Health Implications of Enduring and Emerging Stressors:

Design of the New Jersey Population Health Cohort (NJHealth) Study

October 27, 2023

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Abstract

- **Background:** The New Jersey Population Health Cohort (NJHealth) Study aims to delineate the pathways through which stressors influence health and identify novel factors that can mitigate or amplify these effects.
- **Methods:** The NJHealth Study is recruiting 10,000 New Jersey residents aged 14 and older using two sampling strategies. First, 6,000 individuals from across New Jersey are selected through a four-stage probability sample design, oversampling multi-generational families and minoritized racial/ethnic populations, and low-income groups. Second, a non-probability sample of 4,000 individuals is selected from families with at least one first- or second-generation immigrant, recruited via community outreach and respondent-driven methods. Participants will provide multiple consents for study participation, biological assessments, activity measurement, and record linkage.

  Building on ecosocial, life course, and stress process models, the NJHealth Study employs multi-modal data collection to comprehensively measure stress-related factors at macro- and micro-levels. Macro-level stressors are measured in participants' social and physical environments and micro-level stressors are measured using interviews administered in multiple languages and other respondent-level data sources. Interviews also include assessments of potential stress buffers and amplifiers, cognitive function, activity limitations and self-reported health. In addition, salivary DNA, fasting plasma, and actigraphy data will be collected from consenting participants. Participants will also be asked to provide consent to permit the study team to link their data with secondary sources including health insurance and billing records, electronic health records, social service and employment administrative systems, and death records.

- **Discussion:** The NJHealth Study will generate actionable knowledge for improving health and wellbeing under rapid social changes, particularly among multi-generational families, immigrants, people of color, and low-income families, with focuses on both societal and individual stressors. New Jersey's socioeconomic and demographic diversity, along with its strong secondary data infrastructure, make it an exceptional setting for the study. Strong community support and stakeholder engagement will ensure effective translation of research findings into practical policy and programmatic applications. [311 words]

Keywords (MeSH terms)

Population Health; Health Equity; Stress, Psychological; Social Factors; Social Determinants of Health

Background

The past decades have brought rapid social changes, technological developments, and a host of new stressors into American life, with considerable implications for wellbeing, health, and life expectancy [1-7]. Despite advances in biomedicine, overall life expectancy both in the United States and New Jersey has been stagnant and has recently declined, especially in comparison to peer countries [8-10]. Deaths due to drug overdoses and violence have become endemic [11], while similar trends have not been observed in other wealthy countries [9]. Maternal mortality rates are troublingly high, particularly among African Americans, American Indian, and Alaska Natives [12]. Suicide rates have fluctuated somewhat but have generally increased over the past 35 years, including in 2022 [13], and rates are higher in the United States than most other OECD countries [14]. Global political, social, and climate-related unrest have created stressors that were not experienced by prior generations and have led to sharp increases in the flow of immigrants and asylum seekers to the United States. Beyond individual biological and behavioral factors, awareness of the effects of systemic, sociocultural, and environmental stressors, including climate change, on health over the life course are receiving growing attention [15-18].

Despite strong temporal associations between these seismic societal shifts and declining population health, little is understood about the precise pathways through which enduring stressors, such as common life-course events and emergent stressors associated with political, social, technological, and climate-related developments lead to premature morbidity and mortality. Even less is known about mutable factors that may mitigate or amplify the contribution of stressors to health, especially among historically minoritized groups and immigrants. These areas of inquiry – the roles of both enduring and emerging contemporary stressors on health – are imperative to study within an increasingly diverse and unequal society such as the United States.

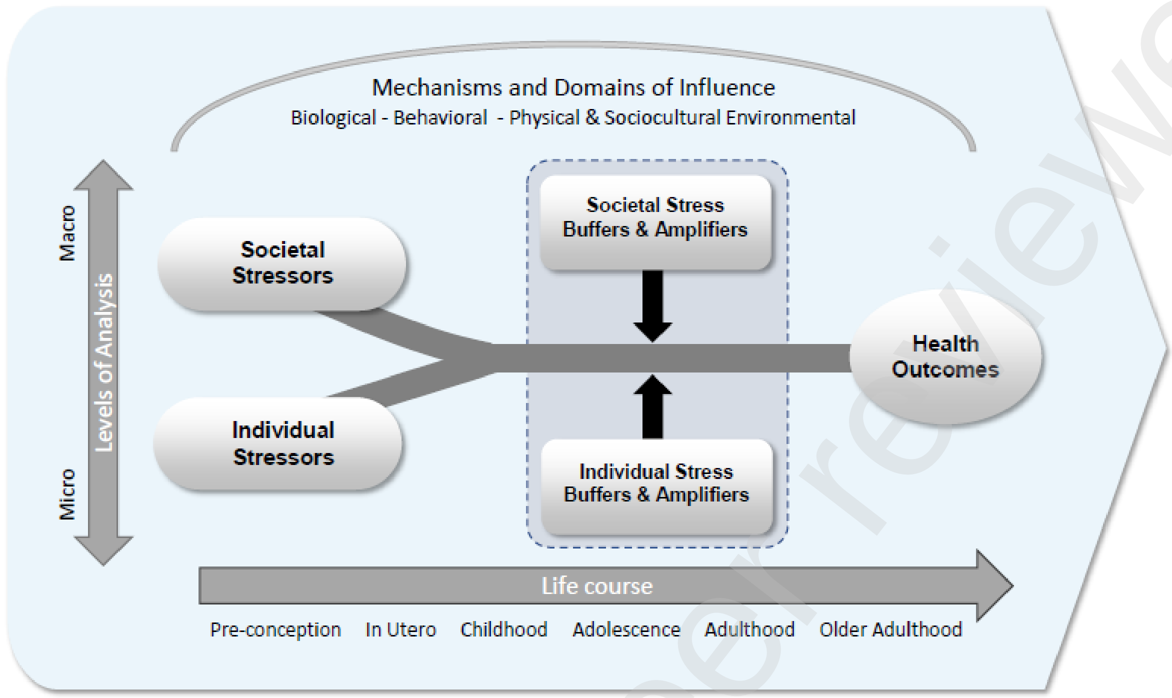
Research on the health implications of stressors is often confined to limited population groups and insufficiently conceptualized to discern mechanisms of action and identify buffers or amplifiers that may alter pathways to adverse outcomes. Guided by ecosocial theories of disease distribution [19-23], stress process models [24-29], life course theories [30-33], and NIH's health disparities research framework [20, 34, 35], the New Jersey Population Health Cohort (NJHealth) Study aims to: 1) Identify how enduring and emerging stressors over the life course contribute to health in diverse populations, and 2) Discover novel factors that buffer or amplify these influences on personal and population health. The NJHealth Study is designed to advance theory and generate practical, actionable knowledge for improving health and wellbeing in the population overall and specifically among diverse groups with a high likelihood of chronic exposure to stressors including those living in multi-generational families, immigrants, people of color, and low-income families. The study site, New Jersey, is among the most diverse states in the nation, with dynamic patterns of immigration from diverse sending countries, and a high proportion of multi-generational families. The likely value of findings is further enhanced, at the outset, by active engagement with community and public policy stakeholders in designing the study.

The NJHealth Study design has several features that promise to strengthen its contribution beyond the scope of earlier cohort-based research. A dual probabilistic and purposive sampling strategy incorporates a unique focus on under-studied groups likely to experience stressors, including discrimination or migration-related events, while at the same time supporting population estimates of key stressors as well as psychosocial and health indicators. Population estimates are critical for developing policies and interventions that specifically address the needs of specific communities or regions and assessing their impact over time. Second, the longitudinal cohort design strengthens causal inferences and permits learning from natural experiments (e.g., climate events) through tracing changes in outcomes among affected populations over time. Third, the measurement of stressors is expanded beyond established domains, capturing emerging stressors such as social media and political polarization (e.g., public discord over gun regulation, ongoing shocks in immigration policy and enforcement), as well as stressors that affect broad communities such as climate events. Finally, our multi-modal data collection plan includes survey interviews, measures of physical activity and movement, assessment of DNA and biomarkers, as well as linkage to extensive administrative and clinical data sources. This enriches operationalization of key outcomes as well as putative mechanisms of action along hypothesized causal pathways.

Conceptual Framework

We designed our research and data collection strategies to investigate diverse pathways through which stressors affect health. Development of the NJHealth Study conceptual framework (Figure 1) was guided by key constructs from ecosocial [19-23] and life course theories [30-33] as well as stress process models [24-29] and NIH's health disparities research framework [20, 34, 35].

Figure 1: NJHealth Study Model of Stressors and Health Over the Life Course



Source: Adapted from Krieger, N. [15, 34] and Pearlin, L.I. [20, 21] and other sources (see text).

Our framework distinguishes societal and individual stressors. *Societal stressors* are those that emanate from the physical or social environment (e.g., local crime or extreme weather events) or via social forces, typically through the exercise of power (e.g., structural racism or healthcare system commercialization [36-38]) that undermine the health of individuals and communities. Ideally, these stressors are studied at a macro, not an individual, level of analysis [20, 22, 38]. *Individual stressors* refer to life events and strains that are often chronic and typically beyond the control of individuals (e.g., bullying, unemployment) or normative transitions (e.g., retirement). Many stressors, such as climate change, act at both societal and individual levels, and are assessed accordingly in the NJ Health Study.

Consistent with both life course theories and ecosocial theories, our framework is sensitive to the occurrence and influence of stressors across the life course [31-33]. In addition, consistent with stress process models [24, 25], our framing places special emphasis on the role of factors that may either buffer (mitigate) or amplify (exacerbate) the impact of stressors on health. Given the framework's grounding in life course theory, we consider how resilience [39] might lead individuals to flourish despite experiencing adversity [40]. The model also reflects relevant dimensions of the NIH health disparities research framework, including the concept of "Domains of Influence" which reflect biological, behavioral, and environmental mediators of health outcomes [20, 28, 34, 35].

Stressors

Stress is registered in neural circuits and often experienced consciously but its origins are commonly environmental. Some environments are more likely to engender a stress response than others. Children who are maltreated or exposed to community violence have worse health outcomes than those who grow up in more peaceful surroundings, due largely to their higher levels of chronic strains [41]. Moreover, social scientists acknowledge that stress is generated at levels of influence that extend well beyond the family or even the local neighborhood. In our measurement strategy, we distinguish between external exposure to societal stress at a macro level of analysis and individual subjective experiences of such stressors at a micro level.

We conceptualize *societal stressors* as occurring at various possible levels of influence. Measurement of stressors at the macro level [20, 34, 35], such as crime or extreme weather events, can be operationalized at the neighborhood or other appropriate geographic unit. Although advances in measurements of environmental stress have existed for decades [42, 43], it is increasingly recognized that the conceptualization and measurement of the social environment and societal stressors in stress research has been inadequate. Some societal stressors, those engendered by government actions for example, have been largely ignored in stress research. As Krieger put it," State-sanctioned discrimination, past and present, is of particular concern." [44]. Our strategy for addressing this gap necessarily relies on assessing both publicly available indicators of discrimination alongside individuals' self-reports of their subjective experiences of discrimination. Similarly, extreme climate events such as heat waves are measurable for a given geographic and point in time, but existential concern about public policies affecting global climate change can only be assessed at the individual level.

Given the scarcity of research on emerging societal stressors stemming from advances in technology, climate change, and other contemporary trends, we augment available measures with novel assessments of stress from evolving social forces, including social media, politics, race relations, climate change, income inequality, immigration trends, reproductive and trans rights, and gun violence. While regional variations in such stressors may allow for geographic-based assessment, their ubiquity (e.g., climate change) and broader societal impacts dictate the need for new measures of perceived effects of contemporary stressors. The risk of being victimized by crime, for example, is certainly higher in some neighborhoods than others, yet risk perception, regardless of objective measures, has been shown to be a strong predictor of reported wellbeing [45].

Social scientists have distinguished five domains of *stressors* experienced by individuals: early life events (e.g., childhood sexual abuse), recent life events (e.g., death of a spouse), chronic strains (e.g., ongoing family discord, perceived discrimination), normative life transitions (e.g., retirement) and the subjective experience of stress [46-48]. Even ostensibly objective life events have a subjective component, and the subjective experience of stress is predictive of health outcomes. For these reasons, the NJHealth Study draws on extensive survey items to assess individual stressors as well as perceived stress.

Stress Buffers and Amplifiers

Although stressors confer risk for outcomes, their influence can be modified by the presence of risk-buffers or risk-amplifiers. The shortcomings of more restricted analyses, ignoring this layer of influences, are highlighted by the salience of the buffering theory of social support [48].

Beyond social support, other potential buffers and amplifiers include resilience [39, 40, 49], religious practices, genetic predisposition, and health-related behaviors (e.g., physical activity, sleep, exercise). Planned analyses of stress effects will also include an examination of putative buffers and amplifiers.

Health Outcomes

There are many possible outcomes for which stressors can play determinative or influential roles in health and wellbeing over time. Accordingly, the NJHealth Study examines a broad range of health outcomes assessed through participant self-reports, biometric assessments, and rich linked secondary source data. Information on new diagnoses or clinical episodes of stroke, heart disease (angina, arrhythmia, myocardial infarction, heart failure), cancer (solid vs. hematological malignancy, primary vs. metastatic vs. recurrent), COVID-19, dementia, liver disease/failure, kidney disease/failure, and accidents (e.g., falls with and without fracture) are collected, as well as their associated predisposing factors such as hypertension, diabetes, hyperlipidemia, and head trauma. Data on conditions that lead to significant disability in the United States such as chronic pain, depression, anxiety, substance use disorder, hearing loss, vision loss, chronic obstructive pulmonary disease, asthma, and arthritis are also collected [50]. Given the on-going COVID-19 pandemic, persistent symptoms implicated in long COVID are noted [51]. These conditions were chosen to enable examination of their suspected role in stress mechanisms and as outcomes of those processes [52-55].

Information on health conditions and interventions (prevention, treatment) are drawn from insurance claims, hospital billing records, electronic health records, and death records; positive health outcomes such as subjective well-being are measured directly. For all outcomes, genomic risk and protective factors will be analyzed alongside stressors, amplifiers, and buffers for comprehensive examinations of their influences on health and wellbeing. For diseases which develop over years or decades, validated plasma biomarkers (e.g., plasma p-

Tau_{181} for Alzheimer's disease, interleukin- and tumor necrosis factor-associated proteins for chronic inflammation) will be examined as intermediate outcomes.

Design and Methods

Design Overview

The NJHealth Study is a prospective cohort of about 10,000 New Jersey residents ages 14 or older. Sixty percent of participants are being recruited using a four-stage probability sample design with the aim of representing the state's household population, with oversampling to ensure representation of individuals in multi-generational families and from lower socio-economic and minoritized racial/ethnic groups.

The remaining forty percent of the sample, recruited using purposive methods adapted from snowball sampling, comprises families with at least one member being a first- or second-generation immigrant. To adequately represent a diverse group of the largest and fastest growing immigrant populations in NJ, recruitment activities are focused on families with at least one first- or second-generation immigrant from China, Dominican Republic, Haiti, India, Jamaica, Korea, Mexico, Nigeria, or the Philippines. The inclusion criteria also includes those who entered the US seeking asylum, under temporary protected status, or related immigration authorities. Multiple interviewees are being recruited in multi-generational households.

The NJHealth Study collects a broad array of measures from multiple sources. Participants are administered an extensive set of interview questions, including psychometric scales assessing the domains described in the conceptual framework. Cognitive testing and biometric measures are administered to participants aged 50 and older. All participants are also asked to provide consent to link their study data to existing administrative records such as healthcare claims, electronic health records, wage history and social program data, as well as to provide DNA samples. In addition, subgroups of participants are asked to provide blood samples for measurement of biomarkers as well as to participate in actigraphy and GPS data collection over a two-week period. Finally, participant home addresses are geocoded to enable linkage of local area measures of social and environmental conditions.

Study recruitment began in late 2022 and is expected to conclude in 2025. The probability sample is being fielded in three replicates, each designed to be representative of the target population to enable early preliminary studies of a statewide cross-section. Sampling weights will be generated to improve population-based estimation. In the probability sample, weights will adjust for differential probabilities of selection and non-response. In the purposive immigrant sample, weights will be calculated to support the adjustment of estimates to distributions of known population characteristics.

Informed consent and, when applicable, HIPAA authorization, are being obtained for each type of data collected. The study was reviewed and approved by the WCGIRB (formally Western IRB).

Study Setting

New Jersey, as the study site, offers several key strengths. It is among the most diverse states, ranking among the top five states in a prominent multidimensional diversity index [56], population share that is foreign-born [57], and in the number of multi-generational households [58]. Further, the study builds on long-standing collaborations with community organizations and public policy stakeholders, based on strong and trusting relationships that will ensure the success of study implementation and value of study findings for communities of interest. These relationships also ensure access to rich secondary data resources for linkage to the primary data collected for the NJHealth Study.

Eligibility and Sampling

The NJHealth Study includes adults and youth, aged 14 and older, who live in New Jersey. Those living in institutional arrangements, such as a nursing facility or prison, and those unable to provide informed consent are ineligible. The address-based probability sample also excludes persons who are unhoused.

Probability Sample. Four-stage probability sampling is used to select N=6,000 individuals living in New Jersey households. In addition to being designed to represent the State's households overall, the design oversamples multi-generational and low-income families and non-Hispanic black and Hispanic individuals. We use a clustered, address-based sample (ABS) to enable efficient in-person data collection. Sampling is performed by RTI International using its augmented ABS sampling frame [59, 60].

Families (defined as a group of persons living in a household who are related by blood, marriage/cohabitation, adoption, or guardianship) are considered multi-generational if they have members in more than one of the age groups: teens (ages 14-17), young adults (18-39), middle-aged adults (40-59) or older adults (60+). In such multi-generational families, we probabilistically select and recruit one member from each generation. The geographic sampling design is also intended to support sub-state regional representation, including urban and non-urban areas.

The four probability sampling stages are:

1. Select 30 primary sampling units (PSUs), constructed from 73 US Census Public Use Microdata Areas (PUMS). Seven diverse PSUs of special public policy interest are selected with certainty and the others are selected probabilistically, oversampling areas with high shares of immigrants.

2. Select 23 Secondary Sampling Units (SSUs) per PSU, constructed from Census Block Groups. High-immigrant SSUs are oversampled.
3. Select 200 Housing Units (HUs) in each SSU. Using models developed by RTI, addresses likely to have multi-generational families are oversampled [61]. Additional subsampling of the HUs in each SSU is then undertaken to achieve completion of the necessary number of household interviews to yield 6,000 completed individual interviews.
4. Within selected HUs, probabilistically select families (if more than one is present) and family members aged 14 and older to be invited for participation.

To implement stage 4 of the sampling strategy, we ask a knowledgeable resident of each sampled household to complete a web-based or telephone enumeration questionnaire. This brief survey records the number and demographic characteristics of each household resident from which one family (multi-family households) and family members are selected to recruit for study participation.

<u>Immigrant Sample</u>. The time surrounding migration to a new host country is often characterized by acute stressors such as disruption of social ties, language barriers, fluctuation in legal status, and insecure employment [62]. This is especially the case among migrants leaving unfavorable conditions in their home countries (e.g., poverty, violence, natural disasters, religious or political persecution). The acculturative stress that ensues post-migration can also be challenging for migrants [63]. Yet surprisingly, research has consistently documented an "immigrant health paradox," demonstrated by the often-superior health status of some immigrants relative to their same-race/ethnic U.S.-born counterparts [64-66]. Although much is known about immigration-related stressors and health in some groups of immigrants, comparatively less is known about the factors that confer health resilience (stress buffers) among immigrants. Further, few studies enable disaggregated assessment of immigrant experiences across diverse sending counties and ethnic groups.

Immigrants are of special interest to the NJHealth Study given shifting and uncertain immigration policy and current high levels of anti-immigrant policy in the United States [67]. The diversity of the New Jersey population allows us to draw a multi-ethnic immigrant sample with diverse migration experiences. We project that the *probability* sample will include about N=1,400 foreign-born individuals, including N=300 arriving in the past decade. To supplement this sample, we are conducting *purposeful* sampling of additional families with members who are immigrants from nine primary countries of origin that have substantial representation in New Jersey (China, Dominican Republic, Haiti, India, Jamaica, Korea, Mexico, Nigeria, and the Philippines). In addition, we are recruiting asylum seekers and others entering the US under temporary immigrant authorities. Our recruitment strategy does not distinguish between legally present and undocumented immigrants.

To recruit households with immigrants, we have adapted respondent-driven sampling (RDS), a non-probabilistic sampling technique that is used to recruit members of populations that cannot feasibly be recruited using probabilistic methods [68, 69]. RDS recruitment begins with “seeds”, who are members of a focal community, to participate in the study. NJHealth Study seeds are recruited from the probability sample, when available, and in partnership with community-based organizations that are closely engaged with the groups of interest.

Initially, any New Jersey household with at least one member who is a first- or second-generation immigrant is eligible for inclusion in the immigrant sample. We then rely on two procedures to concentrate our sample on the specific immigrant groups. First, we conduct recruitment activities with community partner organizations. Second, immigrant sample study participants are asked to refer up to three additional families with immigrant members. They will be permitted to refer immigrant families from non-focal groups, but those participants will not be asked to provide further referrals. We suggest, but do not require, that they refer their own family members who live in New Jersey but not in their household (e.g., a parent or grandparent). We monitor the composition of the immigrant sample and adjust recruitment strategies (e.g., by varying the intensity of joint-recruitment activities with community partners) and inclusion criteria (e.g., by limiting eligibility to households with first-generation immigrants) over time to ensure a balanced immigrant sample.

Sampling Weights. Sample weights will be developed for both the probability and immigrant samples to enable estimates of the 2023 New Jersey household population. The sample *design weight* for the probability sample is specified as the inverse of the probability of selection for the sample members, capturing the respective probabilities of selection at PSU, SSU, HU, family, and person levels and accounting for differential sampling rates. The sum of the design weights serves as an initial estimate of the total population in New Jersey. The weights will then be adjusted to account for differential nonresponse and subsequently post-stratified to ensure they sum to New Jersey population control totals obtained from an accurate population survey source such as American Community Survey (ACS) [70], correcting for sample frame under-coverage. Nonresponse and poststratification adjustments will be accomplished either through weighting class ratio adjustments, or through calibration using generalized exponential models [71] or similar techniques. We will also deploy quasi-population weights for the immigrant sample, adjusting to distributions of the respective immigrant group available in the ACS. Variances of estimates derived from the multi-stage survey design employed for the probability-based sample will be adjusted to account for the underlying design complexities.

Study Data

To support a comprehensive assessment of stressors, stress buffers and amplifiers, and health outcomes, the NJHealth Study draws from multiple data sources, including in-depth interviews, administrative and clinical data linked to individual participants, geospatially linked data (e.g., neighborhood, governmental jurisdiction, or other geographic unit), actigraphy and GPS devices, saliva (for DNA), and blood samples (for biomarkers).

Interviews. Interviews are conducted by trained research assistants with consenting participants in their preferred modality (telephone, in-person, video conferences) and language (e.g., English, Spanish, Hindi, Gujarati, Mandarin, Korean, Creole and Tagalog), with some items such as cognitive assessments (English and Spanish) collected in-person only. Whenever feasible, we use validated instruments, making modifications or developing new items when needed. Table 1 lists major interview domains and topics.

Table 1: NJHealth Study Interview Domains and Topics

Population Characteristics	**Stress Buffers and Amplifiers**
Demographic characteristics	Health services access and use
Age	Barriers to care[2]
Family size and composition	Health insurance status
Gender identity and expression	Health services use, US and overseas
Marital status[2]	Usual place of care[2]
Sex assigned at birth	Individual and family socioeconomic status
Immigration	Education
Age at immigration and length of time in US	Employment[2]
Language preference and spoken at home	Family income and wealth[2]
Nativity and citizenship	Psychological assessment
Reasons for immigration	Life satisfaction
Self-assessed English proficiency	Loneliness
Individual Stressors (micro-level)	Meaning in life
Life events & experiences	Optimism
Adverse childhood events	Personality
Bullying[1]	Rumination
Caregiving	Psychosocial assessment
Criminal justice involvement	Health risk and service use attitudes[2]
Elder mistreatment[4]	Religious practices
Grandparent burden[3]	Social circumstances and engagement
Intimate partner violence[2]	Civic engagement
Race/ethnic discrimination experiences	News media engagement
Perceived stress scale	Social network size
Perceptions of emerging societal stressors[5]	Social support
Social determinants of health	Volunteerism
Financial and material hardship[2]	**Health Assessment**
Food insecurity	Cognitive function[3]
Housing quality and stability[2]	Disability and limitations
Utility security	Activities of daily[4]
Societal Stressors (macro-level)	Disability assessment
Neighborhood conditions	Physical performance measurement[3]
Deprivation index	Health-related behaviors
Racial and ethnic segregation	Daily physical activity[6]
Crime rates, hate crime rates	Sleep
Extreme weather events	Vaccination
Exposure to environmental toxins	Mental and behavioral health
Physical activity opportunities, walkability	Alcohol, cannabis, other substance use
Food, alcohol, cannabis outlets	Anxiety symptoms
Local policies	Depressive symptoms
Local budgets (e.g., police, social services)	Tobacco dependence
Public libraries (e.g., book bans, services)	Suicide risk
School policies (e.g., curricular, speech)	Physical health
	Health conditions, medical history
	Height, weight, waist, hip measurement
	Self-assessed health and change in health

Limited to age groups: [1]14-17, [2]18 and older; [3]50 and older, [4]60 and older. [5]e.g., role of social media, politics, income inequality, race relations, and societal trends. [6]Limited to the actigraphy sample.

Core interview items are administered to all participants, requiring an average of 90 minutes. A supplemental interview that includes a cognitive assessment for those aged 50 years and older is conducted in a second session that averages 35 minutes. Participants are given the option of completing interviews over multiple sessions.

Exposures to Societal Stressors. Societal stressors include a broad array of spatially delimited exposures ranging from environmental toxins to spending on social programs and local education policy. Table 1 provides examples of societal stress measures measured at the macro (i.e., local area) level. Geocoded location information for home addresses of participants will enable linkage to additional local area stressor data over time. In addition, for participants in the actigraphy and GPS subsample (described below), detailed geocoded location information will be available for a two-week period supporting assessment of community and environmental exposures in locations other than their residence (e.g., places of work).

Linked Administrative Records. Four types of administrative records will be linked to the records of consenting study participants (Table 2) including detailed health care claims and encounters, clinical measures, social services enrollment and benefits programs, and education and wage history. The linked data will provide rich, objective, longitudinal information that aligns with the study conceptual framework. These data include laboratory-based measures such as confirmed COVID-19 test results (from a New Jersey registry) and outcomes such as HbA1c (electronic health records), detailed clinical assessments including the Edinburgh Depression Scale scores (birth records) and incident cancer diagnoses (state cancer registry). Health care utilization data include all-payer hospital emergency department and inpatient billing records, and mortality data are collected from New Jersey vital records and the National Death Index. Historical data from these sources are linked when available, with regular updates planned over time. Except for national Medicare and Medicaid claims and the National Death Index, the linked data sources are limited to New Jersey programs, facilities, or populations. The study interview will collect basic health care and social program utilization and health condition data, enabling investigators to fill gaps in administrative records (and vice versa) when needed.

Table 2: Participant-Level Data Linkages

Secondary Data	**Scope** (Earliest Dates and Source)
Health care claims and encounters	
Medicare and Medicaid claims	Services received anywhere in the US (2017, ResDAC)
Commercial insurance claims	Medical and surgical claims (2017-, Selected NJ insurers)
All-payer hospital billing records	Inpatient and emergency department records from all NJ acute care hospitals (201, iPHD)
Emergency Medical Services (EMS) encounters	NJ EMS encounters (2017, iPHD)
Clinical measures	
Maternal Edinburgh Depression Scale[1] and birth vital status	Birth records (2000, iPHD)
Ambulatory visits, diagnostic, lab test values	Electronic health records (2019, selected NJ providers)
Covid-19 lab confirmed diagnosis	NJ residents, (2020-2021 only, iPHD)
Covid-19 vaccination status	NJ residents, (Dec. 2020, iPHD)
Cancer diagnoses and tumor characteristics	Cancers diagnosed or treated in NJ (2017, NJSCR)
Causes of death	Mortality anywhere in the US (2022, NDI and iPHD)
Social service program enrollment and benefit levels	
Supplemental Nutrition Assistance Program (SNAP) Temporary Assistance for Needy Families (TANF) General Assistance (GA) Emergency Assistance (EA)	NJ program enrollment and benefits records (2017, NJDHS)
Employment and education	
Wage history	Employees of NJ employers (2001, NJEEDS)
Unemployment insurance (UI)	NJ UI program claims (2008, NJEEDS)
K-12 education history	NJ primary education and career and technical education (2010, NJEEDS)
Higher education history	NJ higher education institutions (1998, NJEEDS)
Higher education financial aid	NJ higher education institutions (2018, NJEEDS)

[1]2006 forward. Abbreviations: ResDAC = Research Data and Assistance Center; iPHD = NJ Integrated Population Health Data Project; NJSCR = NJ State Cancer Registry; NDI = National Death Index; NJDHS = NJ Dept. of Human Services; NJEEDS = NJ Education to Earning Data System

Actigraphy and GPS. Activity and sleep data from actigraphy and GPS devices allow for more in-depth and objective measures of movement and rest than self-reports in study interviews. Selected participants wear a tri-axial accelerometer watch (CentrePoint® Insight Watch) and carry a GPS-enabled Android-based phone for a two-week period [adapted from IPAQ and SIMPAQ; 72, 73]. Raw accelerometer and GPS data are augmented by a daily mobile phone-based electronic questionnaire recording participant reported sleep and activity time to improve the accuracy of the accelerometer data. Each of these data collection modes can independently provide information about activity and movement over the two-week period. Data will be processed with various software packages (i.e., GGIR, Actilife for accelerometer data and Python with OpenStreetMap [74] for GPS data), generating variables such as activity type, moderate to vigorous physical activity, sedentary bouts, sleep efficiency, time spent in green spaces, and time spent at home.

DNA and Plasma Biomarkers. Stressful life events, chronic strains, and perceived stress interact with genetic, behavioral, and environmental factors to modulate biological risks, onset, and progression of disease. All participants are asked to donate salivary DNA to assess genetic risk for major disease outcomes, and to identify stress amplifiers and buffers at the genomic level. Furthermore, fasting plasma will be collected and banked from a subset (~20%) of study participants for biomarker analyses. Initially, three groups of biomarkers will be measured: 1) inflammatory proteins reflecting common and unique pathways associated with major disease outcomes; 2) protein markers associated with clinical endpoints (e.g., HgbA1c), 3) protein markers associated with disease risks (e.g., phosphorylated tau for Alzheimer’s disease). In addition to future cross-sectional profiling studies (e.g., metabolomics), banked plasma samples will support longitudinal biochemical analysis across time points. .

Data Management

Limitations to existing data collection platforms with respect to one-to-many language mapping, outdated technology stacks, and data storage structure, made them unsuitable for use in this study. Thus, to meet the multi-faceted nature and complex needs of the NJHealth Study, we developed a custom multimodal data collection system called Adhi. Expanding on a previously developed multilingual, longitudinal survey data collection platform [75], Adhi integrates multiple applications on a single platform, facilitating the management of each participant's journey within the study while minimizing data inconsistencies and potential for data security lapses. The platform includes tools allowing for the management of participant consent information and incentive payments. The platform also supports customizable staff roles/permissions allowing for the members of the project team to record data and ensure compliance with privacy and security requirements on a single location while limiting data access to study staff on need-to-know basis. The platform also permits the generation of customized real-time reports on data quality and study progress such as enrollment progress, consent rates, missing data rates, completeness of study components, and individual staff productivity and data quality. Study data can be exported in formats suitable for analysis requirements, including the options for flat files or relational databases. Last, data linkages or additional study components can be easily added to the secure database as study needs evolve.

Discussion

Stress is a significant driver of health over the life course, yet prior research has often been based on relatively narrow definitions of stress exposures and limited to selected groups. The New Jersey Population Health (NJHealth) Study seeks to address these gaps. Based on a comprehensive conceptual framework that adapts elements of ecosocial [19, 20, 34, 35, 38] and life course theories [30, 31], along with stress process models [24, 25], the NJHealth Study will enable assessment of the impact of enduring chronic strains and emerging stressors (e.g., existential threats from climate change or growing partisan discord) on health. As such, it promises to produce actionable findings for improving the health of the population overall and especially among understudied subgroups with a high likelihood of chronic exposure to stressors.

The NJHealth Study has key distinguishing features that will support more comprehensive analyses of the mechanisms through which stressors and stress moderators lead to health outcomes. First, the study expands the measurement of stressors and potential stress buffers and amplifiers beyond those measured at the individual level to broader, societal-level stressors, including spatially defined exposures that have rarely been studied in research on stress and health. Second, the study's dual sampling strategy, using probabilistic and non-probabilistic methods, ensures inclusion of the full diversity of the New Jersey household population with augmented samples of immigrants from sending countries fostering distinctive migration experiences. Third, it uses multi-modal data collection to capture interview responses drawing on established psychometric scales, augmented with DNA, biomarker, and movement data. It also includes linkages to an extensive array of relevant secondary data sources that supports objective health measures and markers of stress (e.g., unemployment, engagement in social services) dating back to as early as 2000 with opportunities for routine updating.

New Jersey is an exceptional setting for the NJHealth Study because of its socioeconomic and demographic diversity, having among the highest share of immigrants in the U.S. New Jersey also has a strong secondary data infrastructure with continuously updated systems of integrated health and socioeconomic administrative data. Finally, the NJ Health study builds on the study team's long-standing relationships with diverse communities and policy stakeholders, which has informed the design and analysis priorities.

Limitations

The NJHealth Study's comprehensiveness and innovation must be considered in light of accompanying limitations. While New Jersey is an exceptional setting for the study, single-state studies cannot be fully representative of the U.S. population. For example, while New Jersey is among the most diverse states, some groups experiencing structural discrimination such as Native Americans or other disadvantages are not well represented. In addition, while the NJHealth Study interview domains draw on well validated measures, many of the measures have not been specifically tested in cultural and language groups that are part of the study. The NJHealth Study will enable further evaluation of the properties of such scales in new populations, but caution is warranted in their current application to some groups.

In addition, although the NJHealth Study is implementing distinctive strategies to enroll immigrant and other at-risk populations, achieving representation even of the New Jersey population is challenging. The NJHealth Study has translated its survey instrument into multiple languages and employs a multi-cultural, multi-lingual group of field staff. Complementing its probabilistic sampling plan, it incorporates a respondent-driven, purposive sampling technique designed to recruit members of key populations that are otherwise difficult to reach. Still, it is not feasible to reflect the full cultural diversity or include all languages spoken by New Jersey immigrants. Like any study of its kind, despite offering monetary participation incentives, the NJHealth Study faces challenges in achieving high participation rates. The use of sampling weights will improve population representativeness, but gaps in representation remain inevitable.

Conclusion

The NJHealth Study design has important advantages compared to prior work on stress and health. As noted, New Jersey offers key advantages including population diversity and data infrastructure. The survey interview's comprehensive assessment of stressors at the individual level is complemented by the capacity for extensive objective measurement of stressors and health made through rich secondary data linkages at the individual and geographic area levels. Data on physical activity, sleep, genotype, and biomarkers add critical depth to analysis of disease risk and outcomes. Strong community support and stakeholder engagement underpinning the NJHealth Study will ensure the effective translation of research findings to benefit practical policy and programmatic applications.

List of abbreviations

ABS	Address-based Sample
HU	Housing Unit
NJHealth	The New Jersey Population Health Cohort Study
PSU	Primary Sampling Unit
RDS	Respondent-driven Sampling
SSU	Secondary Sampling Unit

Declarations

Consent for publication

The study was reviewed and approved by the WCGIRB (formally Western IRB). Informed consent is obtained from participants for each source of participant-level data collection, including interviews, DNA and biomarkers, actigraphy and GPS data, secondary source linkages. The study consent form is available upon request.

Availability of data and materials

Data are not presented in this manuscript; however, de-identified data will be made available upon the completion of the initial round of data collection through public archive to be determined.

Competing interests

The authors declare no competing interests.

Funding

The NJHealth Study is funded by the Robert Wood Johnson Foundation, the State of New Jersey, and Rutgers University. After approval of funding requests, the funders have not played roles in the conceptualization, design, data collection or development of this manuscript.

Authors' contributions

JC, DMM, WTH, SB, MY, and PD led the conceptualization and design of the NJHealth Study. SBC and KBM developed the study probability sampling and weighting design. SB and JC led the development of the non-probability immigrant sample design. DM and SB developed the data collection and management platform and procedures. SB and MK developed field operations strategy and oversee study management. All authors contributed to the study design, instrument development, and data collection strategies.

Acknowledgements

The authors thank NJHealth Study participants for giving their time to advance knowledge on the relationships of stressors to health. We are grateful to our scientific and community advisors for helping to shape the study to maximize its rigor and relevance for improving population health and health equity. The NJHealth Study was enriched by Stephanie Zimmer who contributed to the probability sampling design and Youngjin 'YJ' Chae, who provided research assistance. The content of this manuscript is solely the responsibility of the authors.

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