The Social Side of Community Resilience: Human Capital Modeling

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***Abstract*—Present measures of community resilience – that is, how communities respond or adapt to changes as well as recover from disasters – are often too shallow and fail to account for the gamut of variables contributing to community health. We argue that this problem stems from attempting to measure community resilience with an overly simplistic assessment. It is understandably difficult to construct a predictive model of community resilience. Such a model would need to be composed of variables that represent a range of elements which capture the community's ability to respond to and/or overcome natural or man-made disasters/disruptions, including factors spanning the resilience or (in)vulnerability of houses and buildings, roads and bridges, emergency services, electrical grids, computer and information exchange networks, potable water distribution systems, sanitation systems, and so on. Furthermore, the resilience associated with the aggregate human/social spirit of a community is often marginalized or, in some cases, ignored completely. The disparate nature of such a broad range of variables is that they are measured on different scales, with incongruent units, collected from diverse sources, at dissimilar time intervals. The current paper addresses all three of the challenges associated with (1) incorporating human and social elements of community resilience, (2) representing the complexity of community (social) resilience variables in a single *common latent variable construct* model that addresses concerns about disparate scales, units, sources, and types of data, and (3) creating useful models for both *characterizing* and *predicting* the resilience of a given community. We achieve this by demonstrating a novel technique for translating extant data such that the entire gamut of relevant variables are expressed in terms of their impact on human capital. Our technique then utilizes structural equation modeling techniques to construct causal (and thus, descriptive and predictive) models of community resilience.**

Keywords-human capital modeling, social capital modeling, structural equation modeling, transformation techniques

I. INTRODUCTION

Global changes including international tensions and climate related stresses increasingly impact American communities. Policy makers and the public are also increasingly concerned with the health of American cities in regards to aging American infrastructure amidst rapid technological developments. To address these problems, policy makers and researchers have begun investing in community resilience—that is, investments towards understanding and improving how communities respond and adapt to changes as well as recover from disasters [1]–[3]. Improvements in physical engineering and city infrastructure are often the first consideration for improving community resilience. For instance, improved road systems allow for easier access both in to and out of a city, earthquake-proof buildings reduce risks of structure collapse in the event of an earthquake, and investments in emergency services increase community response time in the event of disasters or threats. Engineered infrastructures in urban communities are necessary ingredients of community resilience in the presence of stressors such as such as economic downturns, natural or man-made disasters, or Carrington Event-like phenomena. However, the ultimate criteria for resilience are the preservation (or restoration) of the human population affected by such stressors. Indeed, it is for the benefit of the human population that infrastructure systems even exist; it is human welfare and quality of life which are ultimately served by fortifying critical infrastructures against stressors.

Social science has a well-established body of literature demonstrating the strong relationship between an individual's *social resilience* and the role of protective factors related to their assemblage of health, well-being, and livelihood 'competencies', 'assets', 'resources', or 'endowments' collectively referred to as *human capital* [1][2][4]–[9] and *social capital* [10]–[13]. Thus, human and social capital are both recognized as crucial in achieving resilience and, through their dynamic interplay, enable a community to respond positively to risks and alter or reduce the effects of adversity [3][6]. Furthermore, individuals are responsible for maintaining and increasing human capital within communities [5][14], and human capital is vital for economic growth [15]. As human capital increases, community conditions improve and new opportunities become available for individuals [16], [17]. In turn, individuals who are higher in human capital are more likely to recognize and exploit new opportunities when they become available within the community [18].

As such, we argue that humans are both the *source* of community resilience and the *beneficiaries* of it. Nevertheless, a major, often unconsidered, aspect of community resilience is social and human capital. A paucity of adequately comprehensive measures of human and social capital creates a major obstacle in assessing community resilience. Present measures fail to capture the intricate relationships between objective quality of life measures, subjective well-being, general political and economic climates, and community demographic factors. Indeed, traditional systems-of-systems models integrating aspects of engineered infrastructures with human behavior are often over-simplified representations of what in actuality are very complex aspects of the social and physical world [19].

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A single measure or survey of human and social capital is an impractical goal for researchers; it is unlikely any one measure could be both comprehensive enough and time-efficient to administer. We embrace more multifaceted representations of human behavior with more complex models. Our model of human capital assimilates data of disparate forms, using disparate units of measure, collected from disparate sources, at disparate scales, and integrates them for the purpose of developing a complex, system-of-systems representation of community health, well-being, and livelihood. Importantly, our complex models are (first and foremost) explicitly motivated by extant scientific literature, and further derived based on data-driven insights from well-established public data sets comprising records from 30 different collection activities spanning 42 years (from 1972 to 2014) across nine different divisions of the United States Census Bureau and assimilated into a single data repository called the General Social Survey (GSS) [20], as well as historical data from the U.S. Bureau of Labor Statistics [21][22] and the World Bank Open Data repository [23].

Using this well-pedigreed data model (c.f., Section II), in Section III we then present a technique for transforming the multifaceted, disparate data into ordinal measures of a *single common construct*: human capital. Once transformed, we next employ advanced statistical techniques in Section IV to characterize both the strength and direction of relationships of community resilience factors (i.e., human and social capital, economic climate, political climate, etc.), which allows us to capture causal (thus, descriptive *and* predictive) models of the social side of community resilience. Section IV presents the results of our initial SEM analysis and discusses some of the limitations associated with the approach. Section V concludes by situating our work in current and prior literature, and makes recommendations on future directions for this sort of research.

II. Social Factors of Community Resilience

We define social aspects of community resilience using a combination of theory and available data (e.g., survey data, public reports, and scientific findings). To begin, we briefly elaborate on the theoretical definitions for the community resilience factors in the present study. Also, we elaborate upon the types of data employed to create these factors.

A. Constituants of Human Capital: SWB and SOL

Folds and Thompson [2] argue that human capital is a complex latent (i.e., not directly observable) construct thatcan be split into two factors: objective quality of life measurements (i.e., *standard of living*) and *subjective well-being* measures. These two factors can be further broken down into sub-factors to account for the broad range of resilience-protective factors related to the assemblage of health, well-being, and livelihood for a given community:

1) Subjective well-being (SWB): The subjective emotions and attitudes a person maintains in regards to their own life are collectively referred to as “subjective well-being” [24][25]. Using the GSS and other public data resources, we integrate at least 25 manifest indicators of general happiness and overall satisfaction with their personal life. The manifest indicators are organized into latent variable constructs representing four principal constituents of subjective well-being [26][27], as initially operationalized by Folds and Thompson [2] for use in our human capital modeling efforts:

a) *Affective Experiences*: the longer-term experiences of pleasant affect (as well as a lack of unpleasant affect) as indicated, for example, via a person’s general perceived happiness in life, in their marriage, and with their cohabitation companion (e.g., partner or roommates).

b) *Global Life Judgements*: a person’s judgements about their sense of purpose and general feelings of optimism towards the future. Examples of global life judgements include a person’s overall belief regarding how interesting they find their own life in general (e.g., whether they consider life to be dull, routine, or exciting), and judgements about the general nature of humanity (whether they believe most other people to be trustworthy, fair, and helpful).

c) *Cognitive Appraisals*: a person’s subjective self-assessment of their own current socioeconomic state relative to their life goals, as well as broader social comparisons. Determinants include financial status self-appraisals, appraisals regarding their career and wages, social status self-appraisals (e.g., social rank and social class), and self-appraisals regarding the relative quality of their domicile.

d) *Domain Specific Satisfaction*: the degree of fulfillment or contentment with important social elements such as satisfaction with their family life, friendships, recreational interests, job, health, and their city of residence.

2) Objective measures of quality of life and standard of living (SOL): Measures of subjective well-being should be complemented with objective measures like income and property value when evaluating community health and livelihood [28]–[30]. When used in tandum with subjective measures such as SWB, objective measures of standard of living (SOL) allow researchers to assess the degree to which a person’s beliefs about present life conditions (e.g., a person’s belief that they are in the upper-middle class) maps on to objective information about their tangible present life conditions (e.g., actual earning wage and property value). We operationalize SOL using 17 indicators from the GSS data to capture objective measures of individual quality of life and standard of living in our human capital model. These indicators include, for example, records of individual’s highest education level attained, the number of people living in their household, type of dwelling (and whether owned or rented), various employment characteristics (part time, full time, student/homemaker, unemployed, retired, etc.), and constant (i.e., annual inflation adjusted) income in dollars. Standard of living is closely connected with subjective well-being—that is, decreases in objective standard of living results in reduced subjective feelings of well-being and increased mental health risks which, which then in turn can further reduce objective standards of living [31]–[35].

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In addition to SWB and SOL, we must also consider other important elements of the social side of community resilience. The next section addresses many of these additional factors.

B. Other Socially Oriented Community Resilience Factors

Together, subjective well-being (SWB) and standard of living (SOL) capture the respective subjective and objective aspects of Human Capital; but, this is only a part of what comprises the social side of community resilience. We must not neglect consideration of individual and community demographics, nor the greater context the community; we need to account for demographic information as well as social perceptions of the national economic conditions, the general political climate, and the general security atmosphere.

1) Demographics: these characteristics form the basis by which "communities" are defined in the first place. As such, it is important to have access to information at the individual and aggregate level about community demographics including aspects of *personal identity* (e.g., ethnicity, age, gender, marital status), *geographic identity* (e.g., city/community size and geolocation), and *cultural identity* (e.g., political and religious affiliations, preferences and practices). Using items from the GSS, we operationalize community demographics at the national and regional levels.

2) Larger contextual environment: the general *political* climate incorporates public opinion regarding the utility and morality of national programs (e.g., satisfaction with healthcare and transportation services) as well as general attitudes about the government (e.g., public trust and perceptions that social liberties are protected). The general political climate influences—and is also influenced by—the general *economic* climate and the general *security* climate. To represent the general economic climate, we access national level historical information from the U.S. Bureau of Labor Statistics [21][22] and the World Bank Open Data repository [23]. This includes annually recorded economic data such as national unemployment rates, consumer price indices, inflation rates, prime lending interest rates, and annual gross domestic product (GDP) per capita. Our representation of the general security climate incorporates community exposure to crimes, feelings of fear, and beliefs of the efficacy of the court system as constructed from data immediately available within the GSS.

III. METHODS

A. Principal Data Source

The General Social Survey has been administered to a representative sample of the American public from 1972 through 2016. The present study used data from the years 1972 through 2014. Survey items include feelings about national spending, community safety, membership and engagement in social groups, income and subjective feelings of financial health. We selected this survey because it offers a long-term examination of social changes within American communities while also providing us with important information that can be adapted to represent the theoretical underpinnings of human and social capital. The GSS consists of hundreds of questions with varying degrees of hypothesized relationships to community resilience. For instance, a person's astrological sign is unlikely to be indicative of their subjective well-being or objective quality of life. For this reason, we went through each question surveyed on the General Social Survey looking for those that were most representative of our theoretical conceptions of the community resilience factors. Items were selected based on evidence from existing scientific literature and a-priori hypotheses about the theoretical makeup of identified community resilience factors.

B. Transforming Dissimilar Data Into a Common Form

Responses to selected items on the GSS were next transformed into ordinal variables—that is, we translated (typically categorical) data into their corresponding linearly ranked associated to either SWB or SOL. Transformations in this case were generally informed by the GSS data itself (e.g., people of lower income score lower in objective quality of life than people with higher income; people with more positive global life judgements score higher on subjective well-being than people with more neutral or negative global life judgements). All ordinal transformations were further vetted using a top-down approach where we identified predominant scientific studies examining the relationship between variables of interest and their hypothesized community resilience factors. Using age variables as an example, we ordinally transformed age response categories in terms of their hypothesized human and social capital clusters, resulting in 5 groups with people between the ages of 15 and 20 having the lowest value (i.e., "1") and people between the ages of 60 and 75—retired and still healthy—having the highest value (i.e., "5").

This transformation step has three important characteristics: (1) it relies on a *systematic*, *principled*, and *scientifically-grounded* mapping of survey item responses to their appropriately ranked (ordinal) impacts on a common construct (human capital), (2) it is *extensible* to any data type, as long as a relationship can be defined in terms of direction and magnitude of influence on a factor or sub-factor within the human capital model (3) once transformed, it allows researchers to employ advanced statistical techniques (such as structural equation modeling) to create causal models with *predictive* capabilities. Fig. 1 illustrates the social aspects of community resilience; the full list of factors considered for the model (discussed in Section II) consists of 68 variables. Because documentation for these factors is voluminous (it is more than 26 pages alone), we provide the factors, the GSS survey items (and response options) associated with those factors, and literature and data-derived rationale for the transformation of the typically non-linear (categorical, or nominal) data into linear (polytomous, or ordinal) data for our model in a supplementary package accompanying this paper.

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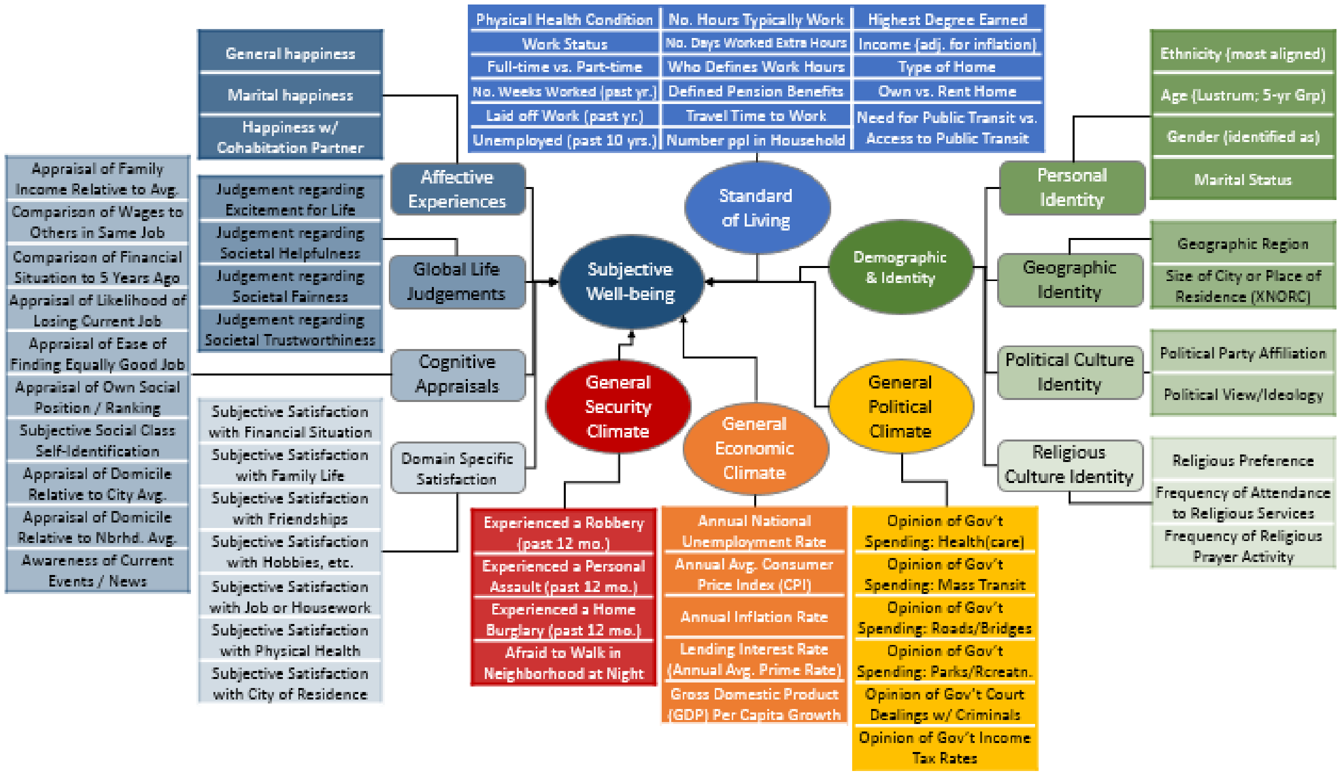

Figure 1. Factors associated with the social side of community resilience.

C. Causal/Predictive Modeling for Community Resilience

Any ordinally transformed variable—like the age variable in our earlier example—can be employed in complex statistical analyses including structural equation models of community resilience. Structural equation modeling (SEM) allows for objective item selection based on the degree to which items "load" onto their respective factors (i.e., the strongest predictive relationships to underlying theoretical factors will have the highest factor loadings). Additionally, SEM models provide information about the viability of hypothesized relationships between variables and factors via model fit indices. All our statistical analyses were performed in R to make our findings easily accessible, replicable, and repeatable.

SEM provides information about the direction and strength of relationships between variables and factors (either directly observable or latent) while assessing the viability of causal relationships among variables and factors [36]. Relationships are assumed to be linear so that changes at the start of a path result in linear changes in variables or factors at the end of a path [37]. To accomplish this, structural equations are computed allowing relationships to be both tested and graphically modeled [38]. When modeling causal relationships or in situations where unknown amounts of error exists in variables and factors of interest, SEM is generally superior to regression [38] making SEM a popular and accepted technique for behavioral and social modeling[39][40]. Because SEM uses a confirmatory approach toward hypothesis and model testing [37][38], it has proven to be an ideal method for modeling hypothesized human capital [14].

The best fitting SEM model is also the most parsimonious model because it accounts for the most variance between factors using the fewest causal paths. Generally, when sample sizes are large—as would be expected in human and social capital contexts—the $\chi 2$ test is biased and, while still reported, is generally not used to assess model fit [37][38], [41]–[46]. Instead, we rely on the comparative fit index (CFI; [47]) and root mean square error of approximation (RMSEA; [48]) to assess model fit. The CFI tests complete covariation between a hypothesized model and actual data providing a value constrained between 0 and 1.00. Values greater than 0.95 generally indicate a well-fitting model [38][42]. RMSEA—the best measure of model fit [38]—examines the extent that models fit a hypothesized population covariance matrix [49]. Discrepancies between population and model covariance matrices are reported as a number constrained between 0.00 and 1.00. Models with RMSEA values between 0.05 and 0.08 are considered to have adequate fit; models with values less than 0.05 have nearly ideal model fit [49].

SEM also provides information about the viability of hypothesized relationships between ordinally transformed survey items and community resilience factors. That is, the

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items that best represent a hypothesized factor will also have the highest factor loading in the model. Items with weak or non-existing (i.e., not significant) relationships to hypothesized sub-factors can be objectively eliminated using this approach.

Ordinal transformation also allows for aggregate examinations into community resilience factors of interest. Once transformed, survey items can be furthered centered to the mean (i.e., subtracting a mean constant from a variable of interest) and then objectively combined (i.e., summed) to form an indicator of total community resilience in an area. Total scores for individual community resilience factors can also be examined allowing for easy graphical representation (e.g., what would be accomplished using a choropleth map) for factors of interest in communities or regions of interest.

IV. Results

We transformed items from the General Social Survey from years 1972 through 2014 into polytomous, ordinal measures of human and social capital, as well as the general political economic, and security climates. We tested the relationships between these variables and their hypothesized factors using a structural equation model (SEM). Model fit statistics regarding the $\chi 2$ test for goodness of fit and the root mean square error (RMSE) for the model were adequate, though the low score for the comparison fit index (CFI) indicates that a model derived from less sparse data—e.g., a model that incorporates additional data sources along with the GSS—would likely be a better fit ($\chi^2 = 251851$, $df = 1476$, $p < 0.00$; CFI = 0.445; RMSEA = 0.053). We explore such models in subsequent research [50]. Fig. 2 shows a graphical representation of the latent variables within our structural equation model, as well as information about the strength of our hypothesized relationships between factors (e.g., subjective well-being, standard of living, demographic data, and the general political, economic, and security climates – all factors are statistically significant).

As is common when relying on a single data source, questions on the General Social Survey were not consistently asked across years, leaving information for many important items unavailable. Thus, even comprehensive surveys like the GSS are often not enough to model community resilience when used in isolation. We argue that future researchers would greatly benefit from either (1) combining multiple surveys, reports, and data sources to create a fully comprehensive measure or, (2) simulating data based on available population statistics. The methods presented in this paper support either initiative; we explore the latter in subsequent research [50].

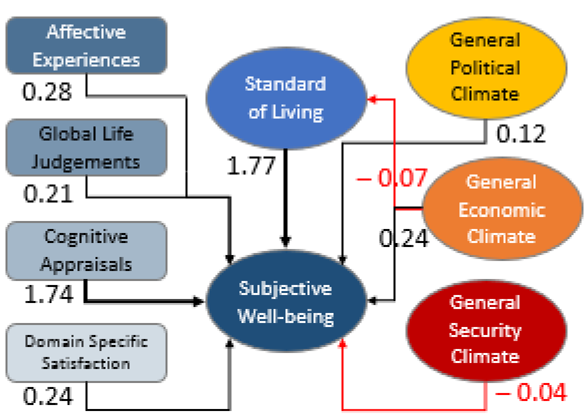

Figure 2. SEM latent variable model with factor weightings.

V. Conclusion

We present a technique for transforming disparate survey data into measures of human and social capital in a community resiliency context. This technique allows researchers flexibility to create complex and representationally accurate models of human and social capital using readily available data. Our technique fulfills many of the requirements for advancing social science research, including methods for enabling researchers to analyze data consisting of huge sample collected over multiple points in time (i.e., large-N and multiple-T; [19]). We also advance social science research because our technique can be quickly utilized to extend exploratory and predictive analyses for researchers interested in human and social capital [19]. Researchers interested in applying this technique for data exploration and prediction should refer to a subsequently submitted paper [50].

Our technique was tested using Folds and Thompson's [2] structural equation model of human and social capital. We also incorporated model structure proposed by McDermott and colleagues [51] who argue that community resilience is composed of an interaction of systems including human and social capital, built environments, and city infrastructure. Our technique and model fit statistics demonstrate reasonably good support for these existing models of human capital and community resilience.

We argue that researchers using this technique in the future—especially those researchers using our technique for simulated data—should incorporate a structural equation model to both check findings and provide further tests of reliability and replicability.

References

[1] D. J. Folds, "A notional model of creation, maintenance, and enrichment of human capital," presented at the 6th International Conference on Applied Human Factors and Ergonomics (AHFE), 2015.

[2] D. J. Folds and V. M. Thompson, "Engineering Human Capital: A System of Systems Modeling Approach," presented at the 8th International Conference on System of Systems Engineering, 2013.

[3] G. Windle, "What is resilience? A review and concept analysis," *Rev. Clin. Gerontol.*, vol. 21, no. 02, pp. 152–169, May 2011.

[4] M. Bartley, I. Schoon, R. Mitchell, and D. Blane, "Resilience as an Asset for Healthy Development," in *Health Assets in a Global Context: Theory, Methods, Action*, A. Morgan, M. Davies, and E. Ziglio, Eds. New York, NY: Springer New York, 2010, pp. 101–115.

[5] G. S. Becker, *Human capital: a theoretical and empirical analysis, with special reference to education*, 3rd ed. Chicago: The University of Chicago Press, 1994.

[6] J. G. Dyer and T. M. McGuinness, "Resilience: Analysis of the concept," *Arch. Psychiatr. Nurs.*, vol. 10, no. 5, pp. 276–282, Oct. 1996.

[7] A. S. Masten, K. M. Best, and N. Garmezy, "Resilience and development: Contributions from the study of children who overcome adversity," *Dev. Psychopathol.*, vol. 2, no. 04, pp. 425–444, Oct. 1990.

[8] J. Mincer, "The Distribution of Labor Incomes: A Survey With Special Reference to the Human Capital Approach," *J. Econ. Lit.*, vol. 8, no. 1, pp. 1–26, 1970.

[9] T. W. Schultz, "Investment in Human Capital," *Am. Econ. Rev.*, vol. 51, no. 1, pp. 1–17, 1961.

[10] J. S. Coleman, "Social Capital in the Creation of Human Capital," *Am. J. Sociol.*, vol. 94, pp. S95–S120, 1988.

[11] R. R. Dynes, "Social Capital: Dealing With Community Emergencies," *Homel. Secur. Aff.*, vol. 2, no. 3, Jul. 2006.

[12] Y. Nakagawa and R. Shaw, "Social Capital: A Missing Link to Disaster Recovery," *Int. J. Mass Emergencies Disasters*, vol. 22, no. 1, pp. 5–34, 2004.

[13] B. Wellman and S. Wortley, "Different Strokes from Different Folks: Community Ties and Social Support," *Am. J. Sociol.*, vol. 96, no. 3, pp. 558–588, 1990.

[14] M. Ruzzier, B. Antoncic, R. D. Hisrich, and M. Konecnik, "Human capital and SME internationalization: a structural equation modeling study," *Can. J. Adm. Sci. Rev. Can. Sci. Adm.*, vol. 24, no. 1, pp. 15–29, Mar. 2007.

[15] M. Novak and S. Bojnec, "Human Capital and Economic Growth by Municipalities in Slovenia," *Manag. Glob. Transit.*, vol. 3, no. 2, pp. 157–177, 2005.

[16] N. Bontis and J. Fitz-Enz, "Intellectual capital ROI: a causal map of human capital antecedents and consequents," *J. Intellect. Cap.*, vol. 3, no. 3, pp. 223–247, 2002.

[17] J. S. Coleman, *Foundations of social theory*. Belknap Press of Harvard University Press, 1994.

[18] P. Davidsson and B. Honig, "The role of social and human capital among nascent entrepreneurs," *J. Bus. Ventur.*, vol. 18, no. 3, pp. 301–331, May 2003.

[19] C. J. Hutto, "Blending Quantitative, Qualitative, Geospatial, and Temporal Data: Progressing Towards the Next Generation of Human Social Analytics," in *Proceedings of the Second International Conference on Human and Social Analytics (HUSO)*, Barcelona, Spain, 2016.

[20] T. W. Smith, P. V. Marsden, M. Hout, and J. Kim, "General Social Surveys, 1972-2014 [machine-readable data file]." NORC at the University of Chicago [producer and distributor], 2014.

[21] The U.S. Bureau of Labor Statistics, "Consumer Price Index Data from 1913 to 2016," *U.S. Inflation Calculator*, 2016. [Online]. Available: http://www.usinflationcalculator.com/inflation/consumer-price-index-and-annual-percent-changes-from-1913-to-2008/.

[22] The U.S. Bureau of Labor Statistics, "Labor Force Statistics including the National Unemployment Rate (Current Population Survey - CPS)," *BLS.gov Databases, Tables, and Calculators*, 2016. [Online]. Available: https://www.bls.gov/data/.

[23] World Bank, "GDP per capita (current US$) and Lending interest rate (%) from 1972 to 1016 [Custom cross-tabulation of data]," *World databank: World Development Indicators*, 2016. [Online]. Available: http://databank.worldbank.org/data/reports.aspx?source=2&series=NY.GDP.PCAP.CD&country=USA.

[24] F. M. Andrews and J. P. Robinson, "Measures of subjective well-being," *Meas. Personal. Soc. Psychol. Attitudes*, vol. 1, pp. 61–114, 1991.

[25] E. Diener, S. Oishi, and R. E. Lucas, "Personality, Culture, and Subjective Well-Being: Emotional and Cognitive Evaluations of Life," *Annu. Rev. Psychol.*, vol. 54, no. 1, pp. 403–425, Feb. 2003.

[26] E. Diener, "Assessing subjective well-being: Progress and opportunities," *Soc. Indic. Res.*, vol. 31, no. 2, pp. 103–157, Feb. 1994.

[27] E. Diener, E. M. Suh, R. E. Lucas, and H. L. Smith, "Subjective well-being: Three decades of progress.," *Psychol. Bull.*, vol. 125, no. 2, pp. 276–302, 1999.

[28] E. Angner, "The Politics of Happiness: Subjective vs. Economic Measures as Measures of Social Well-Being," *SSRN Electron. J.*, 2008.

[29] E. Diener and E. P. Seligman, "Very Happy People," *Psychol. Sci.*, vol. 13, no. 1, pp. 81–84, 2002.

[30] D. Kahneman, A. B. Krueger, D. Schkade, N. Schwarz, and A. Stone, "Toward National Well-Being Accounts," *Am. Econ. Rev.*, vol. 94, no. 2, pp. 429–434, Apr. 2004.

[31] M. Blaxter, *Health and lifestyles*. New York, NY: Routledge, 2003.

[32] D. G. Blazer, R. C. Kessler, K. A. McGonagle, and M. S. Swartz, "The prevalence and distribution of major depression in a national community sample: the National Comorbidity Survey," *Am. J. Psychiatry*, vol. 151, no. 7, pp. 979–986, 1994.

[33] D. P. Goldberg and P. Huxley, *Common mental disorders: a bio-social model*. London ; New York: Tavistock/Routledge, 1992.

[34] H. Meltzer, B. Gill, M. Pettigrew, and K. Hinds, "OPCS surveys of psychiatric morbidity in Great Britain," 1, 1995.

[35] S. Weich and G. Lewis, "Material standard of living, social class, and the prevalence of the common mental disorders in Great Britain," *J. Epidemiol. Community Health*, vol. 52, no. 1, pp. 8–14, Jan. 1998.

[36] P. M. Bentler, *EQS structural equations program manual*. Encino, CA: Multivariate Software, 1995.

[37] J. C. Loehlin, *Latent variable models: an introduction to factor, path, and structural equation analysis*, 4th ed. Mahwah, N.J: L. Erlbaum Associates, 2004.

[38] B. M. Byrne, *Structural equation modeling with EQS: Basic concepts, applications, and programming*, 2nd ed. Mahwah, NJ: Lawrence Erlbaum Associates, 2006.

[39] R. P. Bagozzi and Y. Yi, "Multitrait–multimethod matrices in consumer research: Critique and new developments," *J. Consum. Psychol.*, vol. 2, no. 2, pp. 143–170, Jan. 1993.

[40] R. C. MacCallum and J. T. Austin, "Applications of Structural Equation Modeling in Psychological Research," *Annu. Rev. Psychol.*, vol. 51, no. 1, pp. 201–226, Feb. 2000.

[41] D. W. Gerbing and J. C. Anderson, "Monte Carlo Evaluations of Goodness of Fit Indices for Structural Equation Models," *Sociol. Methods Res.*, vol. 21, no. 2, pp. 132–160, Nov. 1992.

[42] L.-T. Hu and P. M. Bentler, "Evaluating model fit.," in *Structural equation modeling: Concepts , issues, and applications*, R. H. Hoyle, Ed. Thousand Oaks, CA: Sage, 1995, pp. 76–99.

[43] K. G. Jöreskog and D. Sörbom, *LISREL 8: Structural equation modeling with the SIMPLIS command language*. Scientific Software International, 1993.

[44] R. C. MacCallum, M. W. Browne, and H. M. Sugawara, "Power analysis and determination of sample size for covariance structure modeling.," *Psychol. Methods*, vol. 1, no. 2, pp. 130–149, 1996.

[45] H. W. Marsh, J. R. Balla, and R. P. McDonald, "Goodness-of-fit indexes in confirmatory factor analysis: The effect of sample size.," *Psychol. Bull.*, vol. 103, pp. 391–410, 1988.

[46] J. S. Tanaka, "Multifaceted conceptions of fit in structural equation models," in *Testing structural equation models*, K. A. Bollen and J. S. Long, Eds. Newbury Park, CA: Sage, 1993, pp. 10–39.

[47] P. M. Bentler, "Comparative fit indexes in structural models.," *Psychol. Bull.*, vol. 107, no. 2, pp. 238–246, 1990.

[48] J. H. Steiger and J. C. Lind, "Statistically based tests for the number of common factors," in *Annual meeting of the Psychometric Society*, Iowa City, IA, 1980, vol. 758, pp. 424–453.

[49] M. W. Browne and R. Cudeck, "Alternative ways of assessing model fit," in *Testing structural equation models*, K. A. Bollen and J. S. Long, Eds. Newbury Park, CA: Sage, 1993, pp. 445–455.

[50] A. Trani, C. J. Hutto, D. J. Folds, and T. A. McDermott, "Community Works: Predicting Changes in Community Resilience," in *Proceedings of the Third International Conference on Human and Social Analytics (HUSO) (submitted)*, Nice, France, 2017.

[51] T. McDermott, D. Folds, C. J. Hutto, and M. Nadolski, "A Human-Focused, Holistic Model of Community Resilience," *INSIGHT*, vol. 19, no. 4, pp. 66–69, Dec. 2016.