Understanding COVID-19 public health outcomes as a function of community resilience: A framework to inform systemic risk reduction strategies through socio-technical assessments of social vulnerability, workforce exposure, and resource accessibility
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Understanding COVID-19 public health outcomes as a function of systemic risks and community resilience: A socio-technical assessment framework to inform governance strategies on social vulnerability, workforce exposure, and resource accessibility

Authors

Abstract
The COVID-19 pandemic has presented extraordinary challenges to every community across the globe. Yet public health outcomes have exhibited widely disproportionate impacts across communities, revealing significant variances in how systemic risks created or multiplied by the pandemic have affected different communities and the extent to which those communities are capable of exercising coping capacities to maintain resilience. In support of efforts to analyse the effectiveness of public health interventions in the United States, a socio-technical assessment framework characterising social vulnerability, workforce exposures, and resource accessibility was implemented to inform a broader understanding of the pandemic’s dynamics. Social vulnerability metrics were adapted to assess how social determinants of health shape risk profiles and resilience capabilities at local community levels. Workforce exposure, with a focus on those designated as “essential” and “frontline,” was assessed to evaluate how these critical service providers may be impacted by higher risks of transmission. Resource accessibility, including food distribution and healthcare infrastructure capacities, was modelled to analyse whether these are sufficiently and equitably available to meet local demands and shifting conditions. A case study on the City of Chicago elucidated lessons learned for local public health interventions. The assessment results will support local public health agencies in formulating response and recovery strategies. It is critical that these strategies address antecedent disparities in vulnerability, exposure, and accessibility across local communities in order to meet the challenges presented by the COVID-19 pandemic and beyond. A socio-technical assessment approach is key to informing governance strategies on effective, efficient, and equitable systemic risk reduction and community resilience enhancement.

Keywords: community resilience; systemic risks; socio-technical assessment; COVID-19 pandemic; disparities and inequities; City of Chicago

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Introduction

The COVID-19 pandemic has presented extraordinary challenges to every community across the globe. As public and private sector entities endeavour to speed the pace of vaccine development and distribution, an array of non-medical countermeasures have been instituted by national and local governments to alleviate stress on healthcare systems and reduce the risk of community spread (CDC, 2021). These socio-behavioural public health interventions, which include stay-at-home orders, non-essential business closures, social distancing policies, and mask-wearing guidelines, are intended to limit interactions that might transmit the novel coronavirus in public, healthcare, commercial, and industrial settings while still maintaining the basic societal functions that these settings support (CDC, 2021; IASC, 2020).

Yet public health outcomes have exhibited widely disproportionate impacts across communities (Adhikari et al., 2020). These disparities reveal significant variances in how systemic risks created or multiplied by the pandemic have affected different communities and the extent to which those communities are capable of exercising coping capacities to maintain resilience (AMA, 2020). Comparing public health outcomes to the effects of strategies intended to “flatten the curve” of disease cases implicates key questions related to systemic risks and community resilience:

- What underlying susceptibilities to systemic risks cause some communities to face higher rates of negative public health outcomes?
- What fundamental social, economic, and infrastructure characteristics of communities could be better supported to foster community resilience?
- How might a socio-technical assessment framework inform effective, efficient, and equitable governance strategies for pandemic response and recovery?

A research team from the Decision and Infrastructure Sciences Division at Argonne National Laboratory conducted three interrelated assessments to build a broader understanding of how the pandemic has impacted local communities in light of antecedent susceptibilities to systemic risks and community resilience capabilities. Social vulnerability metrics were adapted to assess how social determinants of health shape risk profiles and resilience capabilities. Workforce exposure, with a focus on those designated as “essential” and “frontline,” was assessed to evaluate how these critical service providers may be impacted by higher risks of transmission. Resource accessibility, including food distribution and healthcare infrastructure capacities, was modelled to assess whether these resources are sufficiently and equitably available to meet local demands and cope with shifting conditions.

This paper summarises the Argonne National Laboratory research team’s efforts in conducting these assessments to support local public health interventions in the City of Chicago, and the potential applications for communities throughout the world. Section 2 provides an overview of the challenges involved in assessing systemic risks to inform governance strategies that foster community resilience. Section 3 describes the methodological approaches used to assess social vulnerability, workforce exposure, and resource accessibility. Section 4 demonstrates the application of this socio-technical assessment framework through a case study on the City of Chicago. Section 5 presents lessons learned and discussion to support pandemic response and recovery strategies. Section 6 concludes with a discussion of how the socio-technical assessment framework presented in this paper could inform systemic risk reduction and community resilience enhancements to meet the challenges presented by the COVID-19 pandemic and beyond.
**Problem Statement**

Evaluating the COVID-19 pandemic in the relative context of other recent disaster events illustrates the enormity of its impacts on communities across the globe. Between 2000 and 2019, a total of 7,348 disaster events were recorded worldwide, resulting in approximately 1.2 million deaths and $2.97 trillion in economic losses (UNDRR, 2020). In stark contrast, the global death toll attributed to the COVID-19 pandemic surpassed this 20-year statistic in early November 2020, just nine months after the World Health Organization first declared the outbreak to be a public health emergency of international concern, and has since continued to climb (Johns Hopkins University, 2021; WHO, 2021).

The total economic impact of the pandemic, including government spending, protracted recession, business closures, contractions of per capita income, hampered long-term productivity, and weaker growth, is difficult to quantify. However, the total global lost economic output observed in 2020 alone is estimated to be $3.94 trillion, which is over 1.3 times the total economic losses of all disasters in the preceding 20-year period (Statista, 2021). By these measures of consequence alone, the pandemic could be described as an outlier in terms of human suffering and costs amongst recent disaster events.

However, although extraordinary, the COVID-19 pandemic arguably does not meet all of the criteria that constitute a “black swan” event as originally articulated by Taleb (2007). Global pandemics are rare and clearly carry the potential for catastrophic impacts, but these events do not necessarily meet the criteria of being unforeseeable (Avishai, 2020). Like the existential threat posed by climate change, the pandemic may be more accurately described as a “grey swan” event, as governments had been warned through empirically-driven predictions by numerous subject matter experts over many years that such an event was highly probable to manifest at some point in the future (Taleb, 2007).

Perhaps equally predictable was the extent to which the pandemic has exposed the fragility of systems that our communities depend on in order to operate effectively, efficiently, and equitably (Avishai, 2020). In that context, characterising community resilience aims to assess “the ability of a community exposed to the COVID-19 to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management” (adapted from UNDRR, 2021).

Characterising the resilience of communities to the pandemic is therefore a complex task because it requires understanding communities in all their dimensions of vulnerability, exposure, and coping capacities, as well as the hazards presented by the pandemic. These intrinsic complexities in both the communities themselves as well as the trajectories of development of the pandemic, which impact overall community’s performance through cumulative cascading failures along interdependencies existing between infrastructure, social, economic, and governmental systems, is what constitutes systemic risks (Schweizer and Renn, 2019; United Nations, 2015[a]). Furthermore, this disaster confirmed, as defined by Helbing (2013), that interconnections existing between socio-technical systems supporting communities’ operations can result in large-scale instability and even uncontrollability of the event.

Exercising foresight and taking corresponding action to support fragile systems that might prove to be insufficient to support communities when operating under the pressures of extraordinary circumstances is possible through the integrated efforts of government, the
private sector, the scientific community, and local actors (Gaillard and Mercer, 2012). Bridging the gap between policy and implementation is reflected in the philosophies embodied in the Sustainable Development Goals (SDGs) and the Sendai Framework for Disaster Risk Reduction, which were developed to stimulate cohesive actions that support people, protect the environment, foster prosperity, assure peace, and build partnerships toward a more sustainable future (United Nations, 2015[a] and [b]). Building transdisciplinary knowledge and cross-sector capabilities across diverse stakeholders is a critical step in bolstering these systems to reduce the risk that disaster events might aggravate fragile systems (Signé, 2020).

Methodology

Systemic risks associated with the COVID-19 pandemic have placed particular stress on communities that exhibit underlying inequities in social vulnerability, workforce exposure, and resource accessibility. Accordingly, this assessment focused on these three dimensions of community resilience. Figure 1 illustrates the methodology developed to assess community resilience and systemic risks with the objective to support informed decisions in governance strategies that address pandemic response and recovery (adapted from UNDRR, 2021).

Figure 1. Methodology for Assessing Community Resilience and Systemic Risks.

The sub-sections that follow describe the methodological approaches used for each of the three interrelated analyses. Each sub-section includes a discussion of the foundational concepts of the assessment, the availability of community-level data, and the analytic approaches used. Section 4 presents results derived from the application of this methodology in a case study completed on the City of Chicago.

Social Vulnerability

The extent to which a community can be characterised by certain conditions, including high unemployment, low housing security, and high rates of disease prevalence, may indicate deficits in that community’s ability to manage both acute and chronic hazards (Cutter et al., 2003; IFRC, 2006). These circumstances define a community’s social vulnerability: “conditions
determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards” (UNDRR, 2021). For communities characterised by high social vulnerability, the COVID-19 pandemic has exposed and aggravated predisposed sensitivities across these factors that may lead to a higher rate of negative public health outcomes (WHO, 2020). Disproportionately higher rates of transmission and fatality for these communities result, in part, from “a legacy of cumulative inequities in these and other social determinants of health” (WHO, 2008).

The approach used to assess these community-level social vulnerability factors and the potentially negative public health outcomes resulting from COVID-19 involved the following three steps.

Selecting Authoritative Social Vulnerability Indices

The first step involved surveying and selecting social vulnerability indices from authoritative sources to support this assessment.¹ A wealth of analytic resources exist for evaluating social vulnerability, and unique considerations related to public health figure prominently in many of these resources. Four indices, developed by the U.S. Centers for Disease Control and Prevention (CDC), the U.S. Department of Health and Human Services (HHS), the United Nations Development Programme (UNDP), and the University of Illinois at Chicago (UIC) School of Public Health, were selected. Although there is some overlap in subjects covered, each provides a unique perspective on social vulnerability challenges created or exacerbated by the pandemic. When taken together, these provide a more comprehensive understanding of the challenges that many communities face.

- **CDC Social Vulnerability Index (SVI).** The CDC developed the SVI to assist local public health officials and emergency managers in preparedness and response efforts, including evacuation planning, emergency resource allocations, and shelter needs (CDC, 2020[a]). The SVI assesses four themes related to social vulnerability: socioeconomic status; household composition and disability; minority status and language; and housing type and transportation (CDC, 2020[b]). The value of including the SVI in this assessment is in both its general approach to social vulnerability as well as its specific inclusions of race, ethnicity, and housing security.

- **HHS Social Determinants of Health (SDOH).** As part of the implementation of national health promotion and disease prevention objectives, HHS developed a framework for evaluating community-level social determinants of health (HHS, 2020[a]). The SDOH framework assesses five categories related to social vulnerability: economic stability; education; social and community context; health and health care; and neighbourhood and built environment (HHS, 2020[b]). The value of including the SDOH in this assessment is in its emphases on health factors, community member interaction, and the physical characteristics of local communities.

- **UIC Risk Factor Score (RFS).** Researchers from the UIC School of Public Health developed the RFS to estimate the predicted risk of fatalities from COVID-19 in the City of Chicago (Kim, 2020[a]). The RFS is based exclusively on chronic disease prevalence data from the City of Chicago (Kim, 2020[b]). The value of including the

¹ Rather than developing a novel social vulnerability index as part of this assessment, the adoption of existing and available indices was intended to ensure repeatability or customisation by researchers interested in applying a similar assessment in their countries, regions, or local communities.
RFS in this assessment is in its targeted focus on co-morbidities associated with higher risks of negative COVID-19 public health outcomes.

- **UNDP Inequality-adjusted Human Development Index (IHDI).** The UNDP Human Development Index (HDI) is a widely used assessment tool that measures three general scores of development: a long and healthy life, being knowledgeable, and a decent standard of living (UNDP, 2020[a]). As a companion resource to the HDI, the IHDI adjusts this measure of average achievement to reflect how these scores are “distributed among the population by ‘discounting’ each dimension’s average value according to its level of inequality” (UNDP, 2020[b]). The value of including the IHDI in this assessment is in its quantification of inequality.

### Collecting Data for Social Vulnerability Indices

The second step involved collecting data from 12 sources to derive results for each of the social vulnerability indices selected for this assessment, as listed below.

- **CDC Agency for Toxic Substances and Disease Registry (ATSDR):** data supporting the scoring of each metric in the CDC SVI at the census tract level (CDC, 2020[b]).
- **Chicago Department of Housing:** data on housing composition, density, type, and quality at census tract, community area, and zip code levels (City of Chicago, 2021[a]).
- **Chicago Department of Public Health:** data on access to healthcare and primary care providers at census tract, community area, and zip code levels (City of Chicago, 2021[b]).
- **Chicago Health Atlas:** data on morbidity, mortality, behaviours, healthcare providers, and primary care providers at census tract, community area, and zip code levels (Chicago Health Atlas, 2021).
- **Chicago Public Schools:** data on educational attainment and mean years of schooling at community area and zip code levels (Chicago Public Schools, 2020[a]).
- **Illinois Department of Public Health:** data on health literacy, healthcare and primary care providers at state, county, and census tract levels (Illinois Department of Public Health, 2021).
- **Illinois State Board of Education:** data on educational attainment and expected years of schooling at state and county levels (Illinois State Board of Education, 2020).
- **UIC Institute for Policy and Civic Engagement:** data on civic participation, discrimination, and incarceration at national, state, county, and census tract levels (UIC, 2020).
- **UIC School of Public Health:** data supporting the scoring of each metric in the UIC RFS at the community area level (Kim, 2020[b]).
- **University of Chicago Mansueto Institute for Urban Innovation:** data on social cohesion at county and census tract levels (University of Chicago, 2021).
- **U.S. Census Bureau:** comprehensive data on demographic, education, employment, healthcare, households, life expectancy at state, county, and census tract levels (U.S. Census Bureau, 2020[a]).
Table 1 summarises the social vulnerability indices selected for this assessment along with respective categories, indicators, and sources of data consulted for completing the case study presented in section 4.1.

Table 1. Social Vulnerability Indices and Sources of Data.

<table>
<thead>
<tr>
<th>Index</th>
<th>Categories</th>
<th>Indicators</th>
<th>Sources of Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDC SVI</td>
<td>Socioeconomic Status</td>
<td>Below poverty, Unemployed, Income, High school diploma</td>
<td>CDC ATSDR, U.S. Bureau of Labor Statistics, U.S. Census Bureau</td>
</tr>
<tr>
<td></td>
<td>Household Composition and Disability</td>
<td>Aged 65 or older, Aged 17 or younger, Older than 5 with a disability, Single-parent household</td>
<td>CDC ATSDR, Chicago Department of Housing, U.S. Census Bureau</td>
</tr>
<tr>
<td></td>
<td>Minority Status and Language</td>
<td>Minority group, Speak English &quot;less than well&quot;</td>
<td>CDC ATSDR, U.S. Census Bureau</td>
</tr>
<tr>
<td></td>
<td>Housing Type and Transportation</td>
<td>Multi-unit structures, Mobile homes, Crowding, No vehicle, Group quarters</td>
<td>CDC ATSDR, Chicago Department of Housing, U.S. Census Bureau</td>
</tr>
<tr>
<td></td>
<td>Health and Health Care</td>
<td>Access to Health Care, Access to Primary Care, Health Literacy</td>
<td>Chicago Department of Public Health, Chicago Health Atlas, Illinois Department of Public Health, U.S. Census Bureau</td>
</tr>
<tr>
<td></td>
<td>Neighbourhood and Built Environment</td>
<td>Access to Healthy Food, Crime and Violence, Environmental Conditions, Quality of Housing</td>
<td>Chicago Department of Housing, Chicago Department of Public Health, Illinois Department of Public Health</td>
</tr>
<tr>
<td></td>
<td>Mortality</td>
<td>Heart-related death, Stroke death</td>
<td>Chicago Health Atlas, UIC School of Public Health</td>
</tr>
<tr>
<td></td>
<td>Morbidity</td>
<td>Asthma, Hypertension, Diabetes, Obesity</td>
<td>Chicago Health Atlas, UIC School of Public Health</td>
</tr>
<tr>
<td></td>
<td>Behaviour</td>
<td>Smoking</td>
<td>Chicago Health Atlas, UIC School of Public Health</td>
</tr>
<tr>
<td>UNDP IHDI</td>
<td>Long and healthy life</td>
<td>Life expectancy at birth</td>
<td>U.S. Census Bureau</td>
</tr>
<tr>
<td>Knowledge</td>
<td>Expected years of schooling</td>
<td>Chicago Public School System</td>
<td></td>
</tr>
<tr>
<td>-----------</td>
<td>----------------------------</td>
<td>-----------------------------</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean years of schooling</td>
<td>Illinois State Board of Education</td>
<td></td>
</tr>
<tr>
<td>Standard of living</td>
<td>Gross National Income (GNI) per capita</td>
<td>U.S. Census Bureau</td>
<td></td>
</tr>
</tbody>
</table>

After deriving scores for each of the four social vulnerability indices used in this assessment, the final step involved composite scoring the results. This first required that the results be normalised to a common scoring scale of “0.000” (lowest score equating to lowest social vulnerability) to “1.000” (highest score equating to highest social vulnerability). Three of the four indices selected were already based on this scale; the UIC RFS scores community areas on a “-2.000” (lowest score equating to lowest social vulnerability) to “2.000” (highest score equating to highest social vulnerability), which required that these scores be adjusted. The composite score is based on arithmetic mean, with scores from the four indices for each Chicago community area (CCA) averaged as expressed in the following equation:

\[
Composite_{CCA} = \frac{1}{4} \times [SVI + SDOH + (-0.25 \times RFS + 0.5) + IHDI]_{CCA}
\]

Workforce Exposure

Public health intervention strategies intended to limit human interactions that might transmit the novel coronavirus have resulted in numerous industries designated as “non-essential” being temporarily shut down (Jiang, 2020). For those industries designated as “essential” to basic societal functions and that have thus remained open, the workforces that facilitate these resources and services have been subjected to greater demands, increased stress, and higher potential risks due to the pandemic. Many within the essential category can be further designated as “frontline” workforces, which continue to interact with colleagues and customers in settings that may not allow for adequate social distancing (McKinsey & Company, 2020). These settings present a “situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas” (UNDRR, 2021). In the context of workforce exposure, the “hazard-prone areas” are those settings where work is performed that brings essential and frontline workforces into frequent or close contact with customers, patients, and other members of the workforce, which increases the risk of transmission. If transmissions of the novel coronavirus across these essential and frontline workforces are widespread, the basic societal functions that they maintain may be degraded or disrupted, which could have even greater consequences for both pandemic response and recovery, as well as overall community resilience.

The approach used to assess workforce exposure to COVID-19 and potentially negative public health outcomes involved the following seven steps.

Establishing Baseline Workforce Representations

A baseline workforce representation was first developed to serve as a pre-pandemic reference of the economic profile of each county in the United States. This baseline workforce representation enabled analysts to identify which industry sectors are located in each county, the number of businesses operating in these sectors, the number of people these employ, and the total wages they earn. Data on the number of businesses, employees, and wage levels are available from the U.S. Bureau of Labor Statistics’ Quarterly Census of Economic Wages.
(QCEW) for each North American Industrial Classification System (NAICS) code, which classifies business establishments for the purpose of analysing the U.S. business economy. (U.S. Bureau of Labor Statistics, 2020; U.S. Census Bureau, 2020[a]). The QCEW contains data on each Micropolitan Statistical Area (MicroSA), Metropolitan Statistical Area (MSA), Core-Based Statistical Area (CBSA), and Combined Statistical Area (CSA) in the United States (Office of Management and Budget, 2000; U.S. Census Bureau, 2006).

Delineating “Essential” and “Frontline” Workforces

With a baseline workforce representation for each county and statistical area in the United States identified, these representations were then further delineated by those industries and workforces designated as “essential” or “frontline.” Although no single, authoritative definition of what constitutes these categories existed before the pandemic, the U.S. Department of Homeland Security (DHS) Cybersecurity and Infrastructure Security Agency (CISA) developed its Guidance on the Essential Critical Infrastructure Workforce to assist state, local, tribal, and territorial public health agencies in identifying essential and frontline workforces for COVID-19 response and recovery purposes. The CISA guidance identifies 18 broad workforce categories, including healthcare and public health; law enforcement, public safety, and other first responders; education; food and agriculture; as well as workforces in the critical infrastructure sectors and manufacturing industries (CISA, 2020).

Identifying Essential Workforce Demographic Information

County-level workforce characterisations were then developed using workforce demographic data collected through the U.S. Census Bureau’s American Community Survey (ACS) (U.S. Census Bureau, 2020[b]). The ACS is an annual survey that collects socio-economic information by household. In addition to publishing tabulated subsets of ACS data, the U.S. Census Bureau also publishes Public Use Microdata Samples (PUMS) data, which contain sample records of collected ACS responses (U.S. Census Bureau, 2019). PUMS records are identified geographically using Public Use Microdata Areas (PUMAs), which are statistical areas containing at least 100,000 people and comprised of census tracts (U.S. Census Bureau, 2020[c]). This analysis used the following attributes from the PUMS dataset:

- Public Use Microdata Area (PUMA) code;
- Person weight (PWGTP);
- Age (AGEP);
- Disability recode (DIS);
- Employment status recode (ESR);
- Health insurance coverage recode (HICOV); and
- NAICS recode (NAICSP).

In addition to the well-documented correlation between COVID-19 fatality rate and age, disability status and health insurance coverage status are assumed to affect the overall impact of COVID-19 on employees. However, it should be noted that disability status and health insurance coverage are not intended to represent all potential co-morbidities in this study, but rather are assumed to be proxies for pre-existing health conditions affecting the likelihood of contracting COVID-19 and on negative public health outcomes associated with COVID-19, including time to recover and return to the workforce.²

² The inclusion of health insurance as a variable in the exposure risk assessment reflects the absence of universal health coverage at the national level in the United States. Researchers
Within the PUMS dataset, PWGTP represents the person sample weight of records (U.S. Census Bureau, 2020[c]). As such, it is the primary record attribute against which all other attributes from the PUMS dataset were delineated in this analysis. Given the focus of this assessment on the workforce, the ESR code was first used to filter PUMS records corresponding to individuals not in the workforce. The workforce size (WS) within each PUMA—delineated by age, disability status, health insurance coverage, and industry segment—was assessed by summing the PWGTP of all records corresponding to individuals in the workforce within each delineation. The WS was then aggregated into age groups (AGs), as shown in the following equation:

\[ WS_{PUMA,AG,DIS,HICOV,NAICSP} = \sum_{AGEP \text{ in } AG} WS_{PUMA,AGEP,DIS,HICOV,NAICSP} \]

**Mapping Workforce Data to Chicago Community Areas**

The next step in the analysis was to develop estimates of Chicago community area (CCA) workforce data using PUMA-level workforce data through a two-step process. First, WS data was estimated at the census tract (CT) level by scaling the workforce data at the PUMA-level using the ratio of the population in a census tract to that of the PUMA containing the census tract, as shown in the following equation:

\[ WS_{CT,AG,DIS,HICOV,NAICSP} = WS_{PUMA \text{ containing } CT,AG,DIS,HICOV,NAICSP} \left( \frac{Pop_{CT}}{Pop_{PUMA \text{ containing } CT}} \right) \]

Community area-level workforce data were then estimated by aggregating all census tracts in a community area, as shown in the following equation:

\[ WS_{CCA,AG,DIS,HICOV,NAICSP} = \sum_{CT \text{ in } CCA} WS_{CT,AG,DIS,HICOV,NAICSP} \]

**Projecting Workforce Exposure to COVID-19**

The assessment then combined the developed Chicago community area-level workforce characterisation with mapping of essential and frontline workforces to establish community area-level estimates of each workforce category that are at a risk of exposure to COVID-19. This essential workforce was further delineated based on the ability to maintain business operations remotely. Essential industry segments that were determined to be unable to maintain operations remotely were labelled as “frontline,” while all others were labelled as “essential.” All industry segments that were not labelled as “frontline” or “essential” were labelled as “non-essential.” This NAICS code mapping was then mapped against the NAICSP code in the ACS PUMS dataset. The size of frontline, essential, and non-essential workforces delineated by AG, DIS, and HICOV was determined by summing across NAICSP codes within each workforce category, as shown in the following equations:

---

interested in conducting a similar analysis in countries, regions, or local communities where universal health is available could replace this variable with alternative human development indicators.
WS_{Frontline}_{CCA,AG,DIS,HICOV} = \sum_{\text{Frontline NAICSP}} WS_{CCA,AG,DIS,HICOV,NAICSP}

WS_{Essential}_{CCA,AG,DIS,HICOV} = \sum_{\text{Essential NAICSP}} WS_{CCA,AG,DIS,HICOV,NAICSP}

WS_{Non-Essential}_{CCA,AG,DIS,HICOV} = \sum_{\text{Non-Essential NAICSP}} WS_{CCA,AG,DIS,HICOV,NAICSP}

Estimating Risk of Workforce Exposure

The assessment then estimated the risks posed to frontline, essential, and non-essential workforces in each Chicago community area using the demographic characteristics to five exposure categories (ECs): very high (EC=1), high (EC=2), moderate (EC=3), low (EC=4), and very low (EC=5). "Exposure" in this context is a qualitative valuation that refers to the aggregate potential direct and indirect impacts associated with the COVID-19 pandemic. Figure 2 illustrates the mapping of the workforce demographic characteristics to each workforce EC.

Figure 2. Notional Illustration of Workforce Exposure Categories

All demographic combinations comprising each EC were then aggregated to compute the size of the frontline, essential, and non-essential workforces in each community area falling in each EC, as shown in the following equations:

WS_{Frontline}_{CCA,EC} = \sum_{\text{(AG,DIS,HICOV) in EC}} WS_{Frontline}_{CCA,AG,DIS,HICOV}

WS_{Essential}_{CCA,EC} = \sum_{\text{(AG,DIS,HICOV) in EC}} WS_{Essential}_{CCA,AG,DIS,HICOV}

WS_{Non-Essential}_{CCA,EC} = \sum_{\text{(AG,DIS,HICOV) in EC}} WS_{Non-Essential}_{CCA,AG,DIS,HICOV}
Computing Risks of Workforce Exposure by Chicago Community Area

The final step of the analysis was to compute the percentage of the frontline, essential, and non-essential workforce in each Chicago community area that are at risk of exposure to novel coronavirus transmission that could lead to negative health outcomes. Specifically, the percentage of at-risk frontline, essential, and non-essential workforces in each community area were computed as the ratio of the sum of workforce identified as being at very high (EC=1) and high (EC=2) exposure risk to the total size of the frontline, essential, and non-essential workforce, as shown in the following equations:

\[
\% \text{ Risk}_{\text{Frontline}_{CCA}} = \frac{\sum_{EC\in[1,2]} WS_{\text{Frontline}_{CCA,EC}}}{\sum_{EC} WS_{\text{Frontline}_{CCA,EC}}}
\]

\[
\% \text{ Risk}_{\text{Essential}_{CCA}} = \frac{\sum_{EC\in[1,2]} WS_{\text{Essential}_{CCA,EC}}}{\sum_{EC} WS_{\text{Essential}_{CCA,EC}}}
\]

\[
\% \text{ Risk}_{\text{Non-Essential}_{CCA}} = \frac{\sum_{EC\in[1,2]} WS_{\text{Non-Essential}_{CCA,EC}}}{\sum_{EC} WS_{\text{Non-Essential}_{CCA,EC}}}
\]

Resource Accessibility

Understanding the design and operation of critical infrastructure assets that facilitate these resource supply chains is essential in order to identify local resource “deserts” and to bolster the coping capacities of these communities (OECD, 2019). The definition and list of critical infrastructure sectors vary across countries, but lifeline sectors (i.e., energy and water) as well as food and healthcare sectors are widely recognized as being critical across the globe (OECD, 2019). These infrastructure are critical because they facilitate the delivery of resources that directly support community well-being. Accessibility to these resources comprises the elements of local availability, ease of attainment, and choice between alternatives in where, when, how, and from whom the population served can acquire the resources (FAO, 2006; WHO, 2013). When emergencies challenge the “ability of people, organizations and systems, using available skills and resources, to manage adverse conditions,” the resulting disruptions in accessibility will acutely affect those communities in which coping capacity is already low (UNDRR, 2021). As evident in the COVID-19 pandemic, low accessibility to those resources that support public health may exacerbate systemic risks, leading to a higher potential for exposure to the novel coronavirus and negative public health outcomes.

The approach used to assess community-level resource accessibility and identify resource deserts that reduce coping capacities to mitigate the hazards presented by the pandemic involved the following five steps.

Selecting Resources for Assessment

The first step involved identifying resources that play an important role in supporting coping capacities to the public health hazards presented by the pandemic. This analysis focused on food and healthcare resource accessibility, including local grocery stores, hospitals, and pharmacies that constitute the interface between the critical infrastructure that facilitate the
distribution of these resources and the Chicago community areas served. Although a number of similar resources are critical in supporting coping capacities associated with community resilience, these were selected due to the particular stresses that these infrastructure have operated under throughout the COVID-19 pandemic (Parrella-Aureli, 2021; Ihejirika, 2020).

Identifying Critical Infrastructure Facilitating Resource Supply Chains

The second step involved locating and characterising the grocery stores, hospitals, and pharmacies that fulfil resource supply needs for local communities in Chicago. Data on these critical infrastructure assets, systems, and customer bases was collected from three sources.

- **Asset-level data on points of resource distribution:** open-source datasets (Chicago Health Atlas, 2021), government databases (U.S. Department of Homeland Security, 2021), and geographic information system (GIS) layers (Esri, 2021[a]) on the locations and capacities of grocery stores, pharmacies, and hospitals.
- **System-level data on supply chain management:** information on sector-level operations to understand the design and operation of distribution systems for food and healthcare resource supplies (Chicago Metropolitan Agency for Planning, 2018), as well as the road transportation dataset for the City of Chicago (Esri, 2021[a]).
- **Community-level data on aggregated local needs:** population characteristics, including size, density, and rates of car ownership, for Chicago community areas (U.S. Census Bureau, 2020[b]; Esri, 2021[a]).

This information was compiled in a geo-coded database, which includes descriptions of data attributes, field names, and links to specific databases at a detailed level to support geoprocessing and visualisation.

Modelling Critical Infrastructure Service Areas

The third step involved applying geospatial analysis to define the service areas of identified grocery stores, pharmacies, and hospitals (Esri, 2021[a]). Esri ArcGIS modelling software and its travel-time analysis algorithms and the locations of these assets and the local road network dataset were used to determine the local travel times required to reach the assets from the surrounding communities (Esri, 2021[b]; Esri, 2021[c]). The travel-time algorithms also enable analysts to consider different restriction factors, such as the time of day, the mode of transportation, travel direction, and preferred roads (Esri, 2021[c]).

The results of this travel-time analysis provides a GIS visualisation of the area surrounding each grocery store, pharmacy, or hospital that is accessible to the local community within specified travel times. Figure 3 illustrates an example of the aggregation of polygons representing various travel times required to access specific infrastructure assets facilitating the distribution of critical resources.

---

3 For example, another potentially useful application of this methodology would be to assess accessibility to vaccination sites in order to inform governance strategies that target the most vulnerable populations and maximize the coverage of local vaccination programs.
On the left side of Figure 3, the purple icons represent the locations of critical infrastructure assets where consumers can access resources. On the right side of Figure 3, the polygon shapes derived from the modelling represent local service areas of each of those critical infrastructure assets defined for three travel times required to reach these assets: 2-minute drive time in blue, 5-minute drive time in green, and 10-minute drive time in orange.

Figure 3 illustrates that the population of nearly every community in the City of Chicago can access the resources provided by local critical infrastructure assets within a short drive time. When considering the critical infrastructure asset locations independently from other criteria, it may appear that the resource distribution system is sufficient to fulfil the population’s needs. However, when additional demographic components are included in the analysis in the following step, this seemingly even distribution is further contextualized by the elements of density, redundancy, alternatives, and choice.

Assessing Accessibility “Hot” and “Cold Spots”

The fourth step involved performing spatial joining of demographic data with the service areas modelled for each critical infrastructure asset. The local drive-time polygons were clustered with demographic data to conduct a geospatial “hot” and “cold” spots analysis that compares levels of accessibility to essential resources based on communities’ characteristics across the city. Figure 4 illustrates results for the spatial joining of the data and outputs from Figure 3 for local infrastructure assets.
The concentration of assets within a given travel time are illustrated on the left side of Figure 4. Areas highlighted in red indicate the neighbourhoods with a higher concentration of assets providing resources, and areas highlighted in blue indicate the neighbourhoods with a lower concentration of assets. On the right side of Figure 4, local population density and the local drive-time areas are spatially joined to characterise and compare overall resource accessibility. Areas highlighted in red (“hot spots”) can be characterised as having a high population density with a high concentration of assets, meaning that these areas have access to multiple assets where the resource can be acquired. Areas highlighted in blue (“cold spots”) can be characterised as having a high population density with a low concentration of assets. The GIS analysis presented in Figure 4 illustrates the importance of combining social and technical criteria to characterise resources accessibility, allowing analysts to more accurately identify the potential gaps in density, redundancy, alternatives, and choice between communities in terms of resource accessibility.

**Composite Scoring Resource Accessibility Assessment Results**

After deriving scores for grocery, pharmacy, and hospital accessibility analyses used in this assessment, the final step involved composite scoring the results. The composite score is based on arithmetic mean, with scores from the three indices for each Chicago community area (CCA) averaged as expressed in the following equation:

\[
Composite_{CCA} = \frac{1}{3} \times [Grocery + Pharmacy + Hospital]_{CCA}
\]
Assessment Results: Case Study on the City of Chicago

In March 2020, the National Virtual Biotechnology Laboratory (NVBL) within the U.S. Department of Energy’s Office of Science enlisted a team of national laboratory researchers to analyse the effectiveness of public health interventions in “flattening the curve” of disease cases in the United States (DOE, 2020). The Joint Project on Pandemic Modelling and Analysis Capability built on existing agent-based modelling, risk assessment methodologies, and predictive economic modelling capabilities, coupled with high-performance computing resources, developed and managed by the national laboratories for epidemiological modelling (DOE, 2021).

The project integrated these capabilities and resources in order to address questions of critical importance for informing governance strategies that reduce systemic risks and foster community resilience in light of the pandemic’s impacts:

- Where are disease cases trending toward potential future waves at national and local levels?
- What underlying factors account for why some communities face higher rates of negative public health outcomes?
- Which public health interventions are proving to be most effective in reducing disease cases?
- How should this information drive decisions on pandemic response and recovery strategies?

This section presents a summary of the assessments conducted by the Argonne National Laboratory research team on the City of Chicago in support of this project. Results for the social vulnerability, workforce exposure, and resource accessibility assessments were derived for each of Chicago’s 77 community areas, which represent geographic areas used for statistical and planning purposes by the city (City of Chicago, 2010). These assessment results were also incorporated into epidemiological modelling process to inform local decision making with regard to mask mandates, economic re-opening, and vaccine distribution strategies (Macal et al., 2021).

Social Vulnerability Assessment Results

Figure 5 illustrates the scores from the four social vulnerability indices consulted as part of this assessment for all Chicago community areas, with darker shades of blue indicating community areas with higher social vulnerability scores.

Table 2 lists the community areas with the highest composite social vulnerability scores across the four indices. The scores for each index and the final composite score are presented on a one-point scale (i.e., 0.000 to 1.000), with higher scores representing higher social vulnerability (CDC, 2020[b]; HHS, 2020[b]; UNDP, 2020[b]; Kim, 2020[b]).
Figure 5. Social Vulnerability Scores Derived from the CDC SVI (top left), HHS SDOH (top right), UNDP IHDI (bottom left), and UIC RFS (bottom right) for Chicago Community Areas.
Table 2. Chicago Community Areas with the Highest Social Vulnerability Scores

<table>
<thead>
<tr>
<th>Community Area</th>
<th>SVI Score</th>
<th>SDOH Score</th>
<th>IHDI Score</th>
<th>RFS Score</th>
<th>Composite Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Riverdale</td>
<td>0.903</td>
<td>0.883</td>
<td>0.861</td>
<td>0.866</td>
<td>0.878</td>
</tr>
<tr>
<td>Englewood</td>
<td>0.943</td>
<td>0.802</td>
<td>0.796</td>
<td>0.932</td>
<td>0.868</td>
</tr>
<tr>
<td>West Garfield Park</td>
<td>0.945</td>
<td>0.789</td>
<td>0.741</td>
<td>0.923</td>
<td>0.849</td>
</tr>
<tr>
<td>East Garfield Park</td>
<td>0.912</td>
<td>0.797</td>
<td>0.772</td>
<td>0.91</td>
<td>0.848</td>
</tr>
<tr>
<td>Washington Park</td>
<td>0.892</td>
<td>0.753</td>
<td>0.818</td>
<td>0.874</td>
<td>0.834</td>
</tr>
<tr>
<td>Oakland</td>
<td>0.854</td>
<td>0.78</td>
<td>0.854</td>
<td>0.802</td>
<td>0.822</td>
</tr>
<tr>
<td>North Lawndale</td>
<td>0.87</td>
<td>0.754</td>
<td>0.75</td>
<td>0.858</td>
<td>0.808</td>
</tr>
<tr>
<td>Greater Grand Crossing</td>
<td>0.838</td>
<td>0.77</td>
<td>0.782</td>
<td>0.818</td>
<td>0.802</td>
</tr>
<tr>
<td>West Englewood</td>
<td>0.871</td>
<td>0.76</td>
<td>0.689</td>
<td>0.86</td>
<td>0.795</td>
</tr>
<tr>
<td>Fuller Park</td>
<td>0.888</td>
<td>0.802</td>
<td>0.628</td>
<td>0.851</td>
<td>0.792</td>
</tr>
<tr>
<td>Woodlawn</td>
<td>0.867</td>
<td>0.749</td>
<td>0.66</td>
<td>0.859</td>
<td>0.784</td>
</tr>
<tr>
<td>South Deering</td>
<td>0.884</td>
<td>0.713</td>
<td>0.599</td>
<td>0.908</td>
<td>0.776</td>
</tr>
<tr>
<td>South Shore</td>
<td>0.838</td>
<td>0.729</td>
<td>0.721</td>
<td>0.813</td>
<td>0.775</td>
</tr>
<tr>
<td>South Chicago</td>
<td>0.872</td>
<td>0.731</td>
<td>0.64</td>
<td>0.837</td>
<td>0.77</td>
</tr>
<tr>
<td>Austin</td>
<td>0.87</td>
<td>0.703</td>
<td>0.632</td>
<td>0.833</td>
<td>0.759</td>
</tr>
<tr>
<td>Armour Square</td>
<td>0.91</td>
<td>0.762</td>
<td>0.402</td>
<td>0.902</td>
<td>0.744</td>
</tr>
<tr>
<td>Chicago Lawn</td>
<td>0.881</td>
<td>0.714</td>
<td>0.519</td>
<td>0.854</td>
<td>0.742</td>
</tr>
<tr>
<td>Burnside</td>
<td>0.836</td>
<td>0.787</td>
<td>0.528</td>
<td>0.818</td>
<td>0.742</td>
</tr>
<tr>
<td>Humboldt Park</td>
<td>0.891</td>
<td>0.648</td>
<td>0.525</td>
<td>0.906</td>
<td>0.742</td>
</tr>
<tr>
<td>New City</td>
<td>0.848</td>
<td>0.724</td>
<td>0.539</td>
<td>0.801</td>
<td>0.728</td>
</tr>
</tbody>
</table>

The community areas that ranked in this highest quartile by composite social vulnerability score listed in Table 2 are primarily located on the city’s west, south, southwest, far southwest, and far southeast sides. With regard to the conditions associated with high social vulnerability, these community areas scored particularly high on a common sub-set of indicators:

- **Socioeconomic status.** These community areas generally have higher poverty rates, higher unemployment rates, and lower household income compared to the city averages (CDC, 2020[b]; UNDP, 2020[b]; U.S. Bureau of Labor Statistics, 2020).
- **Educational attainment.** Although Chicago Public Schools set a record-high graduation rate of 82.5% in 2020, significantly lower high school graduation rates for adults were particularly evident in these community areas (Chicago Public Schools, 2020[a] and [b]).
- **Quality of housing.** These community areas generally have some of the lowest home ownership rates and highest densities of multi-unit rental structures in the city (CDC, 2020[b]; City of Chicago, 2021[a]).
- **Incidence of co-morbidities.** These community areas were found to have among the city’s highest rates of pre-existing health conditions associated with higher risks of
negative COVID-19 public health outcomes, including asthma and hypertension (Chicago Health Atlas, 2021; Kim, 2020[b]).

The results revealed stark disparities in the conditions attributed to higher social vulnerability that exist in these community areas compared to more affluent community areas on the city’s north side. The results are also consistent with disparities in the observed rates of disease cases across the city, as “clusters of high and low positivity and confirmed cases were mostly co-located with clusters of high and low vulnerability, respectively” (Bilal et al., 2021).

**Workforce Exposure Assessment Results**

Figure 6 illustrates the percentages of frontline and essential workforces that were assessed to be at “very high” (EC=1) and “high” (EC=2) exposure risk for all Chicago community areas, with darker shades of blue indicating higher percentages of those workforces in both exposure categories. Table 3 lists the community areas assessed to have the largest individual and combined frontline and essential workforces in both exposure categories.

*Figure 6. Workforce Exposure Scores for Frontline Workers (left) and Essential Workers (right) for Chicago Community Areas.*
Table 3. Chicago Community Areas with the Highest Percentages of Workforce Exposure Risks.

<table>
<thead>
<tr>
<th>Community Area</th>
<th>Frontline Workforce at Highest Exposure Risk (%)</th>
<th>Essential Workforce at Highest Exposure Risk (%)</th>
<th>Combined Workforces at Highest Exposure Risk (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edison Park</td>
<td>16.71</td>
<td>18.08</td>
<td>17.69</td>
</tr>
<tr>
<td>Norwood Park</td>
<td>16.65</td>
<td>17.87</td>
<td>17.52</td>
</tr>
<tr>
<td>O'Hare</td>
<td>16.18</td>
<td>16.45</td>
<td>16.38</td>
</tr>
<tr>
<td>Forest Glen</td>
<td>15.16</td>
<td>15.07</td>
<td>15.09</td>
</tr>
<tr>
<td>Irving Park</td>
<td>15.16</td>
<td>15.07</td>
<td>15.09</td>
</tr>
<tr>
<td>North Park</td>
<td>15.16</td>
<td>15.07</td>
<td>15.09</td>
</tr>
<tr>
<td>Albany Park</td>
<td>15.16</td>
<td>15.07</td>
<td>15.09</td>
</tr>
<tr>
<td>Auburn Gresham</td>
<td>16.36</td>
<td>14.09</td>
<td>14.73</td>
</tr>
<tr>
<td>Burnside</td>
<td>16.36</td>
<td>14.09</td>
<td>14.73</td>
</tr>
<tr>
<td>Roseland</td>
<td>16.36</td>
<td>14.09</td>
<td>14.73</td>
</tr>
<tr>
<td>Chatham</td>
<td>16.36</td>
<td>14.09</td>
<td>14.73</td>
</tr>
<tr>
<td>Avalon Park</td>
<td>16.36</td>
<td>14.09</td>
<td>14.73</td>
</tr>
<tr>
<td>Jefferson Park</td>
<td>15.62</td>
<td>14.29</td>
<td>14.63</td>
</tr>
<tr>
<td>Portage Park</td>
<td>15.62</td>
<td>14.29</td>
<td>14.63</td>
</tr>
<tr>
<td>Dunning</td>
<td>15.62</td>
<td>14.29</td>
<td>14.63</td>
</tr>
<tr>
<td>Greater Grand Crossing</td>
<td>18.34</td>
<td>13.21</td>
<td>14.48</td>
</tr>
<tr>
<td>Englewood</td>
<td>18.34</td>
<td>13.21</td>
<td>14.48</td>
</tr>
<tr>
<td>Chicago Lawn</td>
<td>18.34</td>
<td>13.21</td>
<td>14.48</td>
</tr>
<tr>
<td>West Englewood</td>
<td>18.34</td>
<td>13.21</td>
<td>14.48</td>
</tr>
<tr>
<td>South Deering</td>
<td>14.22</td>
<td>14.23</td>
<td>14.23</td>
</tr>
</tbody>
</table>

It is noteworthy that a statistically significant portion of the workforce in every community area of the city, from 5.75% at the low end of the range to 17.69% at the high end, consists of essential and frontline workforces in these exposure risk categories. The community areas that ranked in the highest quartile listed in Table 3 are primarily located on the city’s northwest, south, far southwest, and far southeast sides. The industries represented by workforces in these community areas, however, illustrates some disparities. On the city’s northwest side, essential and frontline workforces were five times more likely to be employed in healthcare and public safety than the city average (U.S. Bureau of Labor Statistics, 2020). On the city’s south, far southwest, and far southeast sides, essential and frontline workforces were five times more likely to work in customer service and logistics (U.S. Bureau of Labor Statistics, 2020). The differences in corresponding income levels carries importance for the interrelated social vulnerability attribute of socioeconomic status, for which the latter group scored significantly higher.

Resource Accessibility Assessment Results

Figure 7 illustrates the resource accessibility scores for the three critical infrastructure assessed along with composite scores for all Chicago community areas, with darker shades of blue indicating community areas with lower resource accessibility. Table 4 lists the community areas that scored the highest individual and composite resource accessibility
scores presented on a one-point scale, with higher scores representing lower resource accessibility.

Figure 7. Resource Accessibility Scores for Local Grocery Stores (top left), Pharmacies (top right), Hospitals (bottom left), and Composite Scores (bottom right) for Chicago Community Areas.
Table 4. Chicago Community Areas with the Lowest Resource Accessibility Scores.

<table>
<thead>
<tr>
<th>Community Area</th>
<th>Hospital Accessibility</th>
<th>Pharmacy Accessibility</th>
<th>Grocery Accessibility</th>
<th>Composite Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>South Chicago</td>
<td>0.954</td>
<td>0.903</td>
<td>0.925</td>
<td>0.927</td>
</tr>
<tr>
<td>East Side</td>
<td>0.973</td>
<td>0.896</td>
<td>0.910</td>
<td>0.926</td>
</tr>
<tr>
<td>Riverdale</td>
<td>0.961</td>
<td>0.886</td>
<td>0.903</td>
<td>0.917</td>
</tr>
<tr>
<td>West Pullman</td>
<td>0.880</td>
<td>0.911</td>
<td>0.945</td>
<td>0.912</td>
</tr>
<tr>
<td>South Deering</td>
<td>0.949</td>
<td>0.880</td>
<td>0.890</td>
<td>0.906</td>
</tr>
<tr>
<td>Calumet Heights</td>
<td>0.925</td>
<td>0.895</td>
<td>0.886</td>
<td>0.902</td>
</tr>
<tr>
<td>South Shore</td>
<td>0.941</td>
<td>0.890</td>
<td>0.867</td>
<td>0.899</td>
</tr>
<tr>
<td>Mount Greenwood</td>
<td>0.854</td>
<td>0.880</td>
<td>0.952</td>
<td>0.896</td>
</tr>
<tr>
<td>Avalon Park</td>
<td>0.920</td>
<td>0.894</td>
<td>0.863</td>
<td>0.892</td>
</tr>
<tr>
<td>Hegewisch</td>
<td>1.000</td>
<td>0.832</td>
<td>0.843</td>
<td>0.892</td>
</tr>
<tr>
<td>Pullman</td>
<td>0.862</td>
<td>0.894</td>
<td>0.918</td>
<td>0.891</td>
</tr>
<tr>
<td>Morgan Park</td>
<td>0.847</td>
<td>0.872</td>
<td>0.943</td>
<td>0.887</td>
</tr>
<tr>
<td>Roseland</td>
<td>0.827</td>
<td>0.904</td>
<td>0.903</td>
<td>0.878</td>
</tr>
<tr>
<td>Beverly</td>
<td>0.807</td>
<td>0.865</td>
<td>0.935</td>
<td>0.869</td>
</tr>
<tr>
<td>Woodlawn</td>
<td>0.829</td>
<td>0.930</td>
<td>0.837</td>
<td>0.865</td>
</tr>
<tr>
<td>Burnside</td>
<td>0.855</td>
<td>0.876</td>
<td>0.839</td>
<td>0.857</td>
</tr>
<tr>
<td>West Englewood</td>
<td>0.695</td>
<td>0.963</td>
<td>0.909</td>
<td>0.856</td>
</tr>
<tr>
<td>Hyde Park</td>
<td>0.765</td>
<td>0.916</td>
<td>0.886</td>
<td>0.856</td>
</tr>
<tr>
<td>Washington Park</td>
<td>0.710</td>
<td>0.952</td>
<td>0.900</td>
<td>0.854</td>
</tr>
<tr>
<td>Englewood</td>
<td>0.713</td>
<td>0.967</td>
<td>0.871</td>
<td>0.850</td>
</tr>
</tbody>
</table>

The Chicago community areas that ranked in the lowest quartile by composite score are primarily located on the city’s west, south, southwest, far southwest, and far southeast sides. Identification of these food and healthcare deserts demonstrates that, although a community area may be within a short travel time to at least one local grocery store, pharmacy, or hospital, inequities in resource accessibility may nevertheless exist due to a lack of density, redundancy, alternatives, and choice. A community area that is served by a single critical infrastructure asset faces an antecedent systemic risk of resource supply disruptions that could result from the pandemic with few if any other local options (Lewis and Petit, 2019; UNDRR, 2017).

This assessment also confirmed the positive correlation between conditions of high social vulnerability and low access to food and healthcare resources in these community areas (Kolak et al., 2018; USDA, 2017). Conditions in these community areas can be uniquely characterised by “more poverty, air pollution, extreme heat and flood damage, and less access to health care and food — all factors that make residents more vulnerable to the coronavirus” (Deaton and Oladipo, 2020).
Summary of Assessment Results

The social vulnerability, workforce exposure, and resource accessibility assessment results present several important dimensions through which a local community’s risk profile and resilience posture can be understood. This effort focused on these individually in light of the unique data types and analytic approaches required to assess each component. However, it is crucial to note that these three dimensions are interrelated and involve variables that are mutually inclusive.

- A community’s social vulnerability is, in part, influenced by socioeconomic factors, including whether its members are employed in essential and frontline workforces that might face higher risks of exposure (CDC, 2020[b]).
- The risk of exposure that workforces face is, in part, influenced by the extent to which community members have more choices in where to access resources that reduce crowding (Parrella-Aureli, 2021).
- The local accessibility of resources provides the community with greater coping capacities that, in part, influence the community’s overall social vulnerability (Kolak et al., 2018).

To best inform governance strategies that address systemic risks and community resilience, the results of these and other assessments of risk and resilience should be taken together to produce a more comprehensive understanding of the interplay between these community characteristics and the extent to which these might multiply risks.

The results illustrated that several Chicago community areas on the city’s west, south, southwest, far southwest, and far southeast sides consistently scored in the lowest quartile of the city. This assessment focused on a quantification of systemic risk and community resilience; however, it is essential for decision makers to consider contextual issues that may account for why these communities face greater challenges.

- These community areas’ demographic makeups are predominantly racial and ethnic minorities, as well as immigrant communities, compared with majority white community areas that scored better across each of the assessments (U.S. Census Bureau, 2020[b]).
- Historic disparities in housing policies play a significant role, as “segregation in Chicago is distinct, and most metrics of stability in which there is a large gap between Black and white populations—homeownership, education, health access—can be traced back to redlining” (Husain et al., 2020).
- Negative public health outcomes appear to track to conditions of poverty, as the “pandemic’s economic fallout has had a devastating and disproportionate impact on the rights of low-income people who were already struggling” (Root and Simet, 2021).

Data on positivity rates and disease cases coincides with these observations and the assessment results. As of January 2021, 10 of the community areas listed in Tables 2, 3, and 4 rank in the top 15 community areas by cumulative COVID-19 incidence rates. Residents in these overall “high vulnerability community areas have been almost 3 times as likely to have died from COVID-19 as low vulnerability community areas” (City of Chicago, 2021[c]).
Lessons Learned and Discussion

The socio-technical assessment framework presented in this paper was implemented to provide data and outputs in support of epidemiological modelling to forecast and visualise COVID-19 transmission rates and dynamics in near-real time. However, the design of this assessment framework proposes a structured and repeatable approach to reducing systemic risks and informing community resilience enhancement strategies in other contexts as well. The proposed multidisciplinary approach combined social sciences, engineering, and GIS techniques to define social, economic, and technical dimensions. The development of a transdisciplinary knowledge process provides a foundation for understanding antecedent and evolving vulnerability, exposure, and accessibility patterns resulting from the COVID-19 pandemic.

The following four lessons learned were identified in the course of completing the social vulnerability, workforce exposure, and resources accessibility assessments, comprising substantive, methodological, and strategic lessons learned for supporting pandemic response and recovery decision-making. These key findings also provide a basis that could inform systemic risk reduction strategies and, ultimately, community resilience enhancements to meet future challenges beyond the COVID-19 pandemic.

- **Lesson 1. Implementing a socio-technical assessment approach will improve the accuracy of predictive epidemiological modelling.** By augmenting the synthetic populations used in agent-based models and integrated in other epidemiological analysis environments with more realistic characterisations of workforces, critical infrastructure, and community specificities, researchers can improve the accuracy of predictive modelling. This augmentation will also provide policymakers with clearer views of which communities require unique assistance and a mandate to implement long-term change (Macal et al., 2020).

- **Lesson 2. Understanding disparities in vulnerability, exposure, and accessibility between demographic groups and geographic areas is critical in order to reduce systemic risks and foster community resilience.** The substantive key finding observed across the three assessments described in this report relates to disparity. These disparities correlate with broad socioeconomic dynamics, including differences in historic capital investments in communities' critical infrastructure and social support systems. Identifying and examining how and why demographic groups and geographic areas are impacted differently are critical steps in preparedness, response, and recovery to all hazards, from public health emergencies to the impacts of climate change on vulnerable communities. This key finding largely echoes those of the CDC and various other healthcare and public health agencies and experts over many decades: “[e]ither we are all protected, or we are all at risk.” (Institute of Medicine, 2002).

- **Lesson 3. Enhancing near real-time situational awareness of how pandemic conditions affect workforces, infrastructure, and communities can form the basis of emerging public health emergency detection capabilities.** Tracking how pandemic conditions affect workforces, infrastructure, and communities is crucial to formulating effective and immediate public health interventions. Enhancing this monitoring of impacts could also support the development of emerging public health emergency detection and forecasting capabilities in order to reduce the impacts of public health emergencies before they cross borders (Iskander and Bianchi, 2021).
• **Lesson 4. A framework assessment is required in order to inform systemic risk reduction.** The results demonstrated that understanding exposure helps us to understand vulnerability and, in turn, that understanding the risks posed by exposure and vulnerability helps us to understand the needs for resilience and sustainability. In order to inform risk reduction in the midst of a pandemic, both qualitative and quantitative assessments of these dynamics are crucial. Effective policy decisions in accordance with the goals articulated in the Sendai Framework for Disaster Risk Reduction must promote equitable, resilient, and sustainable solutions that benefit entire communities, regions, nations, and international constructs. By assessing the interaction between essential workforces, infrastructure systems, and the communities these serve, researchers can be equipped with the tools needed to reduce exposure, vulnerability, and risk, while building equity, resilience, and sustainability.

This paper identifies the processes and techniques used to ensure the reproducibility of the proposed methodology and its application to other communities. Although the study presented benefited from the use of numerous datasets solely available in the United States, the analytic framework proposes a process that can be applied worldwide.

The analytic framework is not limited to the collection of data characterising the social, economic, and technical dimensions of systemic risks. The analysis is very important to understand complex interactions between indicators and to fulfil existing knowledge gaps by developing the information and expertise needed to understand the dynamic effect of the pandemic and implement effective and efficient policy strategies. This approach may prove useful to inform the implementation of the United Nations framework for the immediate socio-economic response to COVID-19 (United Nations, 2020[a]) or the United Nations Comprehensive Response to COVID-19 (United Nations, 2020[b]).

The applicability of the analytic framework is not limited to the pandemic. This process remains valid for all types of systemic risk, including climate change, critical infrastructure cascading failures, or hybrid threats. Systemic risks are the result of interrelated factors constituting a system-of-systems that is constantly evolving. Socio-technical analysis processes such as the one proposed in this paper must be favoured, to understand the synergetic conditions contributing the systemic risks. Many communities and infrastructure systems are still generally operated according to models developed in the mid-20th century, in which public and private capital is contingent on immediate return on investments as opposed to long-term development and opportunity (WEF, 2020). One consequential result of this antiquated strategy is the prolonging of disparities between communities and neighbourhoods in terms of their access to services and resources that are critical to building both coping capacities and long-term economic opportunities. Although the pandemic has presented extreme hardships to communities across the world, these also present a unique opportunity to reflect, reimagine, and reset our urban planning strategies (WEF, 2020). The systemic risks also highlighted the need to integrate social, economic, technical, and environmental considerations if the world will ultimately reach the goals articulated in the United Nations 2030 Agenda for Sustainable Development (United Nations, 2015[b]).
Conclusion

The multidimensional challenges presented by the COVID-19 pandemic have resulted in widely disproportionate impacts across communities. The significant disparities in how systemic risks have affected communities and the extent to which communities are able to exercise resilience to the hazards presented by the pandemic necessitate governance strategies that address these inequities. Policymakers must continuously assess whether the governance strategies that have been implemented or are being contemplated will support effective pandemic response and recovery across all communities. These decisions should be shaped by socio-technical assessments that will enable local public health agencies to build a more complete understanding of how their communities are affected. It is critical that these strategies address disparities in vulnerability, exposure, and accessibility across communities. Near real-time situational awareness of how pandemic conditions immediately affect communities is crucial to the success of public health interventions. A multidisciplinary scientific assessment framework like the one proposed in this paper should inform governance strategies on effective, efficient, and equitable systemic risk reduction and community resilience enhancement.

Acknowledgments

Research was supported by the U.S. Department of Energy (DOE) Office of Science through the National Virtual Biotechnology Laboratory (NVBL), a consortium of DOE national laboratories focused on response to COVID-19, with funding provided by the Coronavirus CARES Act.
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