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DETERMINANTS OF GOVERNMENT HEALTH SCHEME BENEFIT RECEIPT AND HEALTH INFRASTRUCTURE ACCESS: EVIDENCE FROM A HOUSEHOLD SURVEY IN BELAGAVI DISTRICT

Jahnavi. P. Meghannavar[1], Dr. S.T. Bagalkoti[2]

[1]PhD Research Scholar, Department of Economics, Karnatak University, Dharwad. Karnataka State, India.

[2]Senior Professor, Department of Economics, Karnatak University, Dharwad. Karnataka State, India

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---**ABSTRACT**---

This study investigates the determinants of healthcare access and the effectiveness of government health schemes in a selected region of Belagavi district, with a focus on both financial protection and infrastructural availability. Using primary household survey data, we examine scheme awareness, enrolment, and utilization, as well as multidimensional health infrastructure, including proximity to facilities, availability of doctors and medicines, and transport access. Logistic regression analysis reveals that poverty status alone does not significantly predict receipt of government health benefits; enrolment emerges as the strongest determinant. A composite Health Infrastructure Index, analyzed through multinomial logistic regression, shows that distance to facilities, mode of transport, and rural residence significantly influence access, whereas income has a limited effect once infrastructural factors are considered. COVID-19-related disruptions further highlight vulnerabilities in service delivery and transport connectivity. Findings indicate that healthcare inequalities are primarily driven by spatial and administrative barriers rather than economic status alone. Policy recommendations emphasize simplifying enrolment procedures, enhancing awareness campaigns, and strengthening rural healthcare infrastructure to achieve equitable access and effective financial protection.

KEYWORDS: *COVID-19; Logistic Regression, Multinomial Logistic Regression, Health Infrastructure, Poverty Targeting, Healthcare Access, Government Health Schemes* --

INTRODUCTION

Government health schemes are designed to provide financial protection to economically vulnerable households. However, effective targeting depends not only on eligibility criteria but also on awareness, enrolment mechanisms, and infrastructural accessibility. In India, major initiatives such as Ayushman Bharat - PM-JAY aim to reduce out-of-pocket expenditure and improve healthcare access among low-income populations. Yet, empirical evidence at the micro level remains limited regarding whether poorer households are actually more likely to receive benefits. Simultaneously, healthcare access is influenced by multidimensional infrastructure factors including distance to facilities, transport availability, medical personnel presence, and medicine supply. The COVID-19 pandemic further disrupted healthcare delivery and income stability, making it necessary to examine both financial protection and infrastructural access simultaneously.

This study addresses two major questions:

1. Do government health schemes preferentially benefit poorer households?
2. What factors determine disparities in health infrastructure access?

Health Infrastructure Availability and Accessibility

Table 1: Summary Indicators of Health Infrastructure and Service Availability

Indicator	Key Finding (%)
Households within 3 km of facility	72.5
Travel time within 30 minutes	97.8
Doctors always available	78.3
Medicines partially/fully available	97.8
Diagnostic services available	74.2
Neutral to satisfied with public facilities	98.5

Source: Author’s calculation based on primary household survey data.

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Table 1 indicates that physical access to healthcare facilities is generally satisfactory. Approximately 72.5% of households live within three kilometres of a facility, and nearly all households (97.8%) can reach a facility within 30 minutes. Service readiness is relatively strong: doctors are always available for 78.3% of households, medicines are partially or fully available for 97.8%, and diagnostic services are accessible to 74.2% of households. Moreover, 98.5% of respondents reported being neutral to satisfied with public facilities, suggesting overall acceptability of service quality. While infrastructure presence is high, certain gaps remain—for instance, not all households have consistent access to doctors and diagnostic services—which indicates that adequate infrastructure does not always translate into optimal service delivery.

COVID-19 Related Disruptions and System Stress

Table 2: Healthcare Disruptions During COVID-19

Indicator	Percentage (%)
Experienced healthcare disruption	69.2
Main reason: Transport restriction	41.6
Second reason: Overcrowding	30.7
Postponed treatment	12.2
Beds available with difficulty/not available	69.2

Source: Author's calculation based on primary household survey data.

The pandemic significantly stressed healthcare access mechanisms. Nearly 70 percent experienced disruption, primarily due to transport restrictions and hospital overcrowding. Although treatment postponement was limited to about 12 percent, difficulties in securing hospital beds reveal substantial systemic strain. These findings indicate that emergency preparedness mechanisms were inadequate in maintaining uninterrupted healthcare delivery during crises.

Government Health Insurance: Awareness, Enrolment and Utilization

Table 3: Coverage and Utilization of Government Health Schemes

Indicator	Percentage (%)
Insurance coverage before COVID	11.9
Awareness of schemes	25.0
Enrolment in schemes	11.1
Utilized schemes during COVID (among enrolled)	32.5
Reported OOPE reductio (significant/partial)	84.7

Source: Author's calculation based on primary household survey data.

Insurance reach and awareness remain critically low, with only one-fourth aware of schemes and barely 11 percent enrolled. Even among the enrolled population, only one-third utilized benefits during COVID-19. However, those who utilized schemes reported meaningful reduction in out-of-pocket expenditure, demonstrating that schemes are effective when accessed. The central issue therefore lies not in scheme design but in limited outreach, procedural complexity, and enrolment barriers.

Logistic Regression Model to Determine the Benefit of Government Scheme Receipt

To examine whether government health schemes effectively reach economically vulnerable households, a binary logistic regression model was estimated. The dependent variable captures whether a household received benefits under a government scheme (1 = Yes, 0 = No). Key explanatory variables include poverty status (during COVID and post-COVID), awareness of schemes, and enrolment status.

Model Specification

The logistic regression model is specified as:

$$P_i = \beta_0 + \beta_1 Poverty_i + \beta_2 Awarness_i + \beta_3 Enrolment_i + \varepsilon_i$$

Where:

- P_i= Probability that household benefited from the scheme
- Poverty = Economic status of household
- Awareness = Knowledge of schemes
- Enrolment = Participation in scheme

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Results of Logistic Regression

Table 4: Logistic Regression Estimates for Benefit Receipt

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Logistic regression                             Number of obs     =        360
                                                LR chi2(4)        =      51.91
                                                Prob > chi2       =     0.0000
Log likelihood = -29.982328                     Pseudo R2         =     0.4640
```

benefit	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
poverty_during	2.108206	1.600757	0.98	0.326	.4759896	9.337462
poverty_presen	2.176631	1.644303	1.03	0.303	.4951739	9.567799
awarness	2.013197	3.296809	0.43	0.669	.0812755	49.86698
enrolled	79.71478	126.1645	2.77	0.006	3.583796	1773.105
_cons	.0009514	.0013091	-5.06	0.000	.0000641	.0141132

Source: Author's estimation using primary household survey data. Analysis performed using STATA.

A logistic regression model was estimated to examine the factors influencing the likelihood of receiving the benefit. The model was based on 360 observations, and the overall model fit was statistically significant, as indicated by the likelihood-ratio chi-square test (LR $\chi^2(4) = 51.91$, $p < 0.001$). The Pseudo R^2 value of 0.464 suggests that approximately 46.4% of the variability in the dependent variable is explained by the predictors included in the model.

The results indicate that poverty during the reference period has an odds ratio of 2.11, suggesting that individuals who experienced poverty were about 2.1 times more likely to receive the benefit compared to those who did not. Similarly, current poverty status shows an odds ratio of 2.18 and both coefficients are statistically insignificant ($p > 0.05$).

Awareness of the program yields an odds ratio of 2.01, indicating that respondents who were aware are twice as likely to receive the benefit, but merely being aware does not guarantee utilization of benefits.

In contrast, enrolment in the program is a highly significant predictor of benefit receipt, with an odds ratio of 79.71 ($z = 2.77$, $p = 0.006$). This indicates that enrolled individuals are nearly 80 times more likely to receive the benefit than non-enrolled individuals.

Construction of Health Infrastructure Access Index

To examine disparities in health infrastructure, a composite measure of accessibility was constructed using information collected at the household level. Access to health services is multidimensional and cannot be captured by a single indicator. Therefore, multiple components reflecting physical and service availability were combined. The following variables were used:

- Distance to nearest health facility
- Travel time to reach facility
- Availability of doctors
- Availability of medicines

These variables capture both geographical accessibility and service readiness of public healthcare institutions. Each variable was coded such that higher values indicate better access.

Composite Index Computation

A composite index was calculated using the average method:

$$\textit{Access Index} = \frac{\textit{Distance} + \textit{Travel Time} + \textit{Doctors} + \textit{Medicines}}{4}$$

This produced a continuous score representing the overall level of health infrastructure access for each household.

Classification into Access Groups

To facilitate interpretation and regression modelling, the continuous index was divided into. After constructing the Health Infrastructure Index (HII), households were classified into three equal categories using the NTiles (tertile) method. Households were categorised into low, medium and high infrastructure access categories based on composite index scores.

Multinomial Logistic Regression for Determining Health Infrastructure Access

In this model, the medium access group is treated as the reference category against which the other groups are compared. Accordingly, two sets of comparisons are estimated: low versus medium access group and high versus medium access group. The model computes coefficients that represent the change in the log-odds of being in a particular category relative to the base group for a one-unit change in the predictor variable.

Through this approach, the model identifies how socio-economic and infrastructural factors such as income, hospital proximity, transport facilities, and place of residence influence the probability of households experiencing different levels of healthcare access. Overall, multinomial logistic regression provides a comprehensive framework to understand the determinants of disparities in health infrastructure accessibility.

Model Specification

To identify determinants of health infrastructure access, a Multinomial Logistic Regression model was employed. Since the dependent variable (access group) has three unordered categories, multinomial logistic regression is appropriate.

$$\boldsymbol{Access_i = f(Income_i, Distance_i, Transport_i, Place\ of\ Residence_i)}$$

Where:

Dependent Variable:

- Access = Low / Medium / High group

Independent Variables:

- Income_i – Income categories
- Hospital Near_i – Distance to the nearest health facility
- Transport_i – Mode of transportation to the health facility
- $\text{Place of Residence}_i$ – urban/rural

Table 5: Multinomial Logistic Regression Results (Low vs Medium Access)

Multinomial logistic regression — Number of obs = 360; LR chi2(8) = 444.64; Prob > chi2 = 0.0000; Pseudo R2 = 0.5641

Log likelihood = -171.77955

access_group	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
income_category	.034736	.2231684	0.16	0.876	-.402666	.472138
distance	-3.057707	.4024355	-7.60	0.000	-3.846466	-2.268948
mode_of_transport	-.9945517	.3808243	-2.61	0.009	-1.740954	-.2481498
PlaceofResidence	-1.937775	.4553128	-4.26	0.000	-2.830172	-1.045379
_cons	8.974728	1.255137	7.15	0.000	6.514705	11.43475
2	(base outcome)					
3						
income_category	.3148082	.3079458	1.02	0.307	-.2887545	.918371
distance	20.45038	1163.495	0.02	0.986	-2259.957	2300.858
mode_of_transport	.8654089	.7823267	1.11	0.269	-.6679231	2.398741
PlaceofResidence	.2354874	.4741947	0.50	0.619	-.6939172	1.164892
_cons	-80.7439	4653.978	-0.02	0.986	-9202.374	9040.886

Source: Author's estimation using primary household survey data. Analysis performed using STATA.

The goodness and significance of the multinomial logistic regression model indicate that the model fits the data well and provides reliable results. The Likelihood Ratio (LR) chi-square statistic is 444.64 with 8 degrees of freedom, and the associated p-value is 0.000, which is less than 0.05. This confirms that the model is statistically significant overall, meaning the independent variables collectively improve the prediction of healthcare access categories compared to a model without predictors Additionally, the Pseudo R^2 of 0.5641 suggests that approximately 56% of the variation in healthcare access is explained by the included variables, reflecting strong explanatory power for cross-sectional socio-economic data. Overall, the model demonstrates a good fit and effectively captures the determinants of health infrastructure access.

Comparison of Low Access Group versus Medium Access Group

The multinomial logistic regression results indicate that several infrastructural variables significantly influence the likelihood of belonging to the low access group compared to the medium access group. Distance to the hospital shows a strong and statistically significant negative effect ($\beta = -3.06$, $p < 0.001$), suggesting that individuals living farther from health facilities are much more likely to experience poor access to healthcare services. Mode of transport is also significant (β = −0.99, p = 0.009), indicating that households without convenient or private transport options face greater barriers in reaching hospitals, thereby reducing their access level. Place of residence has a highly significant negative coefficient (β = −1.94, p < 0.001), which implies that rural residents are considerably more disadvantaged compared to urban residents in terms of healthcare accessibility. However, income category is not statistically significant (β = 0.03, p = 0.876), showing that economic status alone does not strongly determine access when physical infrastructure factors are considered. Overall, these findings highlight that geographical and transport-related constraints play a more critical role than income in explaining low healthcare access.

Comparison of High Access Group versus Medium Access Group

In contrast, the comparison between the high access and medium access groups reveals that none of the explanatory variables are statistically significant at the 5% level. Income category (β = 0.31, p = 0.307), mode of transport (β = 0.87, p = 0.269), and place of residence (β = 0.24, p = 0.619) do not show meaningful differences between these two groups. Distance also appears statistically insignificant (p = 0.986) with a very large standard error, which may indicate limited variation. This suggests that households in the medium and high access groups share relatively similar characteristics in terms of infrastructure and socioeconomic conditions. Therefore, while infrastructure strongly distinguishes low access populations, it does not clearly differentiate between medium and high access groups. These results imply that once a basic level of access is achieved, additional improvements may depend on factors beyond those captured in the present model.

FINDINGS

The study finds that while physical proximity to healthcare facilities is relatively adequate for most households, effective access is constrained by infrastructural and service-level gaps. Although doctors are largely available and travel time is moderate, medicine supply is often partial and diagnostic services are not universally accessible. The COVID-19 pandemic significantly disrupted healthcare access, primarily due to transport restrictions and hospital overcrowding. Insurance coverage, awareness, and enrolment under government health schemes remain low, limiting financial protection. Logistic regression results show that poverty status does not significantly increase the likelihood of receiving scheme benefits, whereas enrolment is the strongest predictor of benefit receipt. Multinomial regression analysis further reveals that distance, transport availability, and rural residence significantly determine healthcare access levels, while income plays a limited role once infrastructural factors are controlled.

DISCUSSION

The findings suggest that healthcare inequality in the study area is driven more by spatial and infrastructural barriers than by income differences alone. The absence of a significant relationship between poverty and scheme benefit receipt indicates targeting inefficiencies and administrative bottlenecks. Enrolment-based access highlights procedural inclusion rather than economic vulnerability as the key determinant of financial protection. Moreover, the strong influence of distance and rural residence underscores the importance of decentralizing health services and strengthening transport connectivity. Improving rural infrastructure, simplifying enrolment procedures, and enhancing awareness campaigns are therefore essential to ensure equitable healthcare access and effective implementation of government health schemes.

Policy Implications

Government health schemes should focus on reducing administrative exclusion by simplifying enrolment procedures, minimizing documentation requirements, and introducing single-window registration systems. Mobile enrolment camps and proactive identification of eligible households through local bodies can improve inclusion, particularly for digitally excluded populations. Integrating welfare databases may further reduce identification errors and duplication.

Awareness initiatives must go beyond information dissemination by providing on-ground assistance for application and digital registration through village-level facilitation centres and Self-Help Groups. Strengthening grievance redressal mechanisms can also reduce delays and procedural bottlenecks.

Improving rural healthcare access requires strengthening Primary Health Centres and sub-centres with essential diagnostics, medicines, and emergency services. Expansion of mobile medical units, telemedicine, and improved ambulance and subsidized transport networks can significantly reduce geographic barriers. Resource allocation should prioritize underserved rural and peri-urban areas to reduce disparities in healthcare access.

CONCLUSION

The study concludes that while basic physical access to healthcare facilities is relatively adequate, significant disparities persist due to infrastructural limitations and administrative barriers. The COVID-19 pandemic exposed vulnerabilities in transport connectivity, hospital capacity, and service continuity. Econometric findings reveal that poverty alone does not significantly determine access to government health scheme benefits; rather, enrolment and infrastructural factors such as distance and rural residence play a decisive role. These results underscore the need for simultaneous strengthening of rural health infrastructure and simplification of administrative processes to achieve equitable healthcare access and effective financial protection.