The Impact of Social Determinants of Health on Technology Access, Health Behaviors, and Health Status in Southern Arizona

Making Action Possible in Southern Arizona (MAP Dashboard)
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EXECUTIVE SUMMARY

Social Determinants of Health (SDOH) are the environmental conditions in which people are born, live, learn, work, play, worship, and age. These conditions impact a person's overall health, functioning, and quality of life. Approximately 50% of a person's health status is related to social and environmental factors, and 34% is related to individual health behaviors, such as eating a healthy diet, being physically active, avoiding tobacco, and risky alcohol and substance use, getting adequate sleep, and obtaining the recommended immunizations and health screenings. Healthcare organizations rarely collect socially relevant variables on individuals, leaving a gap in our understanding of the community-level SDOH data that can enable stakeholders to ascertain factors that expose individuals or groups in a specific region to risks.

The ability to respond to health threats and support health-promoting behaviors is essential for local, state, and federal stakeholders. Chronic diseases, such as diabetes, cardiovascular disease, cancers, lung diseases, and depression are prevalent in Southern Arizona. The unique population characteristics and geographic disparities in this region, such as inadequate healthcare resources, lack of access to healthy foods, and lower median household incomes are contributing factors for chronic disease. The COVID-19 pandemic further widened the digital divide, impacting educational attainment, income, and access to health-related technologies. Mobile health (mHealth) is increasing in its availability and application in modern society. mHealth provides infrastructure for engaging diverse populations, increasing knowledge, and allowing individuals to monitor, track, and transmit health metrics to improve access to healthcare or promote health behavior changes. mHealth can be used outside of clinical settings, making it ideal for use in areas where healthcare services are lacking. Access to technology in Southern Arizona (SAZ) may play a key role in bridging the divide between SDOH and health outcomes.

This project, funded by a Making Action Possible Grant from the University of Arizona Eller College of Management, used epidemiological data and geospatial analysis to identify communities in Southern Arizona that have health-protective attributes. To characterize the SDOH in SAZ, the researchers developed and validated the Community Connectedness Classification (C3) and an interactive map that shows community-level data. This research resulted in three key findings. More connected communities in Southern Arizona, determined by C3, have 1) greater access to technology, 2) engaged in less high-risk health behaviors, and 3) had higher perceptions of physical, mental, and overall health. The development and practical application of the novel C3 to represent factors related to SDOH in relation to health risk behaviors allows local non-profits, researchers, policymakers, and other change leaders in Southern Arizona to develop targeted interventions, initiatives, and policies that systemically improve the health of residents and their communities, ultimately reducing the economic burden of chronic disease in SAZ and beyond.

Recommendations from this report include 1) continuing to expand access to broadband internet and other technologies that allow SAZ residents to take advantage of the existing mHealth infrastructure and 2) apply C3 in future analyses and utilize the interactive web map to inform the development of interventions, programs, and policies that improve the health and quality of life of SAZ residents and reduce economic burden.

INTRODUCTION

A healthy diet rich in fruits and vegetables, engaging in physical activity, and avoiding alcohol and tobacco have been linked to prevention of cardiovascular disease (CVD), type 2 diabetes mellitus (T2DM), and cancer as well as improved mental and physical health [1-3]. Early evidence suggests that digital health is beneficial for chronic disease management, health promotion for disease prevention and basic health education [4, 5]. In the context of chronic disease, self-efficacy and self-monitoring (e.g., goal tracking), components of many digital health technologies, are independently associated with better diet and more exercise [6].

The impact of the COVID-19 pandemic necessitated and accelerated incorporating technology into healthcare [7]. Recent advances and uptake in technology allow for delivery of health education or management to support medical and public health practice using consumer-focused mobile devices including smartphones, tablets, or laptop computers [8]. While some concerns persist that increasing reliance on digital technologies may have deleterious consequences [9, 10], current evidence suggests that digital health applications, including mobile health (mHealth), electronic health (eHealth), and telehealth, can have a positive impact on health behaviors and healthcare delivery, enhancing health equity [10]. Digital health can potentially meet the health needs of underserved populations in areas where healthcare resources are lacking. Technology access (either through devices such as a smartphone, tablet, or laptop) is required for effective delivery of digital health programming outside healthcare environments. Leveraging connectivity has potential to reach and benefit high-need populations in the context of social determinants of health (SDOH).

SDOH contribute to the overall health of a society. SDOH is defined by the Centers for Disease Control and Prevention as "*conditions in the environment where people are born, live, learn, play, work, worship, and age that affect a wide range of health, functioning, and quality of life outcomes and risks*" [11]. The five domains of SDOH are: 1) economic stability, 2) education access and quality, 3) health care access and quality, 4) neighborhood and built environment, and 5) social and community context. Previous studies have shown that mHealth use is associated with these factors independently, yet these factors are interdependent, and disparities related to health and health behaviors persist [12, 13]. Recent estimates indicate that 16% of a person's health is influenced by clinical healthcare, 34% is related to individual health behaviors (eating a healthy diet, being physically active, not using tobacco, avoiding risky alcohol, substance use, or sexual behaviors, getting enough sleep, getting the recommended immunizations, and preventive health screenings) and the remaining 50% is related to SDOH (47% from social factors and 3% from environmental factors) [14]. Healthcare facilities rarely collect socially relevant variables on individuals [15], therefore community-level SDOH data provides the ability to infer regional risk factors to individual exposures.

A Primer on Southern Arizona

SAZ is composed of the geographic region south of the Gila River in Arizona and was acquired by the United States of America (US) from Mexico during the Gadsden Purchase of 1853 [16]. SAZ includes the following counties: Cochise, Pima, Pinal, Greenlee, Graham, Santa Cruz, and Yuma [17]. There are three primary metropolitan areas in SAZ: Sierra Vista-Douglas, Tucson, and Yuma. Geographic distribution of population density is uneven in SAZ, with approximately 75% of the population residing in metropolitan areas [18]. However, more than 90% of SAZ land mass is considered rural. Additionally, seven federally recognized indigenous tribes are located within SAZ counties [19]. SAZ carries a high disease burden where the most common chronic diseases (CVD, cancer, T2DM, respiratory illness, and depression) are also the leading causes of mortality across all age groups [20]. The estimated annual economic burden of chronic disease in Arizona is $47B in medical costs and $18.6B in lost employee productivity [18]. This may be greater in SAZ, an area that is mostly rural. SAZ also experiences geographic disparities that contribute to SDOH including limited access to healthcare and healthy foods, as well as lower median household incomes [20].

Geographic and Population Characteristics

The population in SAZ is rapidly expanding and simultaneously aging, with the proportion of adults aged 65 years or greater increasing [18]. Over the past two decades, SAZ has experienced substantial population increases, and is one of the fastest growing populations in the US. Maricopa, Sahuarita, Vail, and Marana experienced the greatest growth [21]. This growing population is becoming more racially and ethnically diverse. The percent of the population in SAZ counties that identify as Hispanic is greater than the state average of 31.4% [18]. **Table 1** provides a summary of SAZ regional demographics and characteristics.

Table 1: Geographic Characteristics and Estimated Population Demographics of Southern Arizona by County.

	Cochise	**Graham**	**Greenlee**	**Pima**	**Pinal**	**Santa Cruz**	**Yuma**
Population Size	126,050	39,050	9,404	1,052,030	449,557	47,883	206,990
Land Area, mi^2	6,209.8	4,621.9	1842.0	9,188.7	5,366.4	1,236.2	5,513.8
Population Density	20.2	8.3	5.2	113.6	79.3	38.6	37.0
Aged ≥65 years, %	22.2	13.9	12.8	19.8	20.5	17.9	19.1
Females, %	48.8	46.2	47.8	50.5	48	51.4	42.8
Non-Hispanic White, %	54.4	50.9	44.0	50.3	55.0	55.5	29.2
Hispanic /Latino, %	35.9	33.8	49.0	38.5	31.4	82.7	65.5
Black / African American, %	4.6	1.9	1.9	4.4	5.8	1.1	2.7
American Indian / Alaska Native, %	1.9	13.1	4.6	4.5	6.5	1.5	2.5
Asian, %	2.2	0.8	0.9	3.3	2	0.9	1.5
Native Hawaiian / Other Pacific Islander, %	0.4	0.2	0.1	0.2	0.4	0.1	0.3

Data Source: US Census Bureau, 2021

Technology Landscape

Technological innovations are known as the "4th Industrial Revolution" [22]. Our digital, physical, and biological worlds are converging, impacting the economy, social well-being and physical health. COVID-19 necessitated and accelerated incorporating technology and healthcare [7]. Technology use may enhance health equity for those who can access it.

Technology can be considered as three domains: devices, connectivity, and applications. Expanding access to broadband internet service has been a priority in Arizona to improve public safety, increase access to education, and help Arizonans access healthcare via telemedicine. Arizona presently ranks 36th nationwide for internet access, with 31% of Arizonans under and unserved [23]. A temporary program, Emergency Broadband Benefit, is currently available to eligible AZ households to subsidize internet service and purchase a device [24]. Device access in SAZ is less defined, however recent estimates suggest that internet access and device ownership are increasing among rural adults nationally[25].

Prioritizing Needs

In 2022, AZ was ranked 32nd among all US states in overall population health status [26]. Despite minimal improvement in trends, Arizona's latency may be due to the impacts of SDOH on population health. Health equity is closely tied to SDOH [27]. Needs assessments from Pima, Pinal, Graham, Yuma, Cochise, and Santa Cruz counties all identified health-related priorities related to mental and behavioral health, nutrition, physical activity, overweight and obesity, tobacco use cessation, and cardiometabolic disease prevention [18, 20, 28, 29]. These priorities are consistent with statewide data indicating that chronic diseases such as CVD, stroke, lung disease, cancer, T2DM, and asthma are among the most prevalent, costly, and preventable health problems and are responsible for 70% of all deaths in Arizona [18]. Other needs identified are in alignment with SDOH including health care access, education, economic security, and the built environment.

Cardiometabolic Disease Prevention

Cardiometabolic diseases affect the heart, blood vessels, and endocrine systems. Common diagnoses are CVD, high cholesterol, hypertension, obesity, T2DM, non-alcoholic fatty liver disease (NAFLD), chronic kidney disease and kidney disease failure, heart attacks, and stroke. These diseases are frequent and often cooccurring, yet highly preventable through modifiable factors. Cardiometabolic diseases share common risk factors of unhealthy behaviors, including physical inactivity, a poor diet, tobacco smoking, and alcohol abuse, as well as SDOH factors [30].

Nutrition and Physical Activity

For health benefits and disease prevention current recommendations for nutrition include a balanced dietary pattern that is high in fruits, vegetables, and fiber and low in added fats and sugars [31]. For physical activity, the recommendation is a minimum of 150 to 300 minutes of moderate-intensity or 75-150 minutes of vigorous activity per week in combination with resistance activities that involve major muscle groups at least twice weekly [32]. **Table 2** provides a summary of current US guidelines. Arizona adults are below national averages for achieving nutrition and physical activity recommendations; 9.3-12.2% of adults met fruit and vegetable intake and 51.9% were physically active [33, 34]

Overweight and Obesity

Between 38-66% of diagnosed chronic cardiometabolic diseases in the US are obesity related [35]. Nearly 300,000 deaths annually are attributed to obesity [36]. Four in ten American adults are obese, defined as a body mass index (BMI) of 30 kg/m^2. Arizona is ranked as the 34th most obese state in the US and spends $752 million annually on adult obesity-related medical expenditures [37]. In Arizona, overweight obesity rates are slightly lower than national estimates at 31.3%, but rates have continued to rise over the past decade [38].

Tobacco Use and Alcohol Abuse

Tobacco use, including combustible and smokeless products such as electronic nicotine delivery systems (ENDS), is a significant public health problem and continues to be the leading preventable cause of morbidity and mortality in the US [39]. While the trend in overall use of tobacco products continue to decrease, 19% of US adults are current tobacco users, prevalence is higher in rural areas [40]. An estimated 15.6% of Arizonans use tobacco products, with annual medical costs in the state attributed directly to tobacco product use of $5 billion dollars [41]. Chronic disease morbidity and mortality are linked to alcohol abuse [42]. Approximately half of Arizona adults regularly consume alcohol with 22% reporting binge alcohol use, defined as drinking five or more drinks (for males) or four or more drinks (for females) on the same occasion on at least one day in the past 30 days [43]. The rate per 10,000 individuals visiting the emergency room state-wide related to alcohol use was 10.9, with rates higher in Pima and Graham counties [44].

Table 2: Current National Nutrition and Physical Activity Guidelines for Chronic Disease Prevention and Health Promotion

Dietary Guidelines for Americans, 2020-2025 [45]	
Fruit	2 cup-equivalents a day
Vegetable	2.5 cup-equivalents a day
Fiber	6 ounce-equivalents a day; ≥3 ounces whole grains
Fat	27 grams a day
Protein	5.5 ounce-equivalents a day
Dairy	3 cup-equivalents a day
Added Sugar	≤10% daily calories
Alcohol	≤1 drink a day for women; ≤2 drinks a day for men
Body Weight	Achieve and maintain a healthy weight
Physical Activity Guidelines for Americans, 2018 [32]	
Aerobic	150 minutes a week of moderate intensity or 75 minutes a week of vigorous intensity activity, or an equivalent combination
Resistance	2 days/week of moderate intensity muscle strengthening activities
Flexibility	Stretch major muscle groups on active days
Sedentary Time	Reduce sedentary behavior, break up with activity
Body Weight	Achieve and maintain a healthy weight

Mental Health Promotion

Mental health comprises the psychological, emotional, and social wellness, influencing how individuals think, feel and act and is a critical component of overall health. The experienced state of mental health determines individual stress response and has downstream cascades on physical health [46, 47]. Presence of one or more mental health conditions significantly increases the odds of the onset of chronic cardiometabolic diseases, with a compounding effect of morbidity [46]. Current data indicates that more than one million adults in Arizona are affected by a mental health condition [47], and many cannot receive necessary support. Arizona adults are three times more likely to seek mental health care outside of their insurance network, increasing care and cost burden [18].

Problem Statement

Prevention of chronic cardiometabolic disease and promotion of health behaviors is a priority for SAZ. Technology provides an existing infrastructure to engage diverse populations and increase access to healthcare. However, a current gap remains in our collective understanding of the subtle influence of SDOH on technology access and how technology access influences health behaviors, contributing to physical and mental health, specifically in SAZ. The objective of this study was to explore how SDOH is associated with technology access (device ownership) and how it relates to population health behaviors and health status in SAZ through integrating epidemiologic and geospatial analytic methods.

METHODS

Exposure Data

The US Census Bureau American Community Survey (ACS) is an annual survey that provides community-level population demographic and pertinent SDOH data, including ethnicity, educational attainment, employment, income, housing, language proficiency, and other variables [48]. The ACS produces period estimates over 12, 36, or 60 months. Approximately 1 in 38 US households per year are invited to complete the ACS through random address selection. Data are weighted to represent the area population. For this analysis, five-year estimates (data fielded from 2016-2020) were used. Data were reverse coded as necessary to represent positive and protective SDOH factors (e.g., percent population food secure versus percent population receiving federal food assistance). Multiyear estimates are more reliable than single-year estimates particularly for small geographic areas or subpopulations. All data represent community-dwelling, non-institutionalized adults ≥18 years of age. Additional data was ascertained from the US Census County Business Patterns (CBP) [49, 50].

Community Connectedness Classification (C3) Development

Publicly available ACS data representing positive SDOH factors was merged by ZIP code tabulation area (ZCTA). The ZCTA system was created by the US Census Bureau built from Census Blocks and ZIP Codes to address potential spatiotemporal mismatches; in the majority of cases ZCTA and ZIP Codes are the same for an address [51]. ZCTAs are larger and more diverse than Census Tracts, providing the ability to more reliability estimate SDOH influence in more rural communities and across places [52].

Principal Components Analysis

Principal components analysis (PCA) of Census ZCTA data (n=1521) from four southwestern US states: Arizona, Colorado, Utah, and New Mexico were used to develop C3 using established methods [53]. C3 was evaluated for reliability and validity and met model requirements [54]. Variables were mapped to the five SDOH domains and were restricted to reduce redundancy and remove non-modifiable factors (e.g., age); 13 variables were included in the final model. Missing or insufficient data was imputed using the expectation-maximization (EM) algorithm which is an iterative method that finds maximum likelihood estimates in parametric models [55]. Missing data were imputed with the mean value for the parent county. The factor scoring from the PCA was applied to the ZCTA level dataset. Factor values were classified into deciles where a C3 value of 10 indicates communities with greater connection (high) while a 1 indicates communities with greater isolation (low). The C3 decile value was used as the exposure variable. SAS code for C3 development is provided in the **Appendix**. Subsequent analyses were restricted to ZCTA C3 within SAZ counties (n=118).

Outcome Data

Technology Access- Device Ownership

Household access to three distinct technologies that facilitate telehealth were ascertained from the 2016-2020 ACS: percent of population reporting access to a tablet, smartphone, or laptop/desktop computer. Technology access could overlap and were not mutually exclusive.

Health Behavior Risk Factors

The Centers for Disease Control and Prevention (CDC) Behavioral Risk Factor Surveillance System (BRFSS) is an annual US self-report telephone survey that provides prevalence data related to health-related behavior risk behaviors, chronic health conditions, and use of preventive services [56]. Through random-digital dialing, adults 18 years or older are invited to participate via telephone. Individual responses are combined and then weighted to be representative of the area population. Variables represent the percent of the adult population. BRFSS data from 2018 (midpoint of the 2016-2020 ACS data) were used to evaluate community health risk behaviors related to cardiometabolic disease [57]. This included low fruit and vegetable intake (one or fewer servings per day), physical inactivity (no leisure time physical activity reported in the past 30 days), obesity (body mass index [BMI] of $\geq$30 kg/m^2), smoking (currently smokes on at least some days and has smoked at least 100 cigarettes in their lifetime), and heavy alcohol use (consuming $\geq$ 15 alcoholic drinks per week for men or $\geq$8 alcohol drinks per week for women). Self-reported perceived physical (>14 days poor physical health in past the 30 days), mental (>14 days poor mental health in past the 30 days), and overall health status (reporting very good or excellent overall health in the past 30 days) were also evaluated as outcomes.

Covariates

Population demographics including age, ethnicity, and sex from the five-year ACS were included as model covariates. Median geography of the ZCTA (rurality) was estimated using mean US Department of Agriculture 2010 Rural-Urban Commuting Area (RUCA) codes [58].

Statistical Analysis

Data Acquisition and Management

All publicly available federal data were downloaded from PolicyMap under license to the University of Arizona. Data were cleaned and normalized to improve data integrity prior to analysis [59]. Data were merged by ZCTA and restricted to SAZ counties. All models were adjusted for population demographics (e.g., age, sex, ethnicity, veteran status) and rurality. Analyses were conducted in ArcGIS Pro (ESRI, Redlands, CA, USA), STATA 17.0 (StataCorp LLC, College Station, TX, USA), or SAS 9.0 (SAS Institute, Cary, NC, USA) with an alpha established at 5% for statistical significance.

Primary Analysis

We integrated epidemiologic and geospatial analytical approaches in a two-step process. The Global Moran's *I* and Getis-Ord G_i^* were used to determine if C3 was spatially autocorrelated and identify C3 clustering [60]. Moran's *I* looks at the overall spatial interdependence between regions and tests to what degree a region and the neighboring region are mutually correlated, whereas Getis-Ord G_i^* identifies areas of local heterogeneity with or without overall correlation. Positive Moran's *I* values represent clustering of values while negative represent dispersed values. The closer a Moran's I is to zero, the value clustering is considered more random. Clusters were defined as high (areas of connectedness), low (areas of isolation), and outliers (e.g., ZCTA with a high C3 surrounded by low C3 ZCTA). When the Getis-Ord G_i^* (d) statistic has a positive value that falls within the critical region (5% significance level) the region is identified as a high cluster.

Spatial autoregressive (SAR) using generalized spatial two-stage least squares estimation modeling was used to assess the relationship between C3 and technology access. Generalized spatial two-stage least squares assumes that errors are independent and identically distributed and does not require normality. Additional SAR models were conducted to evaluate associations between C3 and health behavior risk factors and perceived health status accounting for the interaction of technology access. An exploratory geographic information systems (GIS) analysis using geographically weighted regressions (GWR) and density modeling was used to visualize relationships between C3, technology access, and health behaviors. All models met test assumptions.

GIS Process

Cartograph boundary files (TIGER/Line) with 2020 ZCTA boundaries were downloaded from the US Census Bureau website and spatially joined with the ZCTA specific shapefile data and ZCTA-level ACS and BRFSS data. C3 deciles were mapped using choropleth maps.

Stakeholder Engagement

Preliminary findings were first presented to a virtual community forum composed of stakeholders representing non-profits, healthcare administrators and providers, educational institutions, and researchers. This method employs a small group process of information sharing and discussion of community-level impact and is a means to integrate local knowledge and decision making [61]. Feedback was anonymous and informed next steps of C3. Through the community forum, we underwent an iterative process for the naming and interpretation of C3. The community forum provided important feedback to improve data visualization and platform interaction.

RESULTS

C3 Regional Distributions

The variables within the domains of SDOH included in C3 are listed in **Table 3**. Factors that drive higher values included a greater population percent that: 1) have higher household income, 2) are above the federal poverty line, 3) are considered food secure, 4) have internet access, 5) attained higher education, and 6) have a primary care provider.

Table 3: Community Connectedness Classification (C3) Component Loadings and Southern Arizona Averages for 118 communities (ZCTA).

Social Determinant of Health Domain	Factor	Mean (SD)	Coefficient Loadings
Economic	Median Household Income ($)	53312.3 (19285.2)	0.778
	Persons Living Above Federal Poverty Line (% Pop)	41.9 (10.8)	0.770

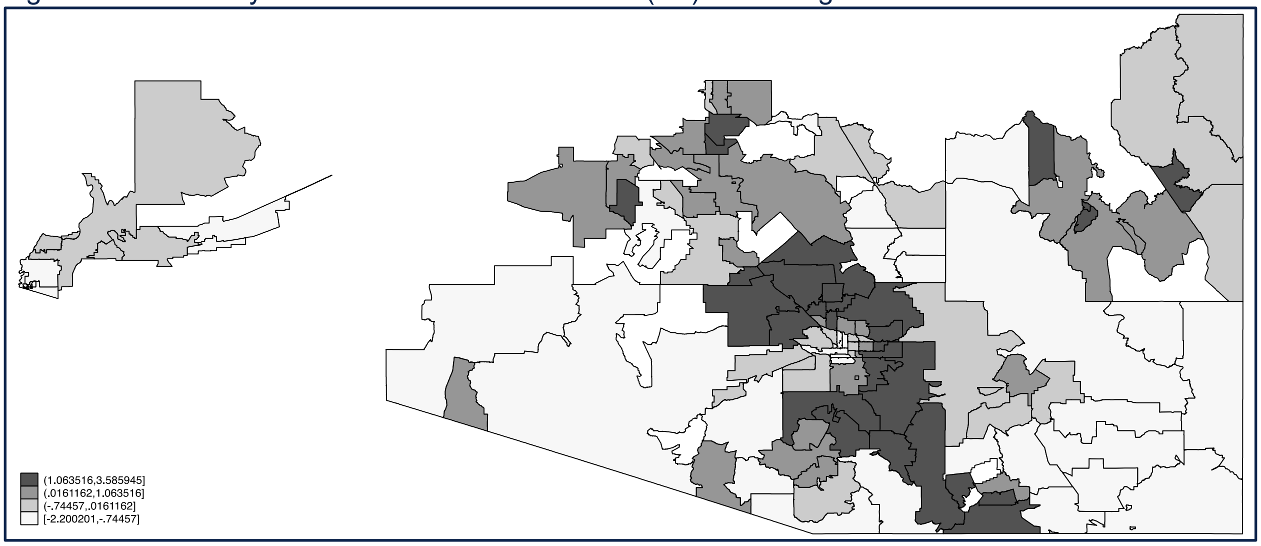
	Civilian Workforce Employed (% Pop)	52.1 (13.6)	0.513
Education	≥ Bachelor's degree (% Pop)	23.4 (15.0)	0.711
Healthcare	Preventive Care- Has Primary Care Provider (% Pop)	71.0 (7.2)	0.588
	Insured- Private or Public (% Pop)	90.5 (7.3)	0.478
Neighborhood	Internet Access (% Households)	46.7 (12.8)	0.728
	Fitness and Recreation Centers (Rate per 100,000 people)	5.7 (3.2)	0.334
	Electric Home Heating (% Households)	45.6 (18.2)	-0.064
	Gas Home Heating (% Households)	39.9 (23.0	0.462
Social	Considered Food Secure (% Families)	45.8 (12.8)	0.748
	Average Size of Household (n)	2.7 (0.6)	-0.231
	English Primary Language Spoken ≥5 years (% Pop)	41.8 (9.2)	0.525

Continuous C3 values within SAZ ranged from 2899 to 18451 across the 118 ZCTAs, representing C3 scores of 1 to 10. The Moran's *I* value for SAZ was 0.29 with a z-score of 2.47 (p= 0.01), indicating significant clustering of C3. Five different ZCTA clusters were identified based on their distinction from neighboring areas (**Table 4**). The majority of ZCTA were unclustered (n= 108, 91%). Higher C3 scores tended to cluster around the metropolitan Tucson region (**Figure 1**). Communities with the highest C3 scores were 85641,85615, 85142, 85718, and 85747. Lower C3 scores clustered in ZCTAs in the southeastern most corner of SAZ. The highest frequency of C3 was 2, characterizing 18% of SAZ communities as isolated (n= 20 ZCTA).

Table 4: Community Connectedness Classification (C3) Localized Clusters Based on the Getis–Ord G∗i (d) Statistic in Southern Arizona

Cluster Type	ZCTA n (%)	C3 Range [Mean (SD)]
Unclustered	108 (91%)	1, 10 [4.68 (2.46)]
High	6 (5%)	5, 10 [8.33 (1.75)]
Low	1 (1%)	2, 2
High Outlier	3 (3%)	9, 10 [9.33 (0.58)]
Low Outlier	0 (0%)	N/A
Total	118 (100%)	1, 10 [4.96 (2.63)]

Figure 1: Community Connectedness Classification (C3) Clustering in Southern Arizona.



Areas that are blank without an outline have insufficient data to calculate C3.

Regional Characteristics

Technology Access

More than half of SAZ households had access to technology either through tablet, smartphone, or desktop/laptop (**Table 5**). The density of access to any technology to concentrated in neighborhoods of metropolitan Tucson, Yuma, Sierra Vista, Sonoita, Fortuna Foothills, Tacna, Dragoon, San Luis, Green Valley, and Apache Junction.

Table 6: *Percent of Households with Technology Access in Southern Arizona by County*

Technology Access	Cochise	Graham	Greenlee	Pima	Pinal	Santa Cruz	Yuma
Tablet	58.9	55.6	58.2	61.4	64.1	50.7	52.1
Smartphone	78.9	80.9	87.7	85.1	84.4	77.5	80.0
Laptop/Desktop	78.7	66.9	59.9	79.7	81.1	66.7	69.5

Health Behaviors and Health Status

In SAZ, approximately one-fifth reported fruit and vegetable intake of less than one daily, nearly one-third were physically inactive, one-third of SAZ adults were obese, almost half were current smokers, and one-fifth reported heavy alcohol use (**Table 6**).

Table 6: Cardiometabolic Health Behavior Risk Factor Summary for Percent of Population by County in Southern Arizona.

Health Behavior	Cochise	Graham	Greenlee	Pima	Pinal	Santa Cruz	Yuma
Low Fruit and Vegetable Intake	18.4	19.8	20.1	17.8	18.5	18.9	20.3
Physical Inactivity	29.5	29.1	32.0	27.7	29.1	31.5	31.3
Obesity	30.7	30.5	33.0	29.7	31.0	32.1	31.5
Smoking	43.2	43.0	40.4	40.2	42.0	41.6	40.0
Heavy Alcohol Use	20.1	22.3	21.1	21.0	20.8	18.7	20.0

Nearly half of adults in SAZ reported good overall health (range 43.4%-48.3%), however, on average 15% reported poor physical health while 12% reported poor mental health (**Table 7**).

Table 7: Population Percent Reported Perceived Health Status by Southern Arizona County

Perceived Health Status	Cochise	Graham	Greenlee	Pima	Pinal	Santa Cruz	Yuma
Poor Physical Health	15.5	15.3	14.9	14.2	14.9	16.5	15.4
Poor Mental Health	12.4	15.0	12.8	12.7	12.5	11.8	21.6
Good Overall Health	46.6	46.5	43.4	48.3	46.7	42.7	42.6

C3 Direct Effects

Technology Access

C3 was significantly associated with technology access for smartphone, tablet, and laptop/desktop in SAZ (**Table 8**). The average direct effect across ZCTAs of a 1-point increase in C3 is to increase population smartphone access two-fold, tablet access by four-fold, and laptop/desktop access by three-fold.

Table 8: ZCTA-Level Direct Effects of C3 on Technology Access in Southern Arizona

Technology Access	SAR ß (95%CI)	*P*-Value
Smartphone	2.32 (1.45, 3.01)	<0.001
Tablet	4.00 (3.17, 4.82)	<0.001
Laptop/Desktop	3.34 (2.32, 4.35)	<0.002

Spatial autocorrelation regression (SAR) models adjusted for population demographics and rurality. ZCTA= 116

Health Behaviors and Health Status

Due to the potential overlap in technology access, smartphone access, the variable with the greatest population percent with access, was included as an interaction term in SAR models for health behaviors and health status. C3 directly effects health behaviors in SAZ when accounting for technology access. C3 was significantly inversely associated with low fruit and vegetable intake, physical inactivity, obesity, and smoking in SAZ (**Table 9**). Most population health behaviors estimated improve is 20-35% for each 1-point increase in C3 for the average direct effect across SAZ ZCTA.

Table 9: ZCTA-Level Direct Effects of C3 on Health Behaviors in Southern Arizona

Health Behavior Risk Factor	SAR ß (95%CI)	*P*-Value
Low Fruit and Vegetable Intake	-0.35 (-0.51, -0.19)	<0.001
Physical Inactivity	-0.32 (-0.48, -0.16)	<0.001
Obesity	-0.20 (-0.35, -0.06)	0.005
Smoking	-0.34 (-0.62, -0.07)	0.01
Heavy Alcohol Use	0.11 (-0.03, 0.24)	0.12

Spatial autocorrelation regression (SAR) models adjusted for population demographics and rurality with an interaction term for smartphone access.

When accounting for technology access, C3 directly effects perceived health status in SAZ (**Table 10**). C3 was significantly positively associated with perceived good overall health, where each 1-point increase in C3 increases overall health by 77%. C3 was significantly inversely associated with poor physical and mental health, with a 1-point increase of C3 decreasing perceived poor physical health by 24% and poor mental health by 22%.

Table 10: ZCTA-Level Direct Effects of C3 on Perceived Health Status in Southern Arizona

Perceived Health Status	**SAR ß (95%CI)**	***P*-Value**
Poor Physical Health	-0.24 (-0.39, -0.08)	0.002
Poor Mental Health	-0.22 (-0.35, -0.10)	0.001
Good Overall Health	0.77 (0.49, 1.06)	<0.001

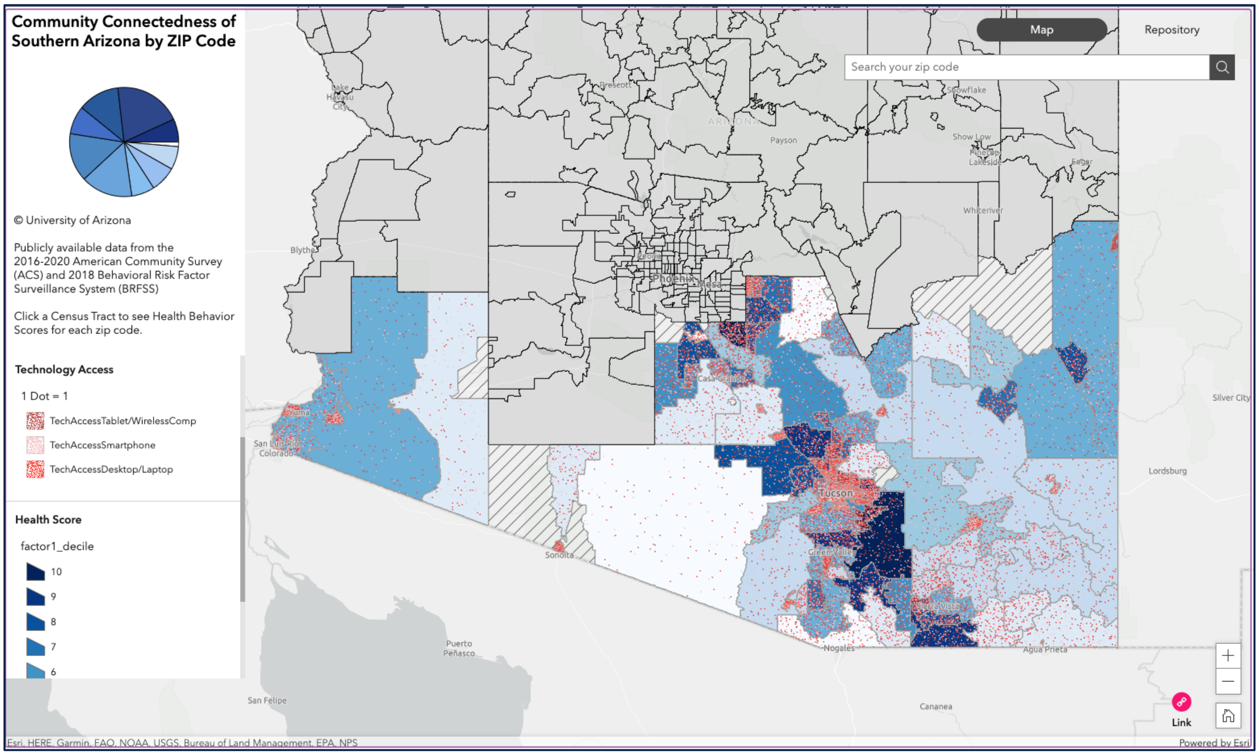
Spatial autocorrelation regression (SAR) models adjusted for population demographics and rurality with an interaction term for smartphone access.

Community Forum

An interactive web-based map was developed to visualize density modeling of C3, technology access, and health behaviors was developed and beta-tested by five local community stakeholders during the virtual community forum. The map properties use a WGS 1984 Web Mercator Coordinate System. Informative features of the map include summary of SAZ C3 through a pie chart, a map legend, and instructions on how to use the map. Interactive features of the beta map included a sharing function, point-of-contact layered navigation, a repository page accessible with University of Arizona credentials, and interactive pop-up windows activated by ZCTA selection which provided regional summary statistics including C3 score.

Results from the community forum of the beta version of the web map provided important feedback to improve the map and accessibility. This included developing a more descriptive key, inclusive choropleth color scheme, and the availability to download specific tables or data set for a selected area (e.g., county, ZCTA). Importantly, potential collaborations and future directions were identified from this meeting, including using the C3 to support grant applications to support local non-profit programming and expanding broadband access in SAZ. This map (**Figure 2**) can be accessed here: https://arcg.is/0L49eb.

Figure 2: Interactive web map of Community Connectedness Classification, technology access, and health behaviors in Southern Arizona.



Click Image to view interactive web-map or copy and paste the URL: https://arcg.is/0L49eb

DISCUSSION

Summary of Principal Findings

Using innovative epidemiologic and geospatial analytical methods, the relationship between SDOH, health behaviors, and perceived health status in SAZ were visualized and analyzed. The key findings from this research are the development and practical application of the novel C3 to represent protective SDOH factors in relationship to health-behavior related risk factors critical to population health outcomes. In SAZ, communities that were more connected (less isolated) had a lower percent of the population engaging in health-behavior related risk-factors and had better perceived physical, mental, and overall health status.

Clinical Practice Integration

Influential factors in C3 which may be the leading drivers for these findings include access to greater household income, food security, internet access, educational attainment, and an accessible healthcare network. A previous study looking at detrimental SDOH factors found that low education, low income and poverty, poor healthcare infrastructure, and social isolation were significantly associated with mortality, and that these effects were greater for older populations [62]. This digital divide is further implicated by unequal access to internet and broadband services for healthcare delivery in rural populations [63]. Health equity for rural underserved populations includes advocating for telehealth reimbursement policies and increasing broadband access for telehealth delivery and reducing travel and time burden [64].

Incorporating community level data, such as the C3, into clinical practice and prediction models may improve precision by accounting for SDOH factors that are beyond an individual's control [65] and prioritize programming. Digital health interventions and programs that consider C3 factors present in this analysis may be a potential target for extending healthcare beyond clinical practice to improve population health. Significant economic and environmental impact is projected from increasing use of telehealth [66], with estimated cost savings on healthcare expenditures from reduction healthcare utilization of 22% [67]. Further, telehealth interventions are cost-effective to deliver and can increase healthcare access in geographically diverse and underserved populations [68]. Separate from telehealth, in the context of chronic disease prevention or management, components of mHealth including goal tracking are independently associated with a better diet and more physical activity [6]. A systematic review of 52 RCTs published between 2014 and 2019 that evaluated mHealth apps designed to promote health behavior change (37 on physical activity, diet, or both, 11 on alcohol and drug use, and 4 on mental health) found high acceptability and improvement in health behaviors [69].

Translation into Digital Health Recommendations

The top health-related priorities cited by SAZ county and local agencies are mental and behavioral health, nutrition, physical activity, overweight/obesity, tobacco use cessation, and prevention of cardiometabolic diseases, as well as improved access to healthcare, improved health education, and SDOH, especially poverty, transportation, and the built environment [18, 28, 29, 34, 47]. Using an mHealth application to track one's own health data in addition to telehealth can be both empowering and cost-effective for patients seeking to change their health behaviors [70].

The current best evidence for mHealth apps supports those that have the potential to improve health-related knowledge related to nutrition, including increasing intake of a variety of fruits and vegetables for adults [71]. mHealth apps can also be an effective way for promoting increased physical activity, especially if they focus more on behavior change and less on aspects of illness [72]. These apps have broad utility for supporting diet and physical activity changes that could reduce overweight and obesity and reduce the incidence of chronic diseases such as cancer, T2DM, and CVD. mHealth applications focused on tobacco cessation are becoming more available and may help some consumers overcome the barrier to accessing tobacco cessation services, but more studies are needed to fully evaluate their efficacy [73]. In that same vein, mHealth applications designed to support or improve access to mental health care exist, but evidence supporting their effectiveness or responsiveness to the needs of the user is limited [74].

Strengths and Limitations

There are notable strengths and limitations to this research. Among the strengths, this analysis used publicly available data, which allows for estimation of population and geographic patterns. While this analysis had a regional focus unique to SAZ, due to the open access nature of the utilized data, the analyses conducted in this study can be replicated in other US regions to identify community level opportunities, strengths, and protective factors. The C3 model developed for this analysis is robust and met established thresholds [54]. C3 was highly correlated to other indices associated with mortality [75]. Compared to these other measures, however, C3 includes factors from all domains of SDOH, while other indices include some, but not all, making C3 the first established comprehensive measure of SDOH. This analysis did not include ecological components unique to SAZ geography, such as the arid environment, which may impact the magnitude and influence of C3 [76]. Additionally, the focus was on adult populations, and differences may be present for pediatric populations. There is potential bias or misclassification from using ZCTA, which is more sensitive to dynamic spatiotemporal changes in the classification of communities compared to smaller and more geographically static Census Tracts. However, due to the typical way in which residential clinical data collected is more likely to include zip code, this approach shifts the findings from conceptual to applicable.

Conclusion

C3 is associated with population household technology access in SAZ. Furthermore, C3 is associated with health behaviors and health status at a population level when accounting for demographics, rurality, and technology in SAZ. Geospatial analysis identified SAZ communities on the ZCTA-level that have positive attributes which may be health protective. An interactive webmap resulting from this analysis provides a power GIS-based tools for local researchers, non-profits, policy makers, and other change leaders in the SAZ community to support initiatives and inform program implementation. These findings can inform policy, healthcare delivery, and intervention design to improve population health on a local level.

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APPENDIX

```
/*Summary: output scores by FIPS code for v5 of the PCA for factor 1 and create quintiles and deciles*/

proc import out=v5 datafile="[redacted].csv"
dbms=csv replace;
run;
/*1521*/
	data v5_factor1;
		set v5;
		drop factor2 - factor4;
	run;
	proc sql;
		create table v5_factor1_reorder as
		select a.state, b.fips_code, b.county_code, b.county_name, b.factor1 as factor1_score
		from sdoh a right join v5_factor1 b
		on a.fips_code=b.fips_code;
	quit;

	/*make quintiles and deciles*/
	proc rank data=v5_factor1_reorder
		groups=10 out=deciles;
		var factor1_score;
		ranks factor1_dec;
	run;

	proc rank data=v5_factor1_reorder
		groups=5 out=quintiles;
		var factor1_score;
		ranks factor1_quint;
	run;

	proc sql;
		create table v5_factor1_dec as
		select a.*, b.factor1_dec
		from v5_factor1_reorder a left join deciles b
		on a.fips_code=b.fips_code;
	quit;

	proc sql;
		create table v5_factor1_dec_quint as
		select a.*, b.factor1_quint
		from v5_factor1_dec a left join quintiles b
		on a.fips_code=b.fips_code;
	quit;

	/*renumber ranks */
	data v5_factor1_dec_quint2;
		set v5_factor1_dec_quint;
		factor1_decile=factor1_dec+1;
		factor1_quintile=factor1_quint+1;
		drop factor1_quint factor1_dec;
	run;

/*output dataset*/
proc export data=v5_factor1_dec_quint2 outfile="[redacted].csv"
dbms=csv replace;
run;
	/*descriptives*/
	ods tagsets.excelxp file="[redacted].xml"
	options(sheet_interval='proc' embedded_titles='yes' sheet_name='factor1');
	proc univariate data=v5_factor1_dec_quint2;
		var factor1_score;
	run;
	ods tagsets.excelxp options(sheet_name='factor 1 by state');
	proc univariate data=v5_factor1_dec_quint2;
		class state;
		var factor1_score;
	run;
	ods tagsets.excelxp options(sheet_name='deciles');
	proc means data=v5_factor1_dec_quint2 n mean std min max;
		class factor1_decile;
		var factor1_score;
	run;
	proc means data=v5_factor1_dec_quint2 n mean std min max;
		class state factor1_decile ;
		var factor1_score;
	run;
	ods tagsets.excelxp options(sheet_name='quintiles');
	proc means data=v5_factor1_dec_quint2 n mean std min max;
		class factor1_quintile;
		var factor1_score;
	run;
	proc means data=v5_factor1_dec_quint2 n mean std min max;
		class state factor1_quintile;
		var factor1_score;
	run;
	ods tagsets.excelxp close;
```