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Research and Applications

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The Community Vulnerability Compass: a novel, scalable approach for measuring and visualizing social determinants of health insights

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Abstract

Objectives: To determine whether a novel digital tool, the Community Vulnerability Compass (CVC), built using large datasets, can accurately measure neighborhood- and individual-level social determinants of health (SDOH) at scale. Existing SDOH indexes fall short of this dual requirement.

Materials and Methods: *Setting*: A cross-sectional study by Parkland Health (Parkland) and Parkland Center for Clinical Innovation (PCCI) to design, build, deploy, and validate CVC in Dallas County/across Texas (2018-2024). *Data Sources*: Parkland Electronic Health Records; population-level data from diverse national datasets. *Statistical Analysis:* CVC's Community Vulnerability Index (CVI), and 4 subindexes were used to classify all 18 638 Texas census-block groups as Very-High, High, Moderate, Low, and Very-Low social vulnerability. Individuals were assigned the vulnerability of their home address census-block group. CVC's classifications were compared against 3 existing SDOH neighborhood tools (Area Deprivation Index [ADI], Social Vulnerability Index [SVI], or Environmental Justice Index [EJI]) and validated against individual-level SDOH screening tools or Z-code documentation. Spearman rank correlation was used for neighborhood-level comparisons and precision/recall, for individual-level comparisons.

Results: Neighborhood-level CVI measurement of social vulnerability strongly correlated with EJI (r = 0.83), SVI (r = 0.82), and ADI (r = 0.79). Individual-level CVI measurement had higher recall than ADI (68% vs 39%, respectively; $P < .001$) and high recall across self-reported SDOH (77%-79.6%). Precision was highest for food needs (75.1%); lowest for safety needs (1.2%).

Discussion: CVC measured a cross-cutting range of neighborhood social vulnerabilities and accurately approximated individual-level SDOH, outperforming existing indexes.

Conclusion: CVC can be leveraged as an accurate and scalable SDOH digital measurement tool.

Lay Summary

Social needs (eg, lack of food or cars) affect health and wellbeing. Hospitals need to know which people have social needs in order to better assist them, quickly and easily, but they need tools to help them do this. Neighborhood indexes can help measure communities' and people's social needs. Existing indexes, however, miss some people or some needs. The Community Vulnerability Compass (CVC) was built to help solve this problem. CVC calculates 5 simple indexes covering a range of social needs and shows them on a user-friendly dashboard. In this study, we show that CVC measures social needs better than existing indexes. CVC can help communities who are trying to get better. Hospitals can also use CVC to assist vulnerable people with high social needs.

Key words: social determinants of health; healthcare disparities; social vulnerability; neighborhood indexes; health inequities.

Background and significance

Social determinants of health (SDOH) are key contributors to individuals' physical and mental wellbeing.[1,2] SDOH (eg, unstable housing and food insecurity) are linked to a higher likelihood of hospital readmission, poor medication adherence, and inappropriate utilization of health services, leading to excessive costs and outcome disparities, especially for chronic diseases (eg, diabetes, asthma, chronic kidney disease)[3–7] and maternal health.[8] Addressing SDOH is a U.S. public health priority and a key focus of the Healthy People 2030 initiative.[9] The Centers for Medicare and Medicaid Services (CMS) has made SDOH a strategic priority, especially following the conclusion of the Accountable Health Communities (AHC) initiative, which demonstrated that

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systematically screening for and addressing 5 key SDOH (housing instability, food insecurity, transportation, utility, and interpersonal safety)[10] among high-risk Medicare and Medicaid beneficiaries was associated with improvements in health outcomes, reductions in acute care services utilization, and costs savings.[11–15] CMS now requires healthcare providers to report SDOH data as part of the ongoing shift toward value-based payment.

To adapt to this new SDOH focus, healthcare delivery systems and public health entities need reliable measurement tools to efficiently integrate SDOH screening and interventions into their operations.

Due to the sheer number of SDOH (many individuals have more than one SDOH challenge), universal screening is a resource-intensive, time-consuming, and operationally challenging endeavor, as illustrated by the mixed adoption of such approaches when introduced in healthcare delivery systems.[16] A potential solution consists of using neighborhood-level indexes of social vulnerability as a scalable solution to approximate individual-level SDOH.[17] Existing indexes have been considered, including Area Deprivation Index (ADI, University of Wisconsin—Madison)[18,19]; Social Vulnerability Index (SVI), Centers for Disease Control and Prevention (CDC)[20]; and Environmental Justice Index (EJI, CDC).[21] ADI uses 17 census variables (eg, income, education, employment) to measure area vulnerability. SVI's 17-variables index measures communities' ability to handle disasters. EJI's 36-variables index measures the impact of environmental issues on health and fairness. Two major problems have arisen from use of these indexes as a scalable solution to assess community- and individual-level SDOH needs. First, neighborhood indexes have shown poor congruence with each other,[22] suggesting that they measure non-overlapping social risk constructs. Second, neighborhood indexes have demonstrated lackluster performance in identifying individual-level SDOH.[23] These 2 attributes are necessary for any tool intended for the dual purpose of measuring neighborhood- and individual-level SDOH and existing indexes' poor performance highlights the challenges of repurposing tools outside of their original intent. As a result, the need persists for scalable measurement tools that reliably assess both community- and individual-level health-related social risk.

Objectives

To address this gap, the Parkland Center for Clinical Innovation (PCCI), in collaboration with Parkland Health (Parkland), developed the Community Vulnerability Compass (CVC), a novel SDOH tool designed to comprehensively capture community- and individual-level social risk into a simple index combined with deep-dive capabilities, to provide transparent and actionable insights for community health equity initiatives, and to support the transition to value-based care. CVC integrates a broad range of clinically relevant SDOH data and metrics into a main index, the Community Vulnerability Index (CVI), which summarizes the interplay of relevant SDOH and health indicators into a simplified metric. CVI incorporates 4 meaningful and complementary subindexes (Household Essentials, Empowered People, Equitable Communities, and Good Health—Figure 1), which in turn comprise 26 individual SDOH indicators (eg, housing affordability, food insecurity, transportation access). All data can be drilled down to the census-block group.

This study goal was to assess how well CVC's components capture individuals' experiences of SDOH. Study objectives included (1) describing the methodology, development, and technical deployment of CVC and 2) validating CVC's performance at the neighborhood level, compared with existing neighborhood indexes, and at the individual level, compared with individual-level SDOH data.

Materials and methods

Study setting

Parkland, Dallas County's safety-net health system, and PCCI, a North Texas nonprofit specializing in data-driven innovation for underserved populations, partnered to leverage multiple public and private datasets to design, develop, deploy, and validate CVC in Dallas County and across Texas.

Study design and period

A cross-sectional study to build CVC (2018-2023) and validate it (September 2023 to June 2024).

Designing and building CVC

CVC was developed using the Healthy People 2030 SDOH framework,[9] to identify SDOH at the census-block group level, then roll up data to larger geographies (eg, census tracts, ZIP Codes, counties).

Data sources

Data were collected from the American Community Survey (ACS),[24] the Health and Transportation Index (H + T index),[25] the Environmental Protection Agency (EPA)'s Walkability Index,[26] USALEEP Life Expectancy,[27] PIAAC Literacy,[28] Air pollution from OpenWeather,[29] Greenspace from ParkServe,[30] and neighborhood safety data from Applied Geographic Solution's Crimerisk.[31] (Full variables list is available in Table S1.) Data sources were identified and selected by PCCI's experts in collaboration with Parkland Health and Dallas County's public health specialists, through an extensive literature review (including conference abstracts), along with expert input from a network of SDOH collaborators developed through PCCI's work on local, regional, state, and national initiatives to address health-related social needs. This expertise helped shape both the data sources selection and analytical approaches.

Data preprocessing and imputation

First, all variables/indicators were calculated at the census-block group level, then rolled up to the census tract, ZIP Code, and County levels using weighted averages, with weights either equally distributed or based on population size or number of households, depending on the variable. U.S Census Bureau crosswalk tables were used to map block groups, census tracts, ZIP Codes, and counties. Missing values were imputed using the weighted average of the nearest 3 geospatially neighboring census-block groups with valid data. Home addresses were geocoded and reverse geocoded, then assigned to the appropriate census-block group.

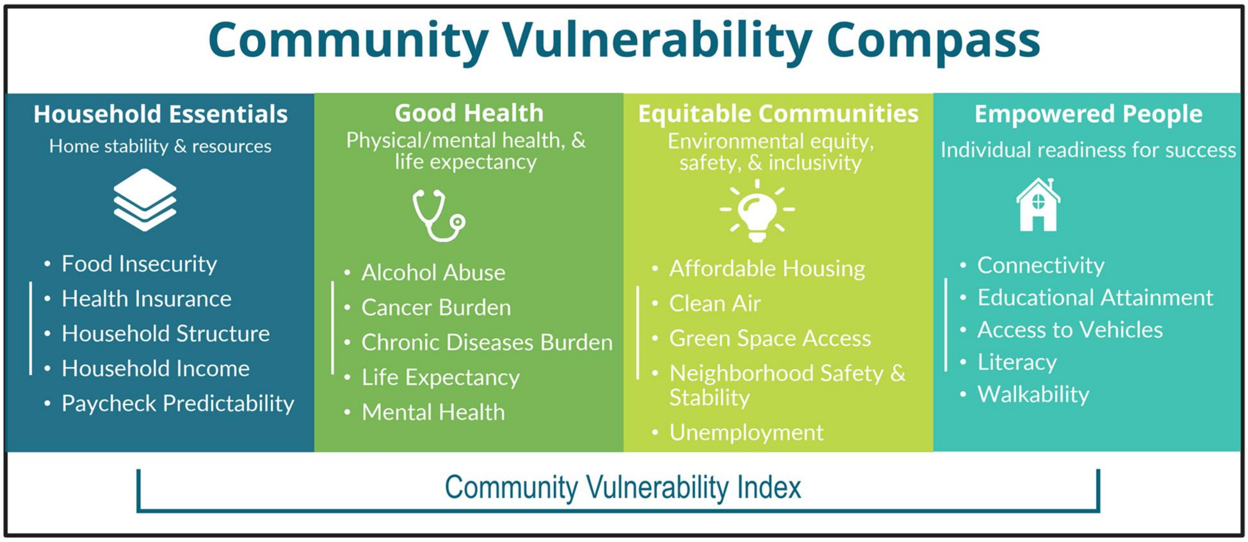

Figure 1. The Community Vulnerability Compass (CVC) framework outlines the overarching Community Vulnerability Index (CVI), the 4 subindexes (Household Essentials, Empowered People, Equitable Community, and Good Health) and the 26 social determinants of health (SDOH) indicators that are included in the indexes.

Operationalizing CVC indexes and indicators

CVC comprises a main index (CVI), 4 subindexes, and 26 indicators (Figure 1). The indicators were selected from over 200 initial variables using a combination of literature review, existing SDOH survey tools, Healthy People 2030 criteria, and PCCI expertise, including from its participation in the Dallas AHC.

The indicators were grouped into 4 meaningful and complementary SDOH domains to calculate the 4 subindexes. *Household Essentials* captures households' capacity to self-sustain (eg, food insecurity, paycheck predictability, household structure). *Good Health* reflects disease burden and wellness across a community (eg, chronic physical, mental, and behavioral health disorder prevalence, life expectancy). *Empowered People* includes enablers of stable, productive lives (eg, educational attainment, internet connectivity, transportation access). *Equitable Communities* encompasses elements of safe, vibrant neighborhoods required for thriving individuals and communities (eg, employment rates, affordable housing, neighborhood safety, green space).

For each geographical area, indicator raw data were processed using Box Cox transformation (Yeo-Johnson method)[32,33] to normalize data distribution. The transformed data were then scaled between 0 and 1, by subtracting the minimum value and dividing by the maximum value in the geographic distribution, with 0 representing the lowest level of vulnerability and 1, the highest. The 4 subindexes were calculated by averaging the scaled values of all appropriate indicators, then re-scaling the index values between 0 and 1 using the same approach described above. Indexes then were ranked and categorized into vulnerability quintiles: Very Low (0-20 percentile), Low (21-40 percentile), Moderate (41-60 percentile), High (61-80 percentile), and Very High (81-100 percentile). Quintiles were balanced to cover ∼20% of census-block group each, using CVI as a tie breaker for quintile assignment of overlapping subindex or indicator values. For instance, if multiple census-block groups had the same subindex values that overlapped 2 quintiles, the CVI value of each census-block group was used to decide which ones were assigned to the lower-risk quintile versus the higher-risk quintile. Quintile categorization simplifies data interpretation and visualization/mapping. Data scaling customized to end-users' geographical level of interest (eg, state, counties, ZIP Codes) is essential for actionable, localized insights and appropriate levels of data discreteness.

CVC data/technology integration and deployment

Figure 2 illustrates CVC's cloud-based technical architecture, data flow logic, and technology integration framework. CVC leverages Power Business Intelligence (Power BI) for advanced data visualization, while the underlying data flows through a custom cascading structure, which enables efficient data retrieval across multiple data sources, geographic levels, and variables. For seamless integration, Power BI pulls data directly from a Structured Query Language (SQL) server that houses all CVC data, which in turn are imported from the original data sources in near-real-time to ensure continuous data updates. All data analytics processes are automated within CVC's cloud-based digital data environment within Microsoft Azure infrastructure (Isthmus), which integrates all data modeling, complex calculations, and geographical rollup and rolldown, to generate the summary output. Isthmus includes a geocoding (through Geocodio API [geocode.io], pygeocodio [1.4.0]) and reverse geocoding technology, which assigns geographical-level attributes (census-block group Federal Information Processing System [FIPS] codes and census tract FIPS codes) to individual home addresses. The backend database and summary data, which display vulnerability quintiles and percentiles, can be seamlessly integrated with various systems, including visualization dashboards, customer relations management systems, and electronic health records. This integration is facilitated through customized application programming interfaces (APIs) and iFrames to create seamless integration of CVC to virtually any system. Front-end users get the benefit of leveraging the data insights for each person and address without delay or lag. The automated end-to-end technology and data integration provided by CVC are crucial for effective implementation across

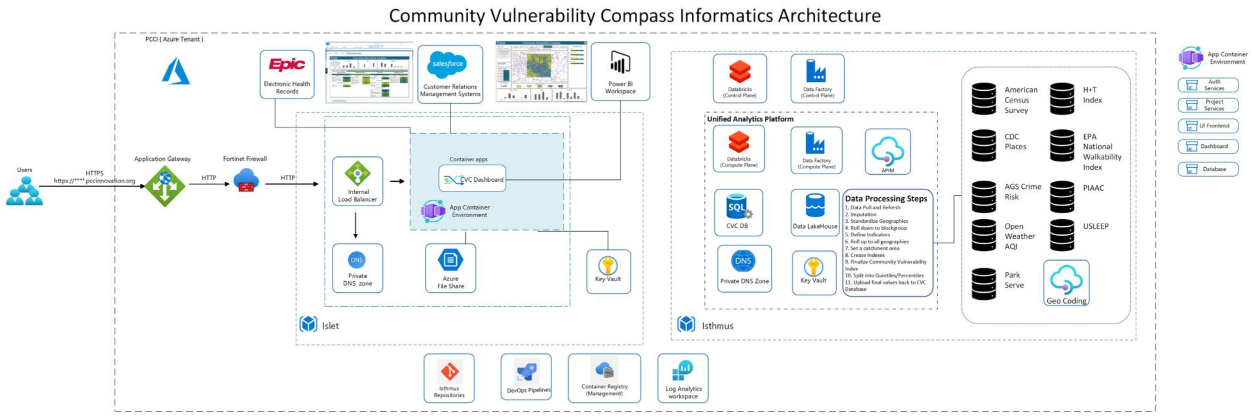

Figure 2. The Community Vulnerability Compass (CVC) cloud-based architecture collects data from various public and proprietary sources. Databricks is used for data processing. Azure Blob Storage and SQL databases are used for storage. CVC interfaces with diverse technologies, including electronic health records (eg, EPIC), Customer Relationship Management (CRM—eg, Salesforce), visualization tools (Power BI), and geocoding/reverse geocoding applications. Data processing steps are automated within the architecture, ranging from imputation to index creation and the output is integrated with above-mentioned end-user technologies.

diverse stakeholders for both geographical- and individual-level data insights.

The CVC dashboard consolidates CVI, the 4 subindexes, and the 26 indicators, each presented with vulnerability quintiles and percentile rankings as an added layer of transparency. CVC's choropleth map dynamically displays vulnerability quintiles using Power BI's hierarchical geographic slicer combined with demographic slicers. Users can access and visualize social vulnerability by seamlessly navigating across geographic layers and filtering data by specific SDOH indexes or indicators, exploring multiple social indicators simultaneously. Users also can zoom into areas with distinct characteristics, to gain insights into existing patterns of disparities and trends.

CVC's backend can be integrated with electronic health records (EHRs) and other healthcare technologies through APIs. Additionally, advanced geocoding and reverse geocoding technologies geocode individual home addresses to generate precise latitude and longitude coordinates, which are then reverse geocoded to identify the corresponding census-block group. Census block group CVC data are then attributed to the individual's home address and linked back with other individual-level data (eg, age, Z-codes) to create a comprehensive dataset incorporating social vulnerability insights alongside EHR and public health data.

CVC is currently integrated with Dallas County Health and Human Services (DCHHS) Client Relationship Management platform through API and a Power BI dashboard. Planned implementations include CVC integration into Epic EHR via Slicer Dicer or by data upload and integration at the patient level.

CVC validation

CVC was validated at both neighborhood and individual levels by comparing CVC subindexes' performance against (1) existing neighborhood-level SDOH indexes (ADI, SVI, and EJI) and (2) individual-level SDOH data.

Validation data sources

Publicly available data on ADI, SVI, and EJI values were accessed and used for neighborhood-level index comparisons. Parkland EHR data were used for individual-level SDOH data.

Validation against existing neighborhood indexes

CVC was validated against ADI, SVI, and EJI. Validation against EJI gauged CVC's ability to capture health-related injustices.

CVI and the 4 subindexes were converted to the appropriate geographic level and risk categorization to match each comparator's geographical granularity and risk categorization schema (ie, census-block group deciles and percentiles for ADI; census tract percentiles for SVI and EJI).

Spearman rank correlation coefficients were calculated and compared across indexes.[18–21]

Validation against individual-level SDOH data

CVI and the subindexes' SDOH rankings were validated against 2 types of EHR-based individual-level documentation of SDOH: Z-codes and self-reported SDOH screening tools.

Validation against Z-code documentation

Z-codes are International Classification of Disease Tenth (ICD-10) codes for SDOH, documented in patient records of clinical encounters. Z-codes were extracted from Parkland's EHR for a 5-year period (October 2018—September 2023) along with patients' home addresses at time of Z-code documentation. Each Z-code was classified by PCCI experts under 1 of the 4 subindexes to support the CVC subindex validation (see Z-code to CVC Crosswalk in Table S2). Patient addresses were geocoded and reverse geocoded to specific census-block groups. Recall rates were calculated as the probability that a patient with a documented Z-code lived in a neighborhood classified as (1) Very-High or High vulnerability by CVI or one of the subindexes (for CVC) or (2) in the top 40% of ADI vulnerability (for ADI). Precision could not be calculated due to the inability to ascertain the absence of SDOH among patients without Z-code documentation. EJI/SVI were excluded from individual-level analyses because their data are not provided at the block-group level.

Validation against SDOH screening data

As part of the Dallas AHC, high-risk Medicare- and Medicaid-insured Parkland patients were systematically screened for 5 CMS SDOH priorities (Food, Housing, Utility, Transportation, and Safety Needs).[15] SDOH screening data and patient home addresses at time of screening were collected from Parkland's EHR. Addresses were geocoded and reverse geocoded into census-block groups.

A precision/recall analysis of CVI and subindexes was performed. Recall rates were calculated as the probability that an individual with a self-reported SDOH lived in a census-block group classified as "Very High or High" vulnerability by CVI or a subindex. Precision was calculated as the probability that an individual living in a census-block group classified as "Very High or High" vulnerability by CVI or a subindex had a self-reported SDOH. This analysis examined the concordance between CMS's 5 SDOH priorities and CVC's 4-domain framework, aligned with Healthy People 2030.

Two-sample t-tests were used for between-group comparisons.

Python (3.12.1) was used for data integration and analysis; Geocodio API(geocode.io) and pygeocodio (1.4.0) for geocoding and reverse geocoding; Python (3.12.1), geopandas (1.0.1), matplotlib (3.9.3), shapely (2.0.6), contextily (1.6.2), and seaborn (0.13.2) for visualization; and Power BI (version 2.124.2028) for dashboarding.

The University of Texas Southwestern Institutional Review Board approved the study (Study Number: STU 122017-030).

Results

CVC overview

The CVC/CVI subindexes were used to classify all 18 638 census-block groups across Texas, with CVI classifying 3728 census-block groups as Very-High (scaled values range: 0.8-1.0), 3727 as High (scaled values range: 0.6-0.79), 3728 as Moderate (scaled values range: 0.4-0.59), 3727 as Low (scaled values range: 0.2-0.39), and 3728 as Very Low (scaled values range: 0.0-0.19) vulnerability. CVC's digital output is a community-facing dashboard and an underlying dataset, displaying both maps and tabular formats at different geographical levels with drill-down options from the CVI to the 4 CVC subindexes to each of the 26 indicators.[34] In Dallas County for instance, South and Southeastern ZIP Codes were the most vulnerable. However, drilling down to census-block groups revealed vulnerability pockets in northern neighborhoods (Figure S1).

CVC technology integration use case

CVC is integrated with DCHHS's Client Relationship Management platform (Figure 3). The home address for all individuals on DCHHS's database is geocoded and reverse geocoded in real-time and mapped to a census-block group. The CVC index, subindexes, and 26 indicators of the census-block group are calculated and assigned to the individual, then linked back to the DCHHS database and displayed through Power BI. DCHHS teams can view CVC's SDOH insights, alongside other public health indicators, to gain a contextual understanding of social barriers to health in the individual's micro-ecosystem. DCHHS leadership and frontline teams use CVC to streamline and target social risk evaluation to more effectively plan outreach events, coordinate programs, such as the Sexually Transmitted Infection program, and support data-driven community collaboratives like the Dallas County Social Care Coalition.

Correlation between CVC and existing neighborhood indexes (ADI, SVI, EJI)

The CVI had a very strong correlation with EJI (r = 0.826), SVI (r = 0.824), and ADI (r = 0.788) (Table 1). Among CVC subindexes, Household Essentials and Empowered People were strongly correlated with SVI (r = 0.851, and r = 0.744, respectively) and ADI (r = 0.75 and r = 0.728, respectively). Equitable Communities was strongly correlated with EJI

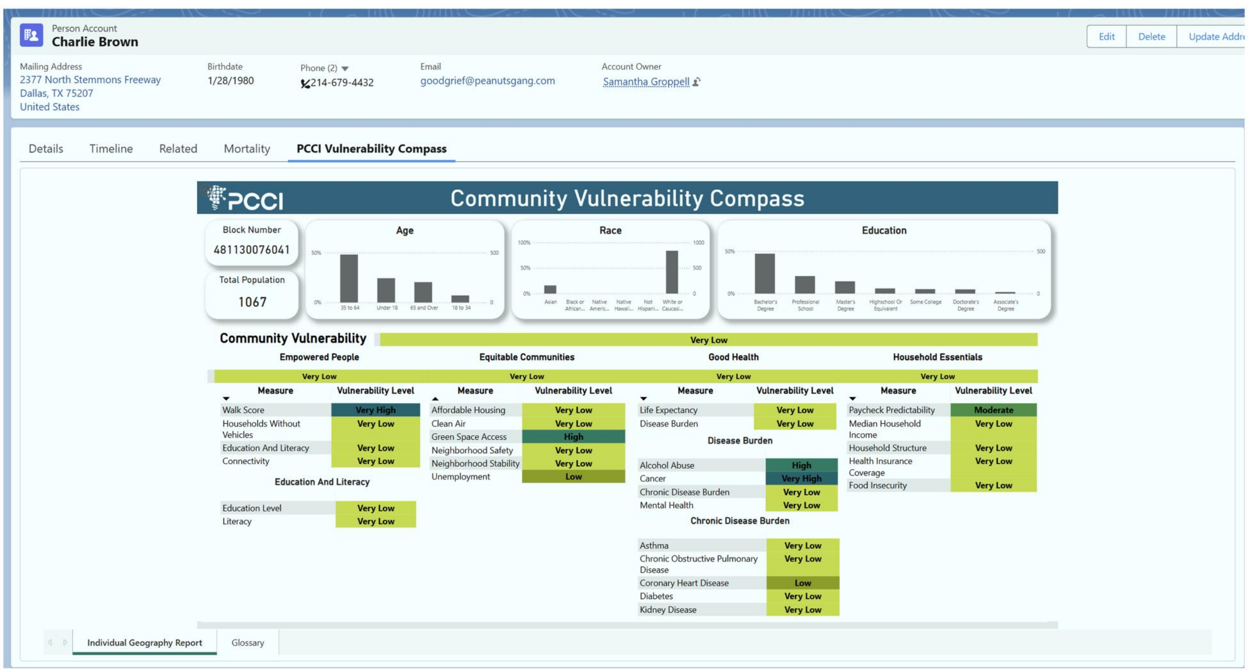

Figure 3. A screenshot of real-time integrated API solutions embedded in the workflow of Dallas County Health and Human Services' (DCHHS) Care Managers. Community Vulnerability Compass insights are presented on their client relations management platform through Power BI.

Table 1. Correlation (Spearman Correlation Analysis) between the Community Vulnerability Index (CVI) or CVC subindexes and Area Deprivation Index (ADI), Social Vulnerability Index (SVI), and Environmental Justice Index (EJI).

Index	Detailed name	Description	Community Vulnerability Index (CVI[a])	CVC[a] subindexes: Empowered People index	Equitable Communities index	Good Health index	Household Essentials index
ADI[a]	ADI STATERNK[a]	Statewide rank (0-1)	0.788	0.728	0.257	0.629	0.747
SVI[a]	Main index	Percentile ranking of summation of all 4 themes	0.824	0.744	0.466	0.535	0.851
	RPL_THEME1[a]	Percentile ranking of socioeconomic theme	0.808	0.666	0.514	0.509	0.859
	RPL_THEME2	Percentile ranking of household composition and disability module	0.626	0.624	0.213	0.462	0.667
	RPL_THEME3	Percentile ranking of minority status and language modules	0.458	0.429	0.318	0.091	0.614
	RPL_THEME4	Percentile ranking of housing type and transportation modules	0.615	0.577	0.387	0.439	0.543
EJI[a]	Main index	Percentile ranking of the summation of health vulnerability, environmental burden, and social vulnerability modules	0.826	0.738	0.614	0.613	0.814
	RPL_SER[a]	Percentile ranking of the summation of environmental burden, and social vulnerability modules	0.696	0.603	0.559	0.470	0.727

All *P*-values for Spearman correlation coefficients are <.001.
[a] CVC: Community Vulnerability Compass; CVI: Community Vulnerability Index; ADI: Area Deprivation Index; SVI: Social Vulnerability Index; EJI: Environmental Justice Index; ADI STATERNK: ADI index ranking using state-level data; RPL-THEME (1-4): the 4 themes of SVI; RPL-SER: a subtheme of EJI.

(r = 0.614, $P < .001$) but weakly correlated with ADI (r = 0.25, $P < .001$). In comparing CVC subindexes and SVI/EJI themes, the strongest correlation was observed between CVC's Good Health and SVI's Socioeconomic Theme-RPL_THEME1 (r = 0.859; $P < .001$).

Validating CVC against individual-level Z-code documentation and compared with ADI

In total, 164 659 Z-codes were documented for 158 139 Parkland patients between October 2018 and September 2023 (Table 2). The mean age was 40.2 years old (SD 22.3). Most patients were minorities (34.3% non-Hispanic Black, 44.0% Hispanics) and female (51.6%). Among patients with a documented Z-code, CVI's recall rate was 68% versus only 39% for ADI, a 75% higher performance ($P < .001$). CVC subindexes also performed better than ADI, ranking from Equitable Communities (recall 75.1% vs ADI 26.9%), Empowered People (recall 64.6% vs ADI 35.9%), Household Essentials (recall 62.1% vs ADI 42.6%) to Good Health (recall 60.6% vs ADI 43.9%). *P-value* < .001 for all comparisons.

Validating CVC against self-reported SDOH survey data

A total of 8861 high-risk Medicare and Medicaid beneficiaries participating in the Dallas AHC had a Parkland EHR-documented SDOH screening (Table 3). The majority were female (70.1%), minority (35.8% non-Hispanic Black, 20% Hispanics), and age 18-65 (68.1%). Among high-risk beneficiaries, CVI had a high recall for all self-reported SDOH, ranging from 77% for utility needs to 80% for safety needs. CVI's highest precision/recall combined performance was for identifying food needs (precision = 75%; recall = 78%). Among the subindexes, Household Essentials had the highest precision/recall combined performance (precision = 75.4%; recall = 74.4%) for its ability to identify food needs. Conversely, Equitable Communities had the lowest precision/recall combined performance (precision = 1.2%; recall = 56.3%) for its ability to identify safety needs. Overall, the subindexes had the best recall rates for identifying food needs and the lowest precision for identifying safety needs.

Table 2. Comparison of CVI[a] and ADI[a] recall rates for individual-level SDOH[a] classification using Z-codes.

	CVI[a] (Dallas County)	CVI[a] (Texas)	ADI[a] (Texas)
	Recall rates (%)		
All Z-codes [b]	67.7	65	39
Empowered People Z-codes [b]	64.6	56.5	37.3
Equitable Community Z-codes [b]	75.1	**82.9**[c]	**28.4**[d]
Good Health Z-codes [b]	60.6	55.5	43.9
Household Essentials Z-codes [b]	62.1	59.9	42.6

All *P*-values <.001.
[a] CVI: Community Vulnerability Index; ADI: Area Deprivation Index; SDOH: social determinants of health.
[b] See Table S2 for details of ICD-10 Z-codes crosswalk with CVC subindexes.
[c] Highest recall rate (bold).
[d] Lowest recall rate (bold).

Discussion

This study sought to validate CVC, a novel digital and data approach to address the persistent need for scalable methods for comprehensive SDOH measurement at both the neighborhood and individual level. CVC's cloud-based infrastructure creates an automated end-to-end process that incorporates multiple social and clinical data sources and integrates with diverse data processing and end-user technologies to bring accurate neighborhood- and proximate, individual-level social vulnerability insights to frontline providers.

CVC showed a strong correlation with existing SDOH indexes (ADI, SVI, and EJI) across multiple social risk domains, demonstrating its ability to identify a cross-cutting range of social vulnerabilities and community equity

Table 3. Community Vulnerability Index (CVI) and CVC[a] subindexes recall and precision rates for self-reported social determinants of health (SDOH) using surveys.

SDOH	Community Vulnerability index		Empowered People subindex		Equitable Communities subindex		Good Health subindex		Household Essentials subindex	
	Precision (%)	Recall (%)	Precision (%)	Recall (%)	Precision (%)	Recall (%)	Precision (%)	Recall (%)	Precision (%)	Recall (%)
Food Need	**75.1**	*77.5*	**75.1**	73.4	**74.6**	55.3	**75.1**	72.9	**75.4**	74.4
Housing Need	36.9	78.6	36.4	73.4	39.1	**59.8**	37.3	74.7	36.3	73.9
Safety Need	*1.2*	**79.6**	*1.0*	*66.0*	*1.2*	56.3	*1.3*	**81.6**	*1.1*	*70.9*
Transportation Need	31.9	79.3	31.9	**75.2**	33.5	**59.9**	32.5	76.0	31.8	**75.7**
Utility Need	42.6	*77.0*	42.7	73.2	41.4	*53.7*	42.3	*71.8*	42.8	74.0

For each CVC index/subindex, the highest values of precision/recall are bolded and the lowest italicized.
[a] CVC: Community Vulnerability Compass.

markers. Additionally, CVC had very good recall rates for individual-level SDOH both when validated against Z-code documentation and against self-reported survey tools (>75%). Overall, CVC either was comparable to or outperformed existing neighborhood indexes in measuring key SDOH at both the neighborhood and individual level. On a technical level, CVC's integration with DCHHS's client relationship management platform brings comprehensive SDOH insights alongside other health insights to key stakeholders and has been useful to support public health programs, facilitate data-driven whole-person care, and inform strategic partnerships for community health equity.

Strengths

Healthcare delivery systems and public health entities increasingly rely on neighborhood vulnerability indexes as proxies for individual-level SDOH. Existing indexes, originally developed to support research and policy,[17] have demonstrated incongruence with one another and poor reliability when repurposed to measure individual-level SDOH.[35,36] The head-to-head validation of CVC against commonly used neighborhood indexes provides direct evidence of CVC's validity and usefulness as a neighborhood SDOH monitoring tool. The strong correlation between CVC and existing neighborhood indexes ($r = 0.82$ vs SVI and vs EJI, $r = 0.87$ vs ADI) far exceeds the modest correlation reported between these indexes[23] and validates CVC's comprehensiveness in capturing a broad range of relevant SDOH domains, only partially captured by each existing index individually. Importantly, CVC's Equitable Communities subindex had a strong correlation with EJI, an established measure of community equity and justice, thus validating CVC's endeavor to incorporate an equity perspective into neighborhood SDOH measurement.

Concerns about neighborhood indexes' inability to accurately measure individual-level SDOH were addressed by validating CVC directly against 2 distinct measures of individual-level SDOH: self-reported surveys and Z-code documentation in a safety-net population. CVC consistently demonstrated high recall rates in identifying individual-level SDOH, both self-reported and as documented by Z-code, outperforming ADI for Z-code documentation (Recall rate: CVC 68% vs ADI 39%). CVC proved to be a more reliable tool to approximate individual-level SDOH than existing neighborhood indexes.[16] CVC performed the best in accurately identifying food needs, which aligns with previous publications showing that neighborhood indexes are better at identifying food and transportation needs than other social needs.[16]

To our knowledge, this is the first study to validate a neighborhood vulnerability index against the 5 key CMS SDOH,[11] and the first to reconcile CMS's SDOH priorities with the Healthy People 2030 framework, 2 key federal health initiatives. As CMS increasingly requires healthcare providers to measure and report SDOH, alignment with CMS priorities was critical to ensure proper vetting of CVC as a tool to support CMS-related initiatives.[37] CVC's recall rates for self-reported CMS-targeted SDOH were 20%-30% higher than published studies of non-CMS SDOH.[16] High recall rates make CVC a good candidate screening tool for hard-to-reach Medicaid/Medicare/uninsured populations as well as traditionally marginalized populations who might underreport SDOH for varying reasons. High recall rates also are a desirable feature for a high-throughput, mass SDOH screening tool for healthcare systems and public health entities.

To our knowledge, no published study has examined neighborhood indexes' ability to measure safety needs. Safety needs encompass domestic violence, a public health problem affecting about 10 million people in the United States every year,[38] yet severely underreported.[39,40] Underreporting, especially among socially vulnerable populations, makes it imperative to develop reliable data-driven tools for seamless monitoring of safety needs at scale. CVC's performance in measuring safety needs was mixed. While recall rates were high (up to 80%), precision was very low (~1%). This poor discriminatory power might partly stem from differences in the conceptualization of safety needs between CVC and individual-level SDOH screening tools. Notwithstanding these discrepancies, the dearth of studies evaluating neighborhood indexes' performance for safety needs highlights a critical gap in the literature and underscores the necessity to develop and validate scalable safety needs measurement tools.

Limitations

Z-code analyses were limited to examining only recall rates due to the lack of systematic documentation of negative SDOH screening in EHRs, which made it impossible to calculate precision. In the absence of universal SDOH screening at healthcare delivery systems, screenings are primarily initiated upon patient request and negative screenings are not systematically documented. Thus, it was not possible to calculate precision rates for Z-code documentation. The well-documented, low adoption of universal SDOH screening across healthcare settings is primarily due to logistics, resources, and cost constraints.[17] As more providers screen and document SDOH, it will be important to encourage systematic documentation of negative screenings to ensure a complete SDOH picture across patient populations. This limitation was mitigated through the self-reported SDOH analysis.

Self-reported SDOH analyses, in turn, were limited to high-risk Medicaid/Medicare beneficiaries. While CVC's performance was strong in this population, study findings' generalizability to lower-risk or non-Medicare/Medicaid populations might be compromised. Further studies in a broader, more diverse patient population would be beneficial.

Conclusion

This study validates that CVC, a novel SDOH approach and digital tool, accurately quantifies neighborhood-level and individual-level social vulnerability using large datasets and displays key insights through interoperable technology integration. CVC's integration with other healthcare technologies seamlessly incorporates critical SDOH insights alongside other data points, providing a comprehensive view to support both public health and healthcare system strategy. CVC's performance as a proxy measure for individual-level SDOH makes it an ideal mass triage tool that public health and healthcare systems can leverage to streamline the measurement and targeting of SDOH interventions efficiently and at scale.

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Supplementary material

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Conflicts of interest

All authors (Y.P., Y.T., V.S., A.K., L.R., O.A., L.W., and S. M.) have no competing interests to declare.

Data availability

The data underlying this article cannot be shared publicly due to the privacy of individuals who participated in the study and contractual obligations with vendors of private data sources. The data will be shared on reasonable requests to the corresponding author, as legally and contractually appropriate.

References

1. Park Y, Mulligan N, Gleize M, et al. Discovering associations between social determinants and health outcomes: merging knowledge graphs from literature and electronic health data. *AMIA Annu Symp Proc*. 2021;2021:940-949.
2. Social determinants of health. Accessed June 6, 2024.https://www.who.int/health-topics/social-determinants-of-health
3. Javed Z, Valero-Elizondo J, Maqsood MH, et al. Social determinants of health and obesity: findings from a national study of US adults. *Obesity (Silver Spring)*. 2022;30:491-502. https://doi.org/10.1002/oby.23336
4. Wylie-Rosett J, DiMeglio LA. Strategies to reduce food insecurity for people with diabetes: a call to action. *Diabetes Care*. 2023;46:245-248. https://doi.org/10.2337/dci22-0058
5. Federico MJ, McFarlane AE, Szefler SJ, et al. The impact of social determinants of health on children with asthma. *J Allergy Clin Immunol Pract*. 2020;8:1808-1814. https://doi.org/10.1016/j.jaip.2020.03.028
6. Iroegbu C, Lewis L, Matura LA. An integrative review: chronic kidney disease awareness and the social determinants of health inequities. *J Adv Nurs*. 2022;78:918-928. https://doi.org/10.1111/jan.15107
7. Barakat C, Konstantinidis T. A review of the relationship between socioeconomic status change and health. *Int J Environ Res Public Health*. 2023;20:6249. https://doi.org/10.3390/ijerph20136249
8. Dagher RK, Linares DE. A critical review on the complex interplay between social determinants of health and maternal and infant mortality. *Children*. 2022;9:394. https://doi.org/10.3390/children9030394
9. Healthy People 2030. health.gov. Accessed June 6, 2024. https://health.gov/healthypeople
10. A guide to using the accountable health communities health-related social needs screening tool: promising practices and key insights. Accessed April 10, 2025. https://www.cms.gov/priorities/innovation/media/document/ahcm-screeningtool-companion
11. Alley DE, Asomugha CN, Conway PH, et al. Accountable health communities—addressing social needs through medicare and

medicaid. *N Engl J Med*. 2016;374:8-11. https://doi.org/10.1056/NEJMp1512532
12. Renaud J, McClellan SR, DePriest K, et al. Addressing health-related social needs via community resources: lessons from accountable health communities: study examines how the accountable health communities model addresses health-related social needs via community resources. *Health Aff (Millwood)*. 2023;42:832-840. https://doi.org/10.1377/hlthaff.2022.01507
13. Parish W, Beil H, He F, et al. Health care impacts of resource navigation for health-related social needs in the accountable health communities model: study examines the health care impacts of resource navigation for health-related social needs within the accountable health communities model. *Health Aff (Millwood)*. 2023;42:822-831. https://doi.org/10.1377/hlthaff.2022.01502
14. Holcomb J, Highfield L, Ferguson GM, et al. Association of social needs and healthcare utilization among medicare and medicaid beneficiaries in the accountable health communities model. *J Gen Intern Med*. 2022;37:3692-3699. https://doi.org/10.1007/s11606-022-07403-w
15. Naeem J, Salazar-Contreras E, Sundaram V, et al. The Dallas Accountable Health Community: its impact on health-related social needs, care, and costs. *NEJM Catal*. 2022;3:1-40. https://doi.org/10.1056/CAT.22.0149
16. Bensken WP, McGrath BM, Gold R, et al. Area-level social determinants of health and individual-level social risks: assessing predictive ability and biases in social risk screening. *J Clin Transl Sci*. 2023;7:e257. https://doi.org/10.1017/cts.2023.680
17. Trinidad S, Brokamp C, Mor Huertas A, et al. Use of area-based socioeconomic deprivation indices: a scoping review and qualitative analysis: study examines socioeconomic deprivation indices. *Health Aff (Millwood)*. 2022;41:1804-1811. https://doi.org/10.1377/hlthaff.2022.00482
18. Singh GK. Area deprivation and widening inequalities in US mortality, 1969–1998. *Am J Public Health*. 2003;93:1137-1143. https://doi.org/10.2105/AJPH.93.7.1137
19. Kind AJH, Buckingham WR. Making neighborhood-disadvantage metrics accessible—the neighborhood atlas. *N Engl J Med*. 2018;378:2456-2458. https://doi.org/10.1056/NEJMp1802313
20. Flanagan BE, Gregory EW, Hallisey EJ, et al. A social vulnerability index for disaster management. *J Homel Secur Emerg Manag*. 2011;8:1-22. https://doi.org/10.2202/1547-7355.1792
21. CDC. Environmental Justice Index (EJI). 2024. Accessed June 6, 2024. https://www.atsdr.cdc.gov/placeandhealth/eji/index.html
22. Rollings KA, Noppert GA, Griggs JJ, et al. Comparison of two area-level socioeconomic deprivation indices: implications for public health research, practice, and policy. *PloS One*. 2023;18:e0292281. https://doi.org/10.1371/journal.pone.0292281
23. Miller-Rosales C, McCloskey J, Uratsu CS, et al. Associations between different self-reported social risks and neighborhood-level resources in medicaid patients. *Med Care*. 2022;60:563-569. https://doi.org/10.1097/MLR.0000000000001735
24. United States Census Bureau. American Community Survey Data. Census.gov. Accessed August 22, 2024. https://www.census.gov/programs-surveys/acs/data.html
25. About the index. H+T Index. Accessed August 12, 2024. https://htaindex.cnt.org/about/
26. US EPA. National Walkability Index user guide and methodology. 2021. Accessed August 22, 2024. https://www.epa.gov/smartgrowth/national-walkability-index-user-guide-and-methodology
27. NVSS—United States small-area life expectancy estimates project. 2023. Accessed August 22, 2024. https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html
28. PIAAC results. Accessed August 22, 2024. https://nces.ed.gov/surveys/piaac/national_results.asp
29. Air pollution—OpenWeatherMap. Accessed August 22, 2024. https://openweathermap.org/api/air-pollution
30. ParkServe®. Trust for public land. Accessed August 22, 2024. https://parkserve.tpl.org/mapping/
31. Applied Geographic Solutions. CrimeRisk. Accessed August 22, 2024. https://appliedgeographic.com/crimerisk/
32. Yeo I-K. A new family of power transformations to improve normality or symmetry. *Biometrika*. 2000;87:954-959. https://doi.org/10.1093/biomet/87.4.954
33. Box GEP, Cox DR. An analysis of transformations. *J R Stat Soc Ser B Stat Methodol*. 1964;26:211-243. https://doi.org/10.1111/j.2517-6161.1964.tb00553.x
34. Community Vulnerability Compass—PCCI. 2023. Accessed August 22, 2024. https://pccinnovation.org/the-community-vulnerability-compass/
35. Telzak A, Levano S, Haughton J, et al. Understanding individual health-related social needs in the context of area-level social determinants of health: the case for granularity. *J Clin Transl Sci*. 2024;8:e78. https://doi.org/10.1017/cts.2024.519
36. Cottrell EK, Hendricks M, Dambrun K, et al. Comparison of community-level and patient-level social risk data in a network of community health centers. *JAMA Netw Open*. 2020;3:e2016852. https://doi.org/10.1001/jamanetworkopen.2020.16852
37. Powers BW, Figueroa JF, Canterberry M, et al. Association between community-level social risk and spending among Medicare beneficiaries: implications for social risk adjustment and health equity. *JAMA Health Forum*. 2023;4:e230266. https://doi.org/10.1001/jamahealthforum.2023.0266
38. Huecker MR, King KC, Jordan GA, et al. Domestic violence. *StatPearls*. StatPearls Publishing; 2024.
39. Gracia E. Unreported cases of domestic violence against women: towards an epidemiology of social silence, tolerance, and inhibition. *J Epidemiol Community Health*. 2004;58:536-537. https://doi.org/10.1136/jech.2003.019604
40. Lenert L, Rheingold AA, Simpson KN, et al. Electronic health record–based screening for intimate partner violence: a cluster randomized clinical trial. *JAMA Netw Open*. 2024;7:e2425070. https://doi.org/10.1001/jamanetworkopen.2024.25070

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https://doi.org/10.1093/jamiaopen/ooaf059
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