes* (ENSR), respectively.

3.2. Computation of the Values of Composite Index w.r.t. the Level of Social Sector Activities

Through the methodology as laid down in Equation 2.6 above, values of composite index were computed for the different districts at each of the five points in time, as also the values pooled over the entire span of time (Table 3.2.1).

Beyond doubt, relative ranking of the districts has undergone some temporal reshuffling. For example, during 1999-2000, Bilaspur and Hamirpur occupied the 1st and 2nd positions, whereas during 2004-05, the two districts swapped their positions (Table 3.2.1). Similarly, Lahaul & Spiti district was at the bottom-most position during 2004-05, but significantly improved to the 7th position during 2018-19. On the whole, the three top-most districts turned out to be Hamirpur (CI = 0.457), Bilaspur (CI = 0.424) and Solan (CI = 0.371). Whereas, on the other extreme, the three bottom-most districts happened to be Kullu (CI = 0.224), Kinnaur (CI = 0.241) and Chamba (CI = 0.256).

Table 3.2.1. Computed Values of Composite Index (CI) at Different Points in Time

District	1999-2000		2004-05		2009-10		2014-15		2018-19		Pooled	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
BLSP	0.468	1	0.444	2	0.415	2	0.409	1	0.384	1	0.424	2
CHMB	0.255	12	0.275	10	0.281	10	0.249	10	0.218	10	0.256	10
HMRP	0.465	2	0.516	1	0.525	1	0.405	2	0.374	2	0.457	1
KANG	0.337	8	0.359	7	0.292	9	0.271	8	0.261	9	0.304	8
KINR	0.280	9	0.289	9	0.255	11	0.202	12	0.182	11	0.241	11
KLLU	0.273	10.5	0.273	11	0.211	12	0.204	11	0.162	12	0.224	12
LSPT	0.273	10.5	0.268	12	0.313	8	0.266	9	0.285	7	0.281	9
MNDI	0.397	4	0.378	5	0.390	3	0.323	5	0.312	5	0.360	5
SHML	0.384	6	0.369	6	0.383	4	0.288	7	0.285	6	0.342	6
SIRM	0.355	7	0.341	8	0.334	7	0.291	6	0.274	8	0.319	7
SOLN	0.439	3	0.407	3	0.366	5	0.328	4	0.315	4	0.371	3
UNNA	0.396	5	0.382	4	0.360	6	0.337	3	0.333	3	0.362	4

3.3. Confirmatory Factor Analysis (CFA)

As already indicated, objective of this part of the analysis was simply to examine if the pre-determined factors (as extracted through the EFA) were capable of representing the dataset adequately or not. As per the analysis, values of Root Mean Squared Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) were computed to be 0.101 and 0.160, respectively. And the values of Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) happened to be 0.940 and 0.935, respectively. Although the values for RMSEA and

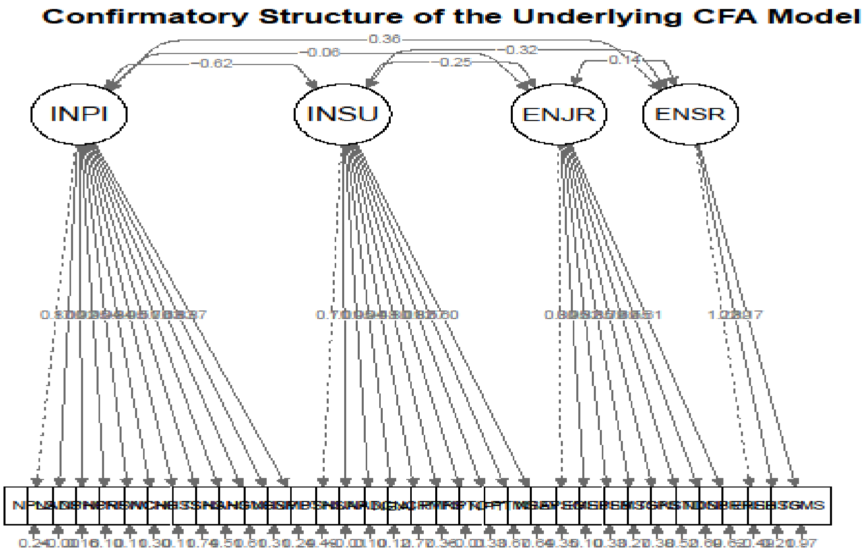
SRMR were not very encouraging (possibly because of relatively small size (=60) of the sample; yet the values for each of CFI and TFI were fairly larger than the threshold value (of

Table 3.3.1. Testing Significance of Estimated Loadings (B) Obtained through Confirmatory Factor Analysis

Latent Factor	Indicator	Estimate B	SE of B	Z-Value	p-Value	LCL of B	UCL of B	Standard Beta
INPI	NPLS	1.000	0.000	NA	NA	1.000	1.000	0.869
	NADS	1.229	0.094	13.038	< 0.001	1.044	1.414	1.001
	NPHC	0.930	0.068	13.630	< 0.001	0.796	1.064	0.915
	NPRS	1.199	0.066	18.037	< 0.001	1.069	1.329	0.948
	NFWC	1.063	0.115	9.235	< 0.001	0.838	1.289	0.944
	NCHC	0.887	0.086	10.344	< 0.001	0.719	1.056	0.838
	NHSS	0.827	0.094	8.802	< 0.001	0.643	1.011	0.945
	TSHS	0.393	0.092	4.264	< 0.001	0.212	0.574	0.513
	NAHS	0.655	0.113	5.821	< 0.001	0.435	0.876	0.702
	NGVC	0.688	0.101	6.827	< 0.001	0.491	0.886	0.625
	NHSP	0.778	0.101	7.663	< 0.001	0.579	0.977	0.829
	NMDS	0.797	0.079	10.125	< 0.001	0.643	0.951	0.873
INSU	PTHS	1.000	0.000	NA	NA	1.000	1.000	0.712
	NUAP	2.337	0.63	3.709	0.0002	1.102	3.572	1.006
	NADC	1.894	0.437	4.336	< 0.001	1.038	2.750	0.949
	NBAI	1.687	0.358	4.714	< 0.001	0.985	2.388	0.936
	NCRM	0.934	0.268	3.483	0.0005	0.409	1.460	0.477
	PTPS	1.393	0.193	7.215	< 0.001	1.015	1.771	0.797
	NPTO	2.187	0.606	3.607	0.0003	0.999	3.376	1.006
	NPTI	1.330	0.406	3.273	0.0011	0.533	2.126	0.819
	PTMS	1.164	0.264	4.407	< 0.001	0.646	1.682	0.575
	NBAY	0.980	0.341	2.878	0.004	0.313	1.648	0.597
ENJR	EPSG	1.000	0.000	NA	NA	1.000	1.000	0.803
	EMSB	1.304	0.120	10.836	< 0.001	1.068	1.540	0.949
	EPSB	0.986	0.014	69.506	< 0.001	0.958	1.013	0.816
	EMSG	1.140	0.138	8.287	< 0.001	0.871	1.410	0.855
	TSPS	0.861	0.098	8.827	< 0.001	0.670	1.053	0.786
	NSTD	0.857	0.129	6.622	< 0.001	0.603	1.110	0.693
	NDSP	0.635	0.146	4.348	< 0.001	0.349	0.921	0.555
	NBRR	0.667	0.128	5.206	< 0.001	0.416	0.918	0.613
ENSR	EHSB	1.000	0.000	NA	NA	1.000	1.000	1.219
	EHSG	0.726	0.084	8.638	< 0.001	0.561	0.891	0.891
	TSMS	0.182	0.280	0.651	0.5153	-0.367	0.732	0.171

0.90). Moreover, all the estimated values (except for the indicator TSMS; Table 3.3.1) of factor loadings were tested to be statistically highly significant. Accordingly, we may accept the laid-down model (as formulated on the basis of the extracted factors) to be fitting well into the available set of data. Finally, the results obtained through the CFA have been portrayed in Fig. 3.3.1.

Figure 3.3.1



4. Concluding Remarks and Policy Implications

As per nature of the constituent indicators, the four latent factors extracted through the application of EFA were named respectively as *Intensity of Physical Infrastructure* (INPI), *Intensity of Service Users* (INSU), *Enrollment in Junior Classes* (ENJR) and *Enrollment in Senior Classes* (ENSR). These factors taken together were capable of explaining nearly *three-fourth* of the variance in the available dataset on 33 indicators. Fairly high values of *Comparative Fit Index* and *Tucker-Lewis Index* obtained through the application of CFA indicated that the underlying model based on the extracted factors fitted well to the data set. As per the computed values on *Composite Index,* there existed fairly wide disparities (with regard to the level of social sector development) among the 12 districts of Himachal Pradesh state; Kullu , Kinnaur and Chamba were detected to be the three bottom-most districts of the state. The findings thus point towards the need to adopt suitable corrective measures by the state government (specifically in respect of the three laggard districts), so as to ensure balanced development of social sector activities in the state.

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Appendix 1. List of the Indicators Considered in the Study

[illegible]	[illegible]	Abbreviation
1.	Number of Primary Schools per 100 sq km	NPRS
2.	Number of Middle Schools per 100 sq km	NMDS
3.	Number of High/ Hr Secondary Schools per 100 sq km	NHSS
4.	Number of Government Colleges per 100 sq km	NGVC
5.	Teacher-School Ratio in Primary Schools	TSPS
6.	Teacher-School Ratio in Middle Schools	TSMS
7.	Teacher-School Ratio in High/ Hr Secondary Schools	TSHS
8.	Enrollment per Lakh of Population in Primary Schools (Boys)	EPSB
9.	Enrollment per Lakh of Population in Primary Schools (Girls)	EPSG
10.	Enrollment per Lakh of Population in Middle Schools (Boys)	EMSB
11.	Enrollment per Lakh of Population in Middle Schools (Girls)	EMSG
12.	Enrollment per Lakh of Population in High/ Hr Secondary Schools (Boys)	EHSB
13.	Enrollment per Lakh of Population in High/ Hr Secondary Schools (Girls)	EHSG
14.	Pupil-Teacher Ratio in Primary Schools	PTPS
15.	Pupil-Teacher Ratio in Middle Schools	PTMS
16.	Pupil-Teacher Ratio in Secondary Schools	PTHS
17.	Number of Hospitals per 100 sq km	NHSP
18.	Number of Dispensary in per 100 sq km	NDSP
19.	Number of CHC/RH per 100 sq km	NCHC
20.	Number of PHC per 100 sq km	NPHC
21.	Number of Beds per Lakh of Population Available in Allopathic Institutions	NBAI
22.	Number of Indoor Patients Treated in All Allopathic Institutions per Institution	NPTI
23.	Number of Outdoor Patient Treated in All Allopathic Institutions per Institution	NPTO
24.	Number of Ayurvedic Hospitals per 100 sq km	NAHS
25.	Number of Ayurvedic Dispensaries per 100 sq km	NADS
26.	Number of Ayurvedic Doctors per Lakh of Population	NADC
27.	Number of Ayurvedic Nurses per Doctor	NANS
28.	Number of Beds (in Ayurvedic institution) per Lakh of Population	NBAY
29.	Number of Family Welfare Centres per 100 sq km	NFWC
30.	Number of Sterilisations Done per Lakh of Population	NSTD
31.	Number of Births Registered per 1000 Population	NBRR
32.	Number of Death Registered per 1000 Population	NDTR
33.	Number of Police Stations/ Police Posts per 100 sq km	NPLS
34.	Number of Crimes per Lakh of Population	NCRM
35.	Number of Unarmed Police Per Lakh of Population	NUAP