Community Works: Predicting Changes in Community Resilience

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***Abstract*—Community resilience is a multidimensional concept that would be difficult if not impossible to measure with a single assessment. To capture this system-of-systems nature of community resilience, we argue that considerations of human and social capital must be included because humans are both the *source* of community resilience and the *beneficiaries* of it. We build on a data transformation method proposed by Hutto and colleagues [7] allowing researchers to create comprehensive measures of community resilience and its underlying social constructs (i.e., subjective well-being and objective standard of living). Using a combination of data simulation via probability sampling and confirmatory factor analysis, we demonstrate the impact of some future (conjectured) proposed legislation—e.g., governmentally provided self-driving cars as a public transportation alternative—on community resilience for three *demographically* defined communities: the elderly, the disabled, and all Americans of legal driving age (i.e., 16+) for each of the *geographically* bounded communities consisting of the 50 United States and the District of Columbia.**

Keywords-human capital modeling, social capital modeling, prediction, human capital investments, social capital investments, disability, self-driving cars, mass transit

I. Introduction

Community resiliency refers to a community's ability to respond to threats and challenges, successfully adapt to changes, and prevent, mitigate, or recover from disasters [1]-[4]. Rather than being a static construct, community resiliency emerges from the harmonic interaction of the quality of existing built infrastructure, the adequacy and efficiency of community emergency response services, and the human and social capital of residents [5][6]. Despite being vital to the measurement and prediction of community resilience, human capital—that is, the knowledge, skills, and attributes of residents that provide value to a community [8]—has been frequently overlooked by community resilience researchers and is often excluded from models of community resilience [8]. For models to capture the multidimensional system-of-systems nature of community resilience, we argue that human and social capital *must* be included because communities would simply not exist without human residents.

An immediate obstacle preventing researchers from successfully integrating human and social capital into models of community resilience is the lack of a single, comprehensive measure of human and social capital that addresses all the necessary variables required to visualize and quantify the human and social side of resilience. It is unlikely that any single measure will ever be comprehensive enough to sufficiently capture human and social capital in a resiliency context [7]. Instead, we propose a data transformation technique that allows researchers and policy makers the option to transform and combine existing data from multiple sources into a single dataset that objectively assesses existing community resilience in a comprehensive and mutable way. We use this technique in the present paper to characterize *existing* community resilience as well as to *predict* the impact of future (conjectured) legislation—the availability of self-driving cars—on different communities. Our technique allows researchers to reliably create extremely representative samples of a population quickly using as many variables as necessary to address important questions about human and social capital in a community resilience context. Because our technique does not rely on any one data source for information, researchers and policy makers can update models to include the most time-relevant population statistics with relatively little effort.

We will briefly define the factors of human and social capital modeled in the present paper. Additionally, we will explain our data transformation technique so that researchers may begin immediately employing our method to improve models of community resilience. Finally, we will provide a hypothetical use-case about the impact of proposed legislation—the availability of governmentally provided self-driving cars—on different communities in the United States.

A. *Crucial Factors of Human and Social Capital*

The most important first step of any community-based model is the definition of a community of interest. Communities can be defined by *geographic* identity such as geolocation or an attributed external border including town limits or people living within a common flood area. Communities can also be defined by the *demographic* attributes of their residents using personal identity (e.g., age, gender, ethnicity) and cultural identity (e.g., political and religious affiliation) to draw community boundaries.

Once a community of interest is identified, researchers and policy makers must consider the general *political* climate (i.e., the extent that residents of a community trust and feel satisfied and secure with the government, and believe civil liberties are protected), the general *economic* climate (i.e., unemployment rates, economic growth, inflation, and gross domestic product per capita), and determine the variables important for measuring human capital for the present time [3]. Human and social capital variables can be split into two

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main factors: subjective well-being and objective standard of living [2]. When included in the same model, subjective beliefs about quality of life can be assessed in relation to objective measures of standard of living illuminating resident biases and assessing the extent to which residents understand their present economic health [17]-[19].

Subjective well-being is a latent factor representing the beliefs, emotions, and attitudes a resident maintains in regards to their life [9-10]. Subjective well-being can be further split into four separate sub-factors [2][11][12]: *affective experiences*, *cognitive appraisals*, *global life judgments*, and domain specific *satisfaction*. Variables related to affective experiences capture a resident's trait affect regarding quality of life as well as personal factors including marital happiness. Variables related to cognitive appraisal capture resident opinions about their present socioeconomic status with respect to their ability to achieve life goals compared to other societal groups. Variables related to global life judgements capture the extent a person believes life is exciting as well as general beliefs about human nature. Finally, variables related to domain specific satisfaction capture the extent residents feel fulfilled and satisfied with life aspects such as career goals, family, and friendships. Building upon the data transformation techniques described in [7], we move beyond overly simplified measures of mood or satisfaction and assess subjective well-being as a multifaceted and complex construct.

Standard of living is a latent factor assessing a resident's *objective* access to present wealth, happiness, comfort, and material goods. At the national level, standard of living is frequently operationalized as gross domestic product (GDP) per capita. At the level of the resident or individual, standard of living can be split into two distinct sub-factors: quality of life and material wealth. Variables related to quality of life capture life expectancy, crime rates, environmental quality and living conditions, and resident's access to goods and services. Variables capturing material wealth assess resident's wages and income, net worth, cost of living, and wealth relative to neighbors. As standard of living increases, so too does subjective well-being [13]-[16].

We extend Hutto et al.'s [7] model to include *community engagement* and *social capital* as further indicators of community resilience. Community engagement is a latent factor representing the extent that residents participate in activities, groups, and relationships within their community and with broader society [20][21]. People who are more engaged within the community tend to measure higher in subjective and objective health and well-being [22]. Social capital is a latent factor representing the frequency of interactions requiring trust and cooperation that occur within a community. These interactions are done for a common, public good rather than simple personal gain [23]-[26] and are typically operationalized through volunteer and charity work (e.g., the amount donated to charity organizations) as well as acts of social trust and kindness (e.g., giving up a seat on a bus for a stranger). Resilient communities tend to be higher in social capital because it allows for a willingness to help residents in emergency contexts [25] as well as a readiness for a community to adapt to change [22].

In combination, these social community resilience factors (e.g., human capital via subjective well-being and standard of living, social capital, and community engagement) provide extensive information about the socioeconomic context within which a community exists. The ability to comprehensively measure each of these factors provides policy makers and researchers with a better understanding of not only how aspects of a resident's social and economic life impact community resilience but also the degree to which proposed changes in any given social variable will impact community health overall.

B. *Our Community Data Simulation Technique*

Our community data simulation technique uses probability sampling to create a representative community of interest. Using this method, researchers can obtain and combine data from multiple relevant data sources to create the comprehensive and complex factors necessary to model community resilience. Upon creating a dataset consisting of both a representative sample and enough variables to adequately model the relevant community resilience factors, researchers are advised to test their assumptions using confirmatory factor analysis or structural equation modeling. Using these confirmatory methods, researchers will then be provided with factor loadings that can be used to create a series of weighted sums easily quantifying total community resilience. Once item and factor weights have been established for each variable and factor of interest, researchers can transform variables using criterion determined by suggested community changes. A new weighted sum would be created using the previously established item and factor weights as well as a combination of the unchanged variables and the transformed variables of interest. This new quantification of community resilience can be compared with previous community resilience to determine if suggested changes yielded meaningful increases in community resilience. Additionally, these results are readily transformed into visual aids to help researchers and policy makers communicate results. We will use the rest of the methods section to break down each step of this process.

For more information on suggested factor creation, we encourage researchers to read Hutto et al.'s presentation for a complex and comprehensive structural equation model of community resilience [7].

C. *A hypothetical use-case for our data transformation technique*

To illustrate and motivate this research, we propose a hypothetical example of a government deciding whether to provide self-driving cars as an aid to national public transit services for people ages 16+. In the first scenario, self-driving cars would only be made available to people with disabilities. In the second scenario, self-driving cars would be provided to both seniors—with and without disabilities—and people with disabilities. In scenario three, self-driving cars would be made publicly available to anyone aged 16+ regardless of disability status. As such, for the purpose of this paper, the communities of interest are defined in two ways: by specific demographic attributes (i.e., age and disability status), and by geographic boundaries (i.e., the 50 U.S. states and the District of Columbia). For the present paper, we focus on how proposed changes would impact community resilience as influenced by human and social capital specifically (rather than community resilience).

II. Methods

We next decompose our community data simulation technique, step-by-step.

Step 1. Identifying data sources and variables

In the previous section, we defined the characteristics of communities of interest and proposed changes to the existing community structure. We now identify data sources containing either raw response data (i.e., the number of people who responded to a specific response option for a given variable) or probability data (i.e., the percent of people who fit within a certain socioeconomic criterion or who maintain a specific belief). To create the present dataset, we turned to polling sources including Pew and Gallup, the U.S. Census Bureau and American Fact Finder, and the General Social Survey.

During this step, researchers may be tempted to exclude variables that aren't directly relevant to proposed changes. We caution against this behavior. The only way that factors of interest can meet our criterion of being comprehensive, multidimensional, and representative is if they include the variables that adequately capture the construct of interest. Not all items may be related to proposed changes, however, all items should adequately, *uniquely*, and comprehensively represent their underlying factor. In this way, researchers can be more comfortable in assuming factors were not created in a way to bias findings to support or refute proposed changes.

Step 2. Create a dataset using probability sampling

Using the probabilities obtained in step 1, we next create a dataset of any size and with any number of potential variables by simulating data using probability sampling. Here, we select a variable (e.g., disability status), determine the categories of interest (e.g., disabled, not disabled), and use existing (verified) population percentages to set the probabilities that a person of a specific sociocultural criterion (e.g., race, sex, age, income, etc.) would be in a specific category. Using statistical software such as R's "sample function", this type of sampling can be performed with near infinite repetitions to generate a population sample of substantial size and extremely representative variability.

Step 3. Determining Factor Loadings for items and sub-factors of interest

With an adequate simulated community dataset in place, we next obtain item and factor loadings via confirmatory factor analysis or structural equation modeling. This is accomplished for all data items relevant to an underlying sub-factor, and for all sub-factors related to a given higher-order factor. To complete this, categorical variables will need to be transformed into continuous variables using the method described by Hutto and colleagues [7]. The relationship between items and factors should be determined using theory—we used a proposed model of community resilience to guide our item/factor relationships [7].

Step 4. Create weighted sums of sub-factors

Because factor loadings represent the degree of association between items and their underlying factors, factor loadings represent an item or sub-factor's weight in a weighted sum or factor score. While factor loadings will not be identical across datasets, similar communities should yield similar factor loadings if samples were created from accurate and representative statistics—especially if created using the same probabilities. Using factor loadings as item weights, we next create a series of weighted sums that, when combined, represent a quantification of community resilience—or human and social capital in the present paper. For example, we can now create a weighted sum using the factor loadings for items representing material wealth and quality of life separately. Using factor loadings for the material wealth and quality of life sub-factors, a weighted sum of standard of living can be obtained. Using factor loadings for standard of living and subjective well-being, a weighted sum of human and social capital can be obtained that will accurately represent underlying human and social capital for any given community. Factor loadings are obtained by performing a series of confirmatory factor analyses as described in step 3.

Step 5. Create new variables representing changes in human and social capital

Once item and factor weights are established, relevant variables can now be recoded per the criterion determined by our hypothetically proposed self-driving car legislation. For example, the availability of governmentally provided self-driving cars in rural areas may allow disabled peoples without access to public transportation services the ability to obtain reliable and affordable transportation, and thus, seek and obtain job opportunities and healthcare services previously unobtainable due to distance. Thus, researchers can assume unemployment rates and commute times among disabled peoples may decrease while general health, income, and social group participation among disabled peoples may increase simply because adequate transportation has been made available.

At this point, researchers may become concerned that transformations may over-exaggerate the impact of proposed changes in legislation. This is a valid fear. We suggest two methods to address this fear. First, researchers should use existing research as well as sound logic to guide assumptions *made a-priori* about the variables selected for transformation and change criterion while avoiding the temptation to change all variables or to alter change criterion after the fact. This helps to ensure that only relevant variables are transformed to be both reliable and objective. Second, researchers should

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test for the impact of multiple scenarios with different change criterion established *a-priori* to account for small, medium, and large effects. For example, the present paper accounts for small changes in commute times (commute times for people taking public transit reduced by ten minutes), medium changes in commute times (commute times for people taking public transit reduced by 20 minutes) and large changes in commute times (commute times for people taking public transit reduced by 30 minutes) to create better models for how communities may change assuming different goals are met.

Step 6. Test that changes in human and social capital are significant and then model the changes

We next apply statistical techniques to test the extent that proposed changes have a significant and meaningful impact on community resilience—or, in our case, human and social capital. This method allows results to be readily represented by visual aids for easy communication to any audience. For communities defined in terms of geographic boundaries, we use choropleth maps to visualize changes in data values using easy-to-see differences in color across a region of interest.

A. Present study

For each state in the United States and the District of Columbia, using a deterministic draw of 1000 females and 1000 males, we simulate an age, ethnicity, and disability representative community. Extending the model developed by Hutto and colleagues [7], we next incorporate more than 100 variables thought to represent community resilience, including variables related to human and social capital. These variables are drawn from myriad data sources as previously described, and constrained to the years 2000-2016 (for the General Social Survey and Census data), or the most recent published public dataset available.

We hypothesized that impacts of government-subsidized self-driving cars on social aspects of community resilience may be *small*, *average*, or *widespread*. For demonstration purposes we apply deterministic "what-if" modeling and simulation using single-point estimates – based on a combination of inductive reasoning and empirically informed heuristics – for each level of impact. *Small* impacts were operationalized in our model by a single unit of increase for directly relevant variables – that is, for example, people may move from "Very Dissatisfied" to merely "Dissatisfied" with their present commute times. In the *average* impact scenario, variables directly related to transit (e.g., commute time/satisfaction and group attendance) would increase by two units while other, more indirect measures that may increase because of readily available and easily accessible transit (e.g., the confidence that a person could find a job as good as the one they presently have) would increase by a single unit. In the *widespread* impact condition, variables directly related to transportation were increased by three units (or until a person hit maximum satisfaction), variables that improve as an indirect result of the availability of new forms of mass transit were increased by two units, and general measures of satisfaction were increased by a single unit.

To investigate the effect on broader community resilience via impacts to human and social capital, these simulated impacts were applied to each scenario of interest—e.g., providing government-subsidized transportation using self-driving cars to either 1) the disabled community alone, 2) the combined communities of disabled and elderly, or 3) to all Americans age 16 and above. If, when compared to no change in mass transit availability, the impact was significantly different, then proposed legislation would be considered "effective".

III. Results and Limitations

In the first scenario, we wanted to see the impact of governmentally provided self-driving cars on disabled people in America. To accomplish this, we selected variables related to the social aspects of community resilience that were likely to be influenced when disabled people are suddenly able to travel greater distances in areas where public transportation or cost effective methods of transit were not previously available. Fig. 1 demonstrates predicted changes in community resilience for each projection. Specifically, we show projected changes in community resilience for three populations (disabled, disabled and older adults, all drivers) in three different scenarios (small, average, and widespread change). Maps demonstrate linear transformations as projected community resilience increases within population for each scenario. All nine projections significantly improved community resilience from baseline predicted values.

Governmentally provided self-driving cars improved community resilience in disabled populations compared to the baseline predicted value of 107.21 (S.D.=3.04). Small scenarios improved community resilience by 17.03 points ($t(50)=40.5$, $p < 0.05$). Average scenarios improved community resilience by 51.03 points ($t(50)=121.34$, $p < 0.05$). Widespread scenarios improved community resilience by 91.03 points ($t(50)=216.45$, $p < 0.05$).

In the second scenario, we wanted to see the impact of governmentally provided cars on both disabled as well as elderly adult populations across America. There was a significant improvement in community resilience compared to baseline. Small scenarios improved community resilience by 14.76 points ($t(50)=34.47$, $p < 0.05$). Average scenarios improved community resilience by 40.76 points ($t(50)=95.19$, $p < 0.05$). Widespread scenarios improved community resilience by 75.76 points ($t(50)=176.93$, $p < 0.05$).

In the third scenario, we wanted to predict the change in community resilience associated with all Americans of legal driving age (i.e., 16+) having access to self-driving cars as a mass-transit alternative. The availability of this form of mass transportation had sweeping positive impacts on community resilience even in the small change conditions when compared to baseline. Small scenarios improved community resilience by 18 points ($t(50)=42.35$, $p < 0.05$). Average scenarios improved community resilience by 51 points

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($t(50)=119.98$, $p < 0.05$). Widespread scenarios improved community resilience by 92 points ($t(50)=216.43$, $p < 0.05$).

We did not weigh the sample size drawn from each state, thus, sparsely populated states like Alaska had the same number of people in our sample as densely populated states such as California because we did not weight the number of people selected from each state based on state population. Despite this, our sample was created to be as representative as possible and was rather large (2000 people per state) so we do not believe that weighting our sample size would influence our findings beyond the point of relevancy.

This method presents a viable series of predictions of what could happen when public policy aimed at improving community resilience is implemented into a given community. The next logical step in our research is to attempt to validate our prediction models and improve our data simulations and transformations using real-world data. For this to happen, researchers must coordinate with policy makers to predict the impact of proposed changes before they are implemented and, once implemented, compare prediction to real-world changes in community resilience. This is a crucial step in advancing community resilience research and it is one that, to our knowledge, has yet to be attempted. In the interim, we encourage researchers to set multiple a-priori criterion levels (e.g., small, average, and widespread impact predictions) to account for a range of possible outcomes. We caution researchers against including only those variables in a prediction model that would change based on proposed policy, and instead, argue for including a wide range of variables that best represent their underlying factor. We also emphasize that decisions to alter variables should be based on experience and supporting evidence in the literature. Adopting this approach should improve predictions and help to keep objectivity while the present method is tested.

IV. Conclusion

Community resilience is a multidimensional process that emerges from the successful interaction of multiple systems including built infrastructure, community services, and human and social capital. We present a data transformation technique that allows researchers to combine information from multiple data sources into a single, comprehensive measure of community resilience (or any system from which community resilience arises).

Our data transformation method involves simulating data through probability sampling, creating weighted sums, and testing for change values. Using three hypothetical scenarios, we demonstrate the efficacy of our method by demonstrating the impact of governmentally provided self-driving cars on human and social capital within communities across America. Results can be readily transformed into visual aids including choropleth maps.

Our method addresses many concerns about the sparsity of survey data and the lack of a cohesive measure of community resilience and its underlying systems using perfectly representative population samples with extremely large Ns. Additionally, our method is inexpensive and expedient, allowing for researchers and policy makers to quickly test the impact of proposed legislation on communities of interest without the administration of a separate measure or survey. Finally, our method is mutable allowing models of community resilience to rapidly change in response to changes in socioeconomic climates. Together, we believe this method represents the first step in next generation prediction of community resilience and its underlying systems.

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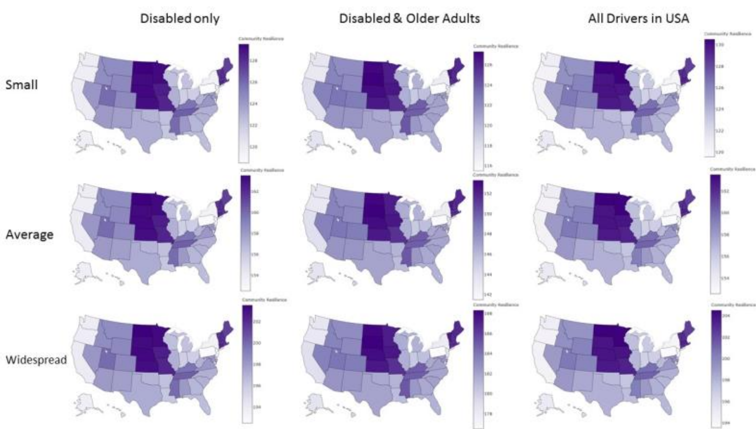

Figure 1. Predicted changes in community resilience: