Infrastructural Inequality and Household COVID-19 Vulnerability in a South African Urban Settlement

S. M. Marcus (*Correspondence author)

Division of Family Medicine, Department of Family Medicine and Primary Care, School of Clinical Medicine, Faculty of Health Science, University of the Witwatersrand, Johannesburg 2000, South Africa. e-mail: simonmmarcus@gmail.com

T. S. Marcus

COPC Research Unit, School of Medicine, Faculty of Health Science, University of Pretoria, Pretoria 0028, South Africa. e-mail: tessa.marcus@up.ac.za

Abstract

COVID-19 has highlighted the importance of household infrastructure in containing the spread of SARS-CoV-2, with Global South urban settlements particularly vulnerable. Targeted interventions have used area or dwelling type as proxies for infrastructural vulnerability, potentially missing vulnerable households. We use infrastructural determinants of COVID-19 (crowding, water source, toilet facilities, and indoor pollution) to create an Infrastructural Vulnerability Index using cross-sectional household data (2018–2019) from Mamelodi, a low-income urban settlement in South Africa. Households were stratified into vulnerability groups by index results; sociodemographic variables were assessed as predictors of index scores; and inequality analysis and decomposition were conducted. Thirty-three percent of households fell in the lowest risk group, 32% in the second, 21% in the third, and 14% in the highest. Dwelling type and geographical ward were associated with changes in index scores, with a shack (adjusted β (aβ) = 3.45, CI = 3.39–3.51) associated with highest increase compared to a house. Wards in more developed areas were not consistently associated with lower index scores in the final regression model. The infrastructural vulnerability of the top 10% of households was greater than the bottom 40%, and inequality was predominantly within (80%) rather than between (20%) wards, and more between (60%) than within (40%) dwelling types. Our results show a minority of households account for the majority of infrastructural vulnerability, with its distribution only partially explained by area and dwelling type. Efforts to contain COVID-19 can be improved by using local-level data, and a vulnerability index, to target infrastructural support to households in greatest need.

Keywords: COVID-19; Built environment; Urban health; Social determinants of health; Epidemiology; Health inequality

Introduction

South Africa's quadruple disease burden has been severely impacted by the COVID-19 pandemic. From first detection of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) on the 5th of March 2020 to the 6th of October 2021, the country experienced over 2.9 million COVID-19 infections—the highest number of confirmed COVID-19 cases in Africa [1]. In the period June 2020 to October 2021, daily new recorded infections ranged from between 1000 and a little over 19,000 [2], and 262,000 excess deaths were recorded, the majority of which are attributable to COVID-19 [3].

Consistent with the international consensus, the South African government's non-pharmaceutical interventions follow two broad strategies: mitigation, through isolation of cases and household contact quarantine; and suppression, through mass public quarantining ("lockdown") and the promotion of individual and public health hygiene practices [4]. Both these intervention strategies have raised the visibility of household infrastructure and its role in SARS-COV-2 transmission and COVID-19 management.

The unequal capacity to follow mitigation and suppression strategies and the unequal health burden of COVID-19 have been increasingly highlighted in the literature [5,6,7]. The risk of infection for household contacts is 10 times higher than for other contacts [8], and household infrastructure, particularly access to water, sanitation, and hygiene (WASH) facilities [9,10,11], as well as crowding [12, 13]], have directly impacted infection rates and disease severity. Also, the significant association found between outdoor air pollution and COVID-19 infection rates and mortality [14] suggests that exposure to biomass fuels, commonly used for heating and cooking in low-income and poor households, is likely to increase risk of infection and disease severity [12].

As De Groot et al. [4] argue, the responses to COVID-19 overlook infrastructural inequalities and the specificity of local contexts in African cities. Thus, while infrastructural interventions to mitigate COVID-19 in South Africa have tended to focus on the homeless [15] and informal settlements, little attention has been paid to the vulnerability of people living in urban settlements where informal and formal dwellings co-exist. Formal dwellings are characterised by complex living arrangements that range in form from collective living quarters, multigenerational households, multiple dwellings on a single plot, multiple families in a single dwelling, and multiple individuals in single shared spaces. Like their informal counterparts, formal accommodation is characteristically spatially congested and crowded internally, with one 11-year panel study reporting 57.6% of houses being consistently overcrowded [16]. In short, access to formal housing is not a guarantee of adequate protective infrastructure to support and protect households during the pandemic and, in combination with informal housing, may result in urban communities with varying degrees of vulnerability.

The complex arrangements of formal and informal dwellings are not unique to South Africa. Many cities have high levels of inequality, and in the Global South, which accounts for the majority of the world's urban population, poverty and infrastructural vulnerability are not limited to informal areas [17]. Additionally, with continued development, expansion, and the proliferation of informal renting, the lines between formal and informal settlements are less clear [18]. Literature on identifying households with compounded COVID-19-related infrastructural vulnerability in the Global South is sparse, and the limited availability of local-level data is one amongst several important reasons behind the failure of governments to tailor responses to support people in urban communities [19].

One such urban community is Mamelodi. Born out of South African land dispossession under the 1913 and 1936 Land Acts, it is part of the City of Tshwane Metropolitan Municipality in the province of Gauteng. Like other townships developed during Apartheid, it was created as a racially segregated residential area for black labour and lies on the periphery of the city, approximately 20 km from the city centre [20, 21]

Although Mamelodi is distant from the city centre, its relative proximity to economic opportunities and its perceived stability make it an attractive place for local and regional migrants [22]. Since 1994, it has expanded significantly through government allocation of formal housing as well as demand-led settlement densification, land invasions, and the establishment of informal shack settlements, especially in the east [22]. This expansion has created a degree of geographic inequality. Compared to East Mamelodi, West Mamelodi is more established, closer to economic opportunities, and has greater investment in infrastructure [22]. However, it also has seen densification through "backyarding", the renting of one- or two-roomed informal structures in the backyard of formal dwellings [23]. With nearly one-fifth of Gauteng's urban population living in backyard dwellings [18], this sizeable and fast-growing housing sub-sector makes households' vulnerability invisible to government support, both because of its informality as well as its illegality [18].

According to Statistics South Africa adjusted 2011 Census data, Mamelodi has a population of 334,577 people living in 110,703 households [24]. With an average household size of 3.3 people, these numbers may suggest there is little overcrowding. This, however, is not likely to be the case for three related reasons: first, there is ongoing rapid population growth, as people continue to in-migrate in search of economic opportunities [20, 22]; second, the rapidly expanding informal housing market is unregulated and difficult to fully quantify; and finally, structures are most often one- or two-roomed dwellings that incorporate communal living areas [18], leaving little space for even three or four occupants.

A combination of social and structural factors, including infrastructure and economic inequalities, has contributed to the high burden of communicable and non-communicable diseases in Mamelodi, including COVID-19 [25,26,27].

This study investigates household-level infrastructural vulnerability to COVID-19 in Mamelodi, using local level data and a factor analysis method of index creation. The aims are to stratify households based on combined infrastructural vulnerability, and to identify the sociodemographic variables that contribute to higher or lower levels of vulnerability in order to make visible especially vulnerable households, as well as analyse inequality in vulnerability across the population.

Methods

Data

Data from AitaHealth™, a mobile community healthcare management application developed by the University of Pretoria's Department of Family Medicine and Mezzanineware (Vodacom), was used in this study. AitaHealth™ is used by community healthcare workers to register households, conduct household environmental and health status assessments, and to support the provision of individual and household healthcare services in the course of doing community-oriented primary care [28].

The data is from the 2018–2019 household registrations and assessments that were conducted door-to-door in six wards—covering 13,985 households, approximately 13% of Mamelodi households. Household registration and assessment occur on a bi-yearly basis with the goal of collecting data for research and health service delivery, and is purposively sampled with a view to be representative of the population.

Variables

All variables are calculated at a household-level, with a household defined as "a person, or a group of persons, who occupy a common dwelling (or part of it) for at least 4 days a week, and who provide themselves jointly with food and other essentials for living" [29].

Infrastructural Determinants of COVID-19

The infrastructural determinants of interest in this study were water source and toilet exposure (variables representative of access to WASH facilities), indoor pollution (which is the household's energy source risk for indoor pollution), and crowding. These four indicators were chosen as they have strong associations with COVID-19 infection and disease severity, and were available for analysis from the data. Households were divided into low-risk (LR), medium-risk (MR), and high-risk (HR) for each of the four infrastructural determinants as defined in Table 1. Household risk divisions for water source, toilet exposure, and indoor pollution are similar to divisions used by the City of Tshwane to monitor development [30]; however, they were adjusted for COVID-19 specificity and to match available data. Households were attributed the lowest possible risk where multiple water sources were reported.

Table 1. Household risk stratification of the infrastructural determinants of COVID-19

Infrastructural determinants	Risk		
	Low-risk	Medium-risk	High-risk
Water source	Piped water inside the dwelling	Access to water on the property (e.g. piped water in the yard)	Access to water *off* the property
Toilet exposure	Private household toilet with associated handwashing facilities	*Either* a private household toilet with no handwashing facilities; *or* a shared toilet with other households with handwashing facilities	A shared toilet with other households without handwashing facilities
Indoor pollution	Household uses electricity, gas, or solar power	Household uses a combination of low- and high-risk sources	Household uses biomass fuels
Crowding (household person-to-room ratio)	≤ 0.5	Between > 0.5 and ≤ 1	> 1

Crowding was calculated based on the number of people per room with the risk divisions accounting for the high levels of COVID-19 spread in household clusters and the fact that the number of rooms reported in the survey contains shared living areas including the kitchen. The definition of HR crowding is the same as the definition of overcrowding used by the US Department of Housing and Urban Development (more than 1 person per room) [31] (p3).

Sociodemographic Variables

The household sociodemographic variables of interest in this study were age of household head, gender of household head, dwelling type, ward (as a proxy for geographic location), household vulnerability status, and occupant ownership of the dwelling.

Age of the household head was grouped into two categories (≥ 65 and those < 65) based on COVID-19 severity risk. Gender of the household head was recorded in the survey as a dichotomous variable and therefore analysed as such in the study. Dwelling types considered "formal housing" were house, room, and collective living quarters, and "informal dwellings" were shack and other (e.g. huts or tents). In the context of Mamelodi, collective living quarters were workers' hostels, school hostels, and orphanages, where facilities, including bedrooms, were shared by groups of individuals.

Wards are geopolitical subdivisions of municipalities and are used for a variety of functions including municipal planning, healthcare delivery, elections, and the national census [32,33,34]. While there is inter- and intra-ward variations in infrastructure and service delivery, in the context of Mamelodi, western wards tend to be more developed [22]. The six wards analysed in this study were 43 and 38 in West Mamelodi, and 16, 40, 100, and 101 in East Mamelodi (Fig. 1) [35].

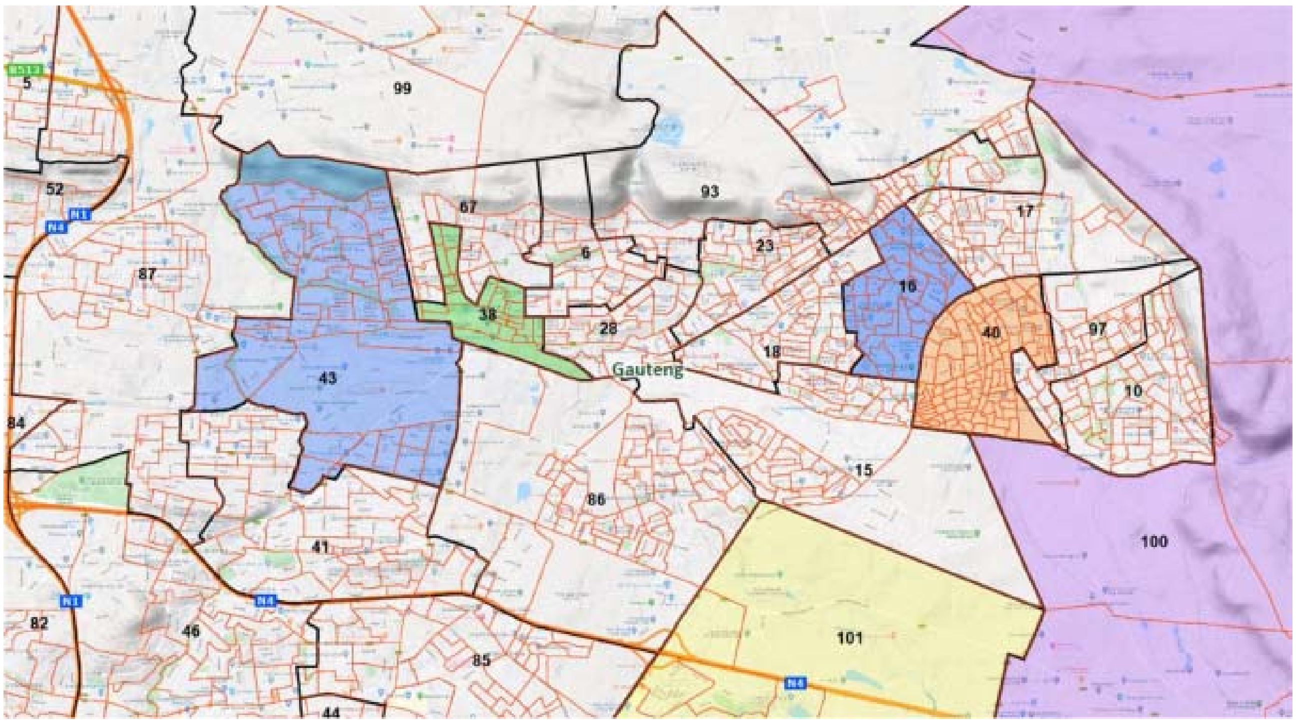

Fig. 1. Ward map of Mamelodi, with the wards where data was collected highlighted

Household vulnerability status was defined by the City of Tshwane's indigent programme, used to identify houses requiring municipal assistance, and based on the status of the household head [36]. Household vulnerability categories were single, couple, single parent, couple parent, pensioner, and child.

Data Analysis

All data analyses were done on Stata® 16. Missing responses and explanatory variable values were imputed using multivariate imputation by chained equations with 20 iterations (see supplemental appendix Table 1). To determine household compounded infrastructural vulnerability, the four selected determinants were combined into an additive Infrastructural Vulnerability Index (IV Index). A factor analysis method of index compilation was used to produce a more data driven, intuitive index. Exploratory factor analysis was performed to assess the factorial structure of the variables, and confirmatory factor analysis to analyse the fit of the model and derived weights. The index was then rescaled to a minimum of four (lowest risk) and maximum of 12 (highest risk), and households were stratified into four vulnerability groups based on their scores.

Multivariate regression analysis was used to determine which sociodemographic variables significantly impacted household IV Index scores. Bivariate analysis was run with each explanatory variable independently, and if its impact was demonstrated to be statistically significant, it was included in the stepwise regression process. Pearson's chi-squared test was used to test statistical significance in both bivariate and multivariate regression analysis with a significance cut-off of < 0.05.

Inequality analysis was performed to further understand the distribution of vulnerability across the population. Two ratio inequality measures, namely the Palma ratio (S90/S40) and p90/p10, were calculated from the IV Index results. The Palma ratio is the ratio of IV Index shares of the top 10% of households (i.e. the most vulnerable 10% of households) to the bottom 40%, and the p90/p10 is the ratio of the IV Index score of the household at the 90th centile to the score of the household at the 10th centile. These two measures were used as they are more intuitively understood, while providing important information about inequality between the least and most vulnerable households [37].

The Atkinson A(1) index was used as the summary statistic of inequality and calculated using Jenkins [38] Stata module. Summary statistics of inequality capture inequality across the range of the distribution, and the A(1) index was chosen as it allows for subgroup decomposition into within-group and between-group inequality [37]. Decomposition provides important information about where the inequality lies, and the A(1) index result was decomposed by the statistically significant sociodemographic variables in the final regression model. The A(1) index result could theoretically range from 0 to 1, with 0 representing absolute equality; however, given the relatively narrow range of the IV Index scores (4–12), a low A(1) result is more likely.

Patient and Public Involvement

Patients and the public were not involved in this study's analysis of previously collected data.

Results

The sociodemographic variables are listed in Table 2. Most household heads were below the age of 65 (81.3%) and were fairly evenly divided between males (48.2%) and females (51.8%). Occupants tended to own their dwellings (69.8%); the most common vulnerability status of a household head was being a single adult (39%); and the most common dwelling types were shack (49.6%), followed by house (37%).

Table 2. Sociodemographic characteristics of study households

Sociodemographic variable	Category	Total ($N = 13{,}985$)	Percentage
Household head: age categories	< 65	11,368	81.3
	≥ 65	2617	18.7
Household head: gender	Female	7246	51.8
	Male	6726	48.2
Dwelling owned by occupants	No	4222	30.2
	Yes	9763	69.8
Household head: vulnerability	Single	5462	39
	Couple	772	5.5
	Couple parent	3073	22
	Single parent	2999	21.5
	Pensioner	1445	10.3
	Child	234	1.7
Ward	Ward 40	7325	52.4
	Ward 38	3182	22.8
	Ward 101	1540	11
	Ward 16	721	5.1
	Ward 43	722	5.1
	Ward 100	495	3.6
Dwelling type	House	5176	37
	Room	1344	9.6
	Collective living quarters	390	2.8
	Shack	6930	49.6
	Other	145	1

Factor Analysis

The four infrastructural determinants were subjected to exploratory factor analysis. A Kaiser-Meyer-Olkin measure of 0.657 and Bartlett's test of sphericity chi-squared of 5880.95 ($p < 0.001$) indicated that correlation structure is adequate for factor analyses [39]. Maximum likelihood factor analysis was used to estimate factor loadings with a Kaiser criterion of eigen values greater than 1, which yielded a one-factor solution (see supplemental appendix Table 2).

A one-factor hierarchical model derived by exploratory factor analysis was further analysed with confirmatory factor analysis. The one factor model had a good fit with a CFI = 0.998, RMSEA = 0.023, and SRMR = 0.008 [40]. The weights derived for the infrastructural vulnerability index were 0.79 for water source, 0.40 for toilet exposure, 0.75 for indoor pollution, and 0.33 for crowding.

Index Results and Regression Analysis

Figure 2 shows the proportion of households within different vulnerability groups based on IV Index scores. The proportion of households declined as the vulnerability increased, with 33% of household in the lowest vulnerability group (4–6), 32% in the second (6–8), 21% in the third (8–10), and 14% in the highest (10–12).

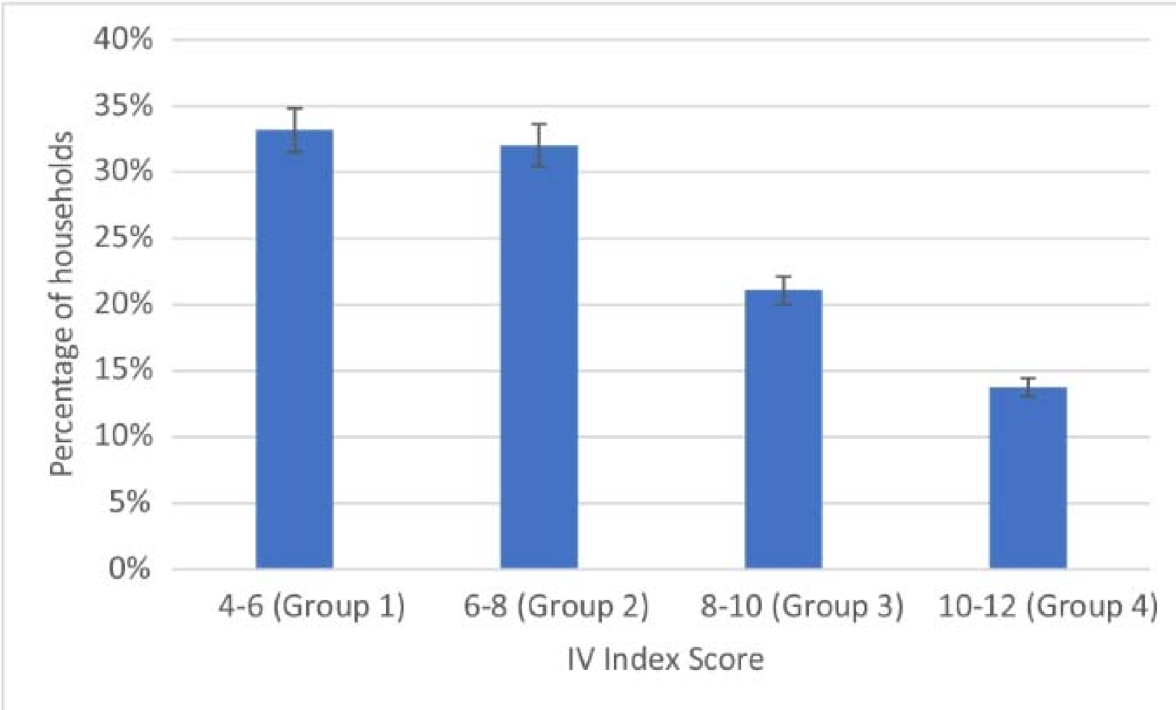

Fig. 2. Proportion of households in different vulnerability groups based on IV Index scores. Group 1 represents the lowest risk group and group 4 represents the highest

Table 3. Sociodemographic predictors of IV Index scores

Variable	Category	Crude β	p value	95% CI		Adjusted β	p value	95% CI	
Household head age category (reference: <65)	-	−0.84	0.000	−0.94	−0.75	-	-	-	-
Household head gender (reference: female)	-	0.34	0.000	0.26	0.41	-	-	-	-
Owner occupied dwelling (reference: no)	-	0.00	0.087	−0.08	0.08	-	-	-	-
Household head vulnerability status (reference: single)	Couple	0.83	0.000	0.66	1.01	-	-	-	-
	Couple parent	0.19	0.000	0.09	0.29	-	-	-	-
	Single parent	−0.12	0.020	−0.22	−0.02	-	-	-	-
	Pensioner	−1.46	0.000	−1.59	−1.33	-	-	-	-
	Child	−0.17	0.287	−0.47	0.13	-	-	-	-
Ward (reference: Ward 43)	Ward 38	1.36	0.000	1.19	1.53	1.16	<0.001	1.04	1.27
	Ward 16	1.48	0.000	1.26	1.70	−0.82	<0.001	−0.98	−0.66
	Ward 40	2.38	0.000	2.22	2.54	0.82	<0.001	0.70	0.93
	Ward 100	4.47	0.000	4.23	4.71	1.39	<0.001	1.21	1.56
	Ward 101	4.19	0.000	4.00	4.38	0.94	<0.001	0.80	1.09
Dwelling type (reference: house)	Room	1.14	0.000	1.03	1.21	1.13	<0.001	1.01	1.24
	CLQ	2.00	0.000	1.84	2.15	1.25	<0.001	1.03	1.48
	Shack	3.38	0.000	3.32	3.43	3.45	<0.001	3.39	3.51
	Other	1.21	0.000	0.97	1.46	1.06	<0.001	0.81	1.31

Results from the bivariate and multivariate regression analysis are reported in Table 3. There was no evidence of multicollinearity amongst the explanatory variables, as the correlation coefficients fell well below the typical cut-off of 0.8 (see supplemental appendix Table 3) [41]. The final model reflects only the significant sociodemographic variables associated with changes in IV Index scores. Ward and dwelling type were found to be significant in the final model, while age of household head, gender, vulnerability status, and dwelling ownership were not.

With house as the reference dwelling type, living in a shack was associated with the greatest increase in IV Index score (adjusted $\beta = 3.45$, CI = 3.39–3.51, $p = < 0.001$), followed by collective living quarters (adjusted $\beta = 1.25$, CI = 1.03–1.48, $p < 0.001$), room (adjusted $\beta = 1.13$, CI = 1.01–1.24, $p < 0.001$), and other (adjusted $\beta = 1.06$, CI = 0.81–1.31, $p < 0.001$).

In the bivariate analysis, moving wards from west to east (ward 43, 38, 16, 40, 101, and 100) was associated with increasing IV Index scores, as demonstrated by the crude β values. However, in the final model, ward 16 was associated with a lower score (adjusted $\beta = -0.82$, CI = -0.98 to -0.66, $p < 0.001$) than ward 43, while higher scores were associated with ward 100 (adjusted $\beta = 1.39$, CI = 1.21–1.56, $p < 0.001$), ward 38 (adjusted $\beta = 1.16$, CI = 1.04–1.27, $p < 0.001$), ward 101 (adjusted $\beta = 0.94$, CI = 0.80–1.09, $p < 0.001$), and ward 40 (adjusted $\beta = 0.82$, CI = 0.70–0.93, $p < 0.001$). Pensioner-headed households were associated with a significantly lower IV Index score in the bivariate analysis (crude $\beta = -1.46$); however, no household head vulnerability status was found to be statistically significant in the final model. The final model had an adjusted R-squared of 0.634.

The Atkinson A(1) index for the study population's IV Index results was 0.05, the Palma ratio was 1.19, and the p90/p10 result was 2.26 (Table 4). The A(1) index was decomposed by dwelling type and ward—the sociodemographic variables associated with significant changes in IV Index scores. Dwelling type decomposition showed 60% of the total A(1) inequality was between and 40% within dwelling types. Ward decomposition showed 20% of inequality was between and 80% within wards.

Table 4. Inequality measures of the IV Index results

Inequality measure	Subgroup	Total	Within	Between
A (1)	Total	0.05	-	-
	Ward		0.04	0.01
	Dwelling type		0.02	0.03
Palma ratio	-	1.19	-	-
p90/p10	-	2.26	-	-

Discussion

The results of this study highlighted four key findings. First, the proportion of households decreased as infrastructural vulnerability index scores increased. The highest proportion of households scored in the lowest vulnerability group (4–6), and over 60% of households were in the lowest two groups. While there is a degree of infrastructural vulnerability amongst most households, the majority have access to some infrastructure that can support and protect them during the pandemic.

Second, there is significant inequality in the distribution of infrastructural vulnerability across the population. As demonstrated by the Palma ratio, the top 10% of households with the highest scores account for a greater proportion of vulnerability than the bottom 40% of households. The inequality is further highlighted by the p90/p10 ratio, with the household at p90 having a score 2.26 times higher than the household at p10. Even though the majority of IV Index scores were in the lower vulnerability groups, a minority of more deprived households account for the majority of the infrastructural vulnerability to COVID-19.

Third, infrastructural vulnerability to COVID-19 varies considerably within and between different dwelling types. Living in a shack was associated with the greatest increase in vulnerability score—more than twice as high as the next most significant dwelling type. However, even that increase would not account for a shift from the lowest vulnerability group to the highest. Furthermore, living in rooms and collective living quarters, both forms of formal housing, was associated with greater IV Index scores than living in informal housing defined as other. Decomposition of the A(1) index further highlights the variability, as 60% of the inequality was between dwelling types and 40% within dwelling types.

These findings demonstrate that having formal housing does not guarantee access to adequate COVID-19-related infrastructure, and substantial infrastructural inequality exists between households defined as the same dwelling type. This is consistent with studies in the Global South looking at various forms of intersecting COVID-19 vulnerability. Studies in Kenya [42], Brazil [43], and India [44] have highlighted how factors such as high-population density and poor water supply are not limited to informal areas, and emphasise the importance of understanding local contexts when implementing policies to control the pandemic. Infrastructural vulnerability to COVID-19 cannot be subsumed under dwelling type, and interventions to support households during the pandemic should consider the vulnerability of households not simply as a function of household or settlement type alone.

Fourth, the infrastructure in more developed wards does not extend to the most vulnerable households in those wards. In the bivariate analysis, households in more westerly wards were associated with lower IV Index scores. However, this pattern was not consistent in the final regression model. Once other sociodemographic variables were accounted for, ward 16 in East Mamelodi was associated with the lowest index scores of any ward. Additionally, wards 100 and 101 in the east were associated with similar changes in index scores as ward 38 in the west. Decomposition of the A(1) inequality index by wards augments this finding as 80% of the inequality lies within wards and 20% between. Thus, the reduction in infrastructural vulnerability associated with greater levels of development in West Mamelodi does not extend to the more impoverished households in those wards, and, in some cases, their marginalisation compounds their vulnerability.

The results of this study highlight the complexity of infrastructural COVID-19 vulnerability. Vulnerable households face a double burden, with higher risk of infection and severe COVID-19, and less capacity to safely follow mitigation and suppression strategies. In this study, a minority of households accounted for the majority of infrastructural vulnerability, confirming De Groot et al.'s contention of structurally differentiated "privileged capacity to comply" [4] (p261). Thus, rather than being a matter of choice, these households do not have the infrastructure to adequately follow government guidelines and are largely deprived of the opportunity to protect themselves.

Infrastructural inequality in urban settlements makes identifying vulnerability particularly challenging as varying degrees of relative advantage and disadvantage exist within the same communities. The IV Index is a tool that can be used to identify vulnerability, pinpointing households that have been previously invisible to support systems. This would be useful internationally, particularly in the Global South where mixed formal and informal dwelling arrangements are ubiquitous. Beyond COVID-19, the IV Index can be modified to address other diseases and conditions, based on their infrastructural determinants, and it may also be a useful tool to improve the focus and rapidity of infrastructural support in future pandemics.

COVID-19 has required everyone to change the way they go about their everyday lives. For many individuals and households, however, the ability to make these changes safely and effectively is beyond their reach due to infrastructural inequalities that increase their vulnerability. As highlighted in this study, household vulnerability is not simply a function of dwelling type or location, and identifying marginalised households is key to an equitable response.

Limitations

The study has several limitations. The choice of wards for analysis was determined by the AitaHealth™ data available in 2018/2019. The data was purposively sampled, which may create sampling bias. Some household-level data are self-reported and thus are not objectively verified. Lastly, the choice of sociodemographic variables for analysis was limited by the data available, and additional variables such as household income or legal residency status in the country may have been useful.

Conclusion

Our study offers a practical approach to measuring contextually relevant infrastructural vulnerability to COVID-19 and identifying highly vulnerable households. Analysis of the IV Index results from Mamelodi highlights the complexity and inequality of infrastructural vulnerability in an urban settlement. As a key pillar of COVID-19 mitigation and suppression strategies, targeted infrastructural interventions that use local-level data to contextualise and stratify vulnerability, could improve their impact without missing impoverished groups in formal housing or more developed areas.

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Ethics Approval

This project is covered under the Researching the Development, Application, and Implementation of Community Oriented Primary Care (COPC) ethics protocols approved by the University of Pretoria Faculty of Health Science Research Ethics Committee (102/2011).

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