Published in final edited form as:

Nurs Outlook. 2019 ; 67(4): 293–301. doi:10.1016/j.outlook.2019.05.011.

Ways of Knowing in Precision Health

Elizabeth Corwin, PhD, RN, FNP-C, FAAN[a], **Nancy S. Redeker, PhD, RN, FAHA, FAAN**[b], **Therese S. Richmond, PhD, CRNP, FAAN**[c], **Sharron L. Docherty, PhD, PNP, FAAN**[d], **Rita H. Pickler, PhD, RN, FAAN**[e]

[a]Edith F. Honeycutt Chair in Nursing, Nell Hodgson Woodruff School of Nursing, Emory University, 1520 Clifton Rd, Atlanta, GA 30322

[b]Beatrice Renfield Term Professor of Nursing, Yale University School of Nursing, PO Box 27399, West Haven CT 06516-0972

[c]Andrea B. Laporte Professor of Nursing, Associate Dean for Research & Innovation, University of Pennsylvania School of Nursing, 418 Curie Blvd, Fagin 330, Philadelphia, PA 19104

[d]Associate Professor, Duke University School of Nursing, DUMC 3322, 307 Trent Drive, Durham, NC 27710,

[e]The FloAnn Sours Easton Professor of Child and Adolescent Health, Martha S. Pitzer Center for Women, Children & Youth, The Ohio State University College of Nursing, 1585 Neil Avenue, Columbus, OH 43210,

Abstract

Precision health can provide an avenue to bridge and integrate ways of knowing for research and practice. Nurse scientists have a long-standing interest in using multiple sources of information to address research questions of significance to the profession and discipline of nursing, which can lead to much needed contributions to precision health care. In this paper, nursing scientists discuss emerging research methods including omics, electronic sensors, and geospatial data, and mixed methods that further develop nursing science and contribute to precision health initiatives. The authors provide exemplars of the types of knowledge and ways of knowing that, using these and other advanced data and analytic strategies, may advance precision health within the context of nursing science.

Keywords

precision health; knowing; omics; geospatial; sensors; mixed methods; complexity

Corresponding Author: Rita H. Pickler, PhD, RN, FAAN, The Ohio State University, College of Nursing, 1585 Neil Avenue, Columbus, OH 43210; Work phone: 614-292-5265; Work fax: 614-292-4948; Home phone: 804-319-9703; pickler.1@osu.edu.

Precision Health: Ways of Knowing

In 1978, Carper published her landmark paper on the fundamental ways of knowing in nursing. Carper classified patterns of knowing used to develop knowledge and theory to guide practice: empirical, personal, ethical, and esthetic (Carper, 1978). Only empirical knowledge resulted from science. Personal knowledge resulted from personal self-understanding and empathy, while ethical knowledge developed from an awareness of moral questions and choices. Esthetic knowledge, often referred to as “the art of nursing,” came from an awareness of the immediate situation while being embedded in immediate practical action,

Precision health is the use of multiple sources of information (e.g., genomic, biological, behavioral, environmental) about individuals and populations to provide targeted, predictive and personalized care (Chambers, Feero, & Khoury, 2016; Lyles, Lunn, Obedin-Maliver & Bibbins-Domingo, 2018). Precision health provides a contemporary model to bridge and integrate ways of knowing to guide practice. Nurse scientists have a long-standing interest in using multiple sources of information to address research questions of significance to nursing practice. In particular, contemporary nurse scientists have a deep interest in finding and promoting strategies to manage adverse symptoms of chronic conditions, promote long-term health, and prevent illness and comorbidities across health conditions, settings, and the lifespan through research using biological, genetic, and behavioral information (National Institute of Nursing Research, 2016).

In this paper, based on presentations given by members of the Science Committee of the Council for the Advancement of Nursing Science (CANS) at CANS’ 2018 State of the Science Conference, nurse scientists discuss approaches and provide exemplars of the types of knowledge and ways of knowing that, in a unified sense, may advance the science of precision health. In the first three sections, we provide examples of these approaches, omics, electronic sensors, and geospatial data, relative to the broader definition of precision health research. Although the authors acknowledge that generally these data types are most congruent with Carper’s empirical knowing, we acknowledge the need to consider this empirical knowledge within the broader context of knowing in nursing, including personal and ethical ways of knowing. In the final section of the paper, we discuss mixed-methods approaches that take into account the complexity inherent in precision health science, bringing together the multiple ways of knowing for nursing scientists engaged in the development of knowledge essential for the provision of safe and effective nursing care. Table 1 provides a summary of the exemplar approaches described in this paper and their potential strengths and limitations for addressing important questions in nursing science.

Incorporating Omics to Tailor Nursing Assessment, Intervention, and Evaluation

Dr. XXX, XXX University

Omics, an emerging scientific approach, can lead to knowledge that supports the nursing process and patient care. The expansion of information available through increasingly sophisticated -omics methods, including genomic, epigenomic, proteomic, metabolomic, and microbiomic technology and big data analytics, enables greater precision in designing nursing assessment, intervention, and evaluation processes. We offer two exemplars to illustrate how data derived from the incorporation of omic technology can inform the nursing process and potentially revolutionize how we plan care. The first example describes the use of genomic technology to investigate risk factors for experiencing high caregiver burden, and the second focuses on consideration of the vaginal microbiome related to pregnancy outcomes.

In the first exemplar, we randomly assigned 127 family caregivers of patients with heart failure to one of three interventions: 1) usual care; 2) education alone; or 3) education plus exercise (Dunbar, et al., 2016). In addition to testing the efficacy of the interventions on health outcomes, the researchers gathered data from participants on a genetic trait, the caregiver's serotonin-receptor transporter genotype, and considered the modifying effect of this trait in the analyses. Although the neurotransmitter serotonin is known to influence mood (Fakhoury, 2016), and selective serotonin-reuptake inhibitors (SSRIs) are often prescribed to reduce depressive symptoms, the exact mechanism by which SSRIs act remains unknown (Lutz, 2013; Andrews, Bharwani, Lee, Fox, & Thomson, 2015). Researchers have hypothesized that SSRIs may affect the function of the serotonin transporter, thereby influencing the availability of serotonin to bind to post-synaptic receptors.

The gene coding for the serotonin-transporter receptor, 5-HTTLPR, exists as two major polymorphisms, long (L) and short (S) alleles, (Odgerel, Talati, Hamilton, Levinson, & Weissman, 2013), leading to the potential for any given individual to have genotypes, L/L, L/S, or S/S. Over a decade ago, Caspi et al., (Caspi, et al., 2003) reported that carrying even one S allele increased the risk of depression especially with increasing exposure to life stressors. The greatest risk occurred when the S allele was present in a homozygous state (the S/S genotype); the least risk occurred in those with the homozygous L/L genotype. Although these associations remain under investigation (Odgerel et al., 2013; Risch, et al., 2009; Karg, Burmeister, Shedden, & Sen, 2011), we included an exploratory aim in our caregiver study to investigate the influence of polymorphisms in the serotonin promoter region on how family caregivers responded to the long-term burden of caregiving. Our analyses (Dunbar, et al., 2016) showed that, based on the Center for Epidemiologic Studies Depression Scale (Radloff, 1977), symptoms of depression were indeed highest in caregivers with the S/S genotype as were self-reports of caregiver burden (Oberst, Thomas, Gass, & Ward, 1989). Currently, we are investigating whether baseline knowledge of caregiver 5-HTTLPR genotype might help tailor specific interventions, providing targeted support for caregivers with the S/S genotype.

The second exemplar involves our current study (Corwin, et al., 2017) in which we are investigating the oral, vaginal, and gut microbiome during pregnancy in African American women with the goal of identifying potentially modifiable risk factors for preterm birth (Martin, Hamilton, Osterman, Driscoll, & Drake, 2018; DeFranco, Hall, & Muglia, 2016). Our preliminary data suggest a few such risk factors may be important, including the use of vaginal hygiene products targeted to African American women. If the association between hygienic product use and composition of the vaginal microbiota holds in further analysis, midwives and women's health nurse practitioners would have an interventional approach for risk assessment and targeted prenatal education. In the future, probiotics to manipulate the vaginal microbiome may likewise be recommended. Finally, we are examining how chronic stress exposure related to racial discrimination may influence the microbiome-gut-brain axis (Dinan & Cryan, 2017; Yang, et al., 2016) and stress-related metabolites and metabolic pathways activated or suppressed across the lifespan. Importantly, in our preliminary analyses of metabolic pathways (Corwin et al., 2018) associated with increased exposure to chronic stress in pregnant women, we have found stress-related alterations in pathways that interfere with energy production and stimulate inflammation, two areas carrying significant implications for embryonic development and preterm birth.

Strengths and Limitations to Omic Data

Although carrying great potential, there are strengths and limitations to the use of omic technology in research. Omic technology in research can lead to greater understanding of normal physiological processes as well as disease processes. Results of research using these technologies can provide guidance for screening or diagnosing health conditions and may lead to new ways of assessing patient response to interventions or treatments. It is also possible in a single research study to use different omic technologies, thus potentially providing greater mechanistic understanding of complex biological relationships, perhaps facilitating the development of highly personalized precision health treatments.

However, omic technology and the accompanying data analysis and interpretation are in their infancy. For example, it is unlikely in genomic research that one gene alone determines a condition as complex in its etiology as depression or the subjective experience of caregiver burden. In microbiome research, there exists significant variability in the accuracy and appropriateness of various platforms and pipelines used to identify microorganisms and to conduct sophisticated analyses, calling into question certain findings. Likewise, the significance or clinical targetability of either genetic polymorphisms or metabolites and metabolic pathways is often not clear. For most types of omic research, concerns related to privacy, reproducibility, and translation to practice must be recognized and addressed. As scientists address these hurdles however, incorporating omics into nursing research will expand the lens by which health care providers assess, treat and evaluate patients.

Real Time Electronic Sensors in Everyday Life: What can we measure & how can we use them for precision health research?

Dr. XXX, XXX University Schools of Nursing and Medicine

Recent advances in electronic sensors enabling real time monitoring of human behavior, biology, and environment provide many opportunities for research and ultimately clinical practice related to precision health. Examples of electronic technology include devices for monitoring of physical activity, sleep characteristics, falls (e.g., accelerometers), light levels, body position, respiratory rate, symptoms, biochemical phenomena (e.g., glucose, blood alcohol concentrations, oxygenation), electrophysiological phenomena (e.g., electrocardiography, heart rate, blood pressure), and others. While many of these phenomena were measured and recorded in clinical settings in the past, increasing availability of miniaturized devices, memory and data storage capability, electronic interfaces to view and store the date, and more widespread availability to researchers, clinicians, and consumers facilitate measurement and use for research. Sensor data can identify people at risk for chronic conditions and their complications. Sensor data can also identify people most in need of interventions to promote wellness behavior (e.g., sleep, diet, physical activity). Sensors can deliver interventions focused on safety, environmental management, symptoms, and self-management. Data from electronic sensors are also useful in measuring outcomes of these interventions for research and in clinical practice.

For example, wrist actigraphs enable continuous assessment of motor activity for evaluation of activity patterns and sleep. In our research, we documented changes in the rest activity rhythm over time that corresponded with recovery after cardiac surgery (Redeker, Mason, Wykpisz, Glica, & Miner, 1994). Associations between changes during the first postoperative week and functional recovery and length of hospital stay demonstrate how actigraph-derived data increase understanding of important health outcomes (Redeker, Mason, Wykpisz, & Glica, 1995). We found that circadian patterns in activity-rest were associated with fatigue, depressive symptoms, excessive daytime sleepiness and functional performance in people with heart failure (Jeon, Conley, & Redeker, 2018); these parameters are amenable to intervention. In another example, researchers have shown that sleep characteristics, including sleep duration, bed times, and awakening times and changes over time are important to health in many populations, including low income children (Ordway, Sadler, Canapari, Jeon, & Redeker, 2017). These data help predict which children are most in need of sleep promoting interventions and evaluate the effects of sleep -promoting interventions.

Strengths and Limitations of Sensor Data—Advantages of emerging real time electronic sensors for health-related phenomenon include their ecological validity and the ability to collect continuous or repeated objective data in real time. Emerging sensor technology enables valid measurement of data across clinical, home, and community settings. This attribute of sensors allows understanding of these phenomena during everyday life and in health care settings. Sensors further allow understanding of how phenomena may change over time, between settings, and in response to interventions, environmental stimuli, and changes in health. For example, temporal changes may be linear or non-linear or may reflect cyclic variations such as infradian (duration longer than a day), ultradian (duration shorter than a day), circadian (about a day) or other rhythmic or seasonal patterns. This is particularly useful given the dynamic nature of health, recovery, and treatment, as well as developmental and seasonal changes in biobehavioral phenomena. Sensor data are particularly important given increasing evidence that robust circadian rhythms are associated with good health (Abbott, Malkani, & Zee, 2018; Brainard, Gobel, Scott, Koeppen, & Eckle, 2015).

Real-time sensors also present the opportunity to combine data from a variety of sources for research and clinical purposes. For example, researchers evaluated the association between rest-activity rhythms and glycemia measured with a continuous glucose monitor among youth with Type I diabetes (Grey & Rechenberg, 2018). Complex analysis of rhythmic patterns in sensor data and associations among data from multiple sensors used to measure biological (e.g., electrocardiographical data, alcohol concentrations in the blood, tissue oxygenation) and envinronmental factors (e.g., ambient temperature, light levels, sound levels) is possible as is combining sensor data with self-report and medical record data. There is also increasing capability to upload sensor data directly into the medical record.

Researchers should consider several limitations when using electronic sensors. Although, many sensors of biological and behavioral data provide the user with the ability to view the data or variables obtained with the data over time on the device itself or an electronic interface (e.g., tablet, computer, smart phone) there is limited evidence about the outcomes of these applications. Moreover, the theoretical underpinnings of the applications are not always explicit. Further, there is a need for thorough understanding of the phenomenon (e.g., frequency of occurrence, dimensions, range and variability) as it occurs in people in order to match physical properties of the device and its validity in the specific population. For example, wrist actigraph measures of sleep were more concordant in younger, compared with older adults with heart failure (Jeon, Conley, & Redeker, 2019). Thorough understanding of the sensitivity, specificity, range, and accuracy of electronic sensors, as well as needs for calibration are important. These concerns encompass the physical properties of the device as well as the mathematical electronic algorithms used for scoring and interpretation; scoring algorithms are not always clearly documented or available. There is little comparability between most electronic sensor devices, especially those produced by different companies. Thus, devices may not be interchangeable for research purposes.

Characteristics of the researcher and the study participant are important to consider. While some devices are simple to apply and produce readily interpretable data, others require more time, knowledge and skills, time and training, and complex statistical approaches to data analysis for research purposes. Application and correct use of many devices often require knowledge and skills, recall, and/or manual dexterity. Environmental influences (e.g., moisture, lighting, ambient temperature) should be considered; devices that require skin contact may be influenced by perspiration. There are potential cultural and social considerations regarding comfort with remote monitoring due to concerns about privacy (Mittelstadt, 2017), especially when data are collected and stored through the internet or in the electronic medical record. Additional ethical concerns have emerged related to “ownership” of data and the potential loss of autonomy and self-determination if health care providers or policy makers use the data for decision-making, especially related to payments for health care services.

Place Matters: Geospatial Data and its Contribution to Precision Health

Dr. XXX, University XXX

The use of precision science has the potential to change health care fundamentally by allowing providers to target precisely the right interventions to the right individual at the right time. This is a laudable but challenging goal given the diversity of people and communities with whom we work, the seemingly intractable disparities, and the enduring health inequities that exist in the U.S. and globally. Here, we discuss the contribution of geospatial approaches to nursing science as we seek to improve health and well-being through precision science. Most simply, maps help represent and digest spatially distributed information, for example, using maps to pinpoint the number of firearm shootings in the U.S. over the course of a year. In this case, each point on the map is a shooting and one can visually examine the distribution across the country (e.g., https://www.gunviolencearchive.org/). The strength of easily viewing gun shooting distribution is offset by the limitation that it can be misleading because population density varies significantly between urban and rural America. It is essential to integrate the population base (the denominator) and represent the rate to depict accurately the burden across geographic regions.

Geospatial techniques can confirm or dispel commonly held beliefs, for example, the perception that firearm violence is exclusively an urban problem. In an elegant analysis, Branas, Nance, Elliott, Richmond and Schwab (2004), used the U.S. Department of Agriculture urban-rural continuum codes to characterize each U.S. county and examined the rates of firearm homicides and suicides. The rate of firearm homicide was highest in urban areas and the rate of firearm suicide was highest in rural areas. In an adjusted regression analysis, the relative risks for firearm suicide and homicide when taken together were comparable across all county types (urban, rural) demonstrating rural firearm suicide is as important a problem as urban firearm homicide. This technique’s strength is the quantitative examination of the distribution of health problems across the urban-rural continuum.

Geospatial techniques permit the examination of community characteristics that affect health and well-being. Building on a set of interviews with youth who had been assaulted with firearms and randomly drawn population controls, Kondo, South, Branas, Richmond, and Wiebe (2017) examined the association of urban tree cover and gunshot assaults. Urban tree cover and the locations of the gun assaults and the activity paths of the controls (non-assaulted youth) were mapped. In adjusted conditional logistic regressions, tree cover was inversely associated with a gun assault suggesting that changing places may be protective and increase safety. The limitation of this technique is the possibility that unmeasured environmental factors could account for the outcome. The strength is that these findings is the ability to identify potential points of intervention beyond the individual level.

Application of geospatial techniques can occur without classic mapping. For example, community partners identified a problem at a housing plus agency that provided subsidized housing for single parent, housing-unstable families living in a low-resource community. The program required parents to work part-time and to accrue educational credit towards a college degree, however, not all parents were meeting the education requirement. Individual client characteristics did not provide an explanation for the variation. Thus, our team examined potential effects of neighborhood on educational credit accrual. We geocoded the addresses of the 152 housing units located within a 2-mile radius; a geocode is set of coordinates that precisely place a location on the earth’s surface (http://pro.arcgis.com/en/proapp/help/data/geocoding/what-is-geocoding-.htm). Administrative environmental data were appended to each geocoded address (e.g., census, American Community Survey, crime, resources). We then examined detailed environmental characteristics at the micro-environmental level (e.g., the census block group) with educational credit accrual. Taking into account important analytic considerations (e.g., clustering within a block group) and working with GIS experts and statisticians with expertise in spatial analysis, we completed an analysis demonstrating that individuals living in housing units on census block groups with higher levels of violent crime rate accrued educational credits more slowly than those who lived on block groups with moderate or lower levels of violent crime (Tach, Jacoby, Wiebe, Guerra, & Richmond, 2016). These findings open up new points of intervention for nursing science, indicating the environments in which people live are important to address.

Strengths and Challenges to Geospatial Data—Geospatial analysis can give insight into current health and risks for future health problems. Parent-child dyads living in pervasively violent, low-resource neighborhoods independently mapped their activity paths for a specific day demonstrating significant constraints on child movement throughout the neighborhood due to fear for safety (Jacoby, Tach, Guerra, Wiebe, & Richmond, 2017). In many cases, children were not allowed out of the home due to safety concerns, limiting physical activity and potentially placing these children at risk for future chronic health problems.

One challenge with using geospatial data is that the data come from sources partitioned by established administrative boundaries (e.g., block face, census block group, census tract, zip code). These boundaries may not 1) mirror the neighborhood as defined by the individual or community, and 2) accommodate the fact that people move through multiple physical environments in the course of the day. Our team demonstrated the possible mismatch of self-identified vs. administratively identified neighborhoods by requesting that youth draw their neighborhood on a map (Basta, Richmond, & Wiebe, 2010). In some cases, the neighborhood did not even include the home residence. Further, youth drew their activity paths over the course of a day and these paths extended beyond their self-identified neighborhood. Thus, as we consider exposures in the environment, we must recognize the limitations of considering risk purely as a static phenomenon versus dynamic.

Geospatial techniques continue to evolve, providing a picture of the integration of spatial and temporal factors that affect health and well-being. For example, Wiebe et al. (2016) used a sophisticated approach to map daily activity paths in a case control study seeking to identify risks for youth assault. Mapping an activity path can be completed sitting side by side with a youth on a realistic map/photo of their neighborhood, allowing the youth to detail their movements from the moment of awakening until the time of assault (or in the controls until they go to sleep at night). These paths can then be appended to dynamic changing risks and protections over space and time, identifying risks for assault more accurately.

We can embrace the use of geospatial techniques to study rigorously the upstream social determinants of health. To do so, we must carefully consider the strengths, such as visualization, ability to consider urban rural differences and population characteristics, and effects of neighborhood characteristics on individual health. We must also address the challenges of dealing with spatial autocorrelation, the artificial nature of administrative boundaries, and the fact that there are environmental factors not measured or available in existing data sources that could provide alternative explanations for outcomes of interest.

Leveraging Mixed-Methods to Capture Complexity

Dr. XXX, XXX University

A key original precept of precision health is the integration of omics level data on the individual, cohort, or population, with data from other sources such as behavior, environment and lifestyle to inform precision care (Lyles et al., 2018). This attempt to capture the complexity inherent in human responses to health and illness through the integration of multiple sources of information on the individual, is likely to promote clinical care that maximizes the outcomes that the individual most cares about and minimizes those not likely to be helpful (Kohane, 2009). Mixed-methods provides a methodological frame to capture this level of complexity by not only guiding the collection of the most relevant information on an individual, cohort or population, but also the integration, configuration, and synthesis of the information into results that allow targeted, predictive and personalized care. The mandate of mixed-methods is to take account of any relevant information available related to the phenomenon of study, regardless of the methodologies that produced them. At its heart is the combination of diverse data sets to address questions of significance (Bazeley, 2018a).

For example, nursing science research that integrated omic, sensor, and geospatial data could provide a holistic means by which to conduct precision assessment, intervention development, and outcome evaluation. One such project along these lines might be consideration of pediatric obesity in light of omic, sensory, and geospatial factors. For instance, microbiota, like all other living organisms, demonstrate a diurnal rhythm. Collecting sensory data on children’s 24-hour heart rate, respiratory rate and energy consumption through wearable technology could be analyzed in light of their activity paths over the course of a day, including geospatial data on time spent outdoors, and in light of the diurnal production by gut-microbiome of certain short-chain fatty acids known to carry anti-inflammatory and anti-obesity properties. This snapshot could provide a better picture of the complex metabolic and social contributors and their interactions to this national epidemic.

Strengths and Challenges of Mixed-Methods—Mixed-methods involves the integration of varied approaches, sources of data, methods of data collection and/or strategies for analysis towards achieving the purpose of the study (Bazeley, 2018a). Neo-Kantian philosopher Wilhelm Windelband described two approaches to knowledge generation: nomothetic and idiographic (Salvatore & Valsiner, 2010). Nomothetic knowing, historically used in the natural sciences, has a tendency towards law-like generalizations. Idiographic knowing, historically used in the humanities and arts, has a tendency towards particularized knowledge of contingent or context-dependent profiles. The ability for nursing scientists to develop knowledge that builds upon a relationship between the uniqueness of individual or cohort health/illness profiles and their lawfulness is a key challenge. A key strength of mixed methods approaches is that they can move us between nomothetic (e.g., average profiles/responses) and idiographic knowing (e.g., unique profiles/response).

One of the core strengths of mixed-methods approaches as applied to precision health is that, through the of use of varied approaches, data, methods and analytic models, researchers have the capability to develop local, contextualized understandings, based upon multi-level, socio-cultural perspectives. This capability extends to participant-centered intervention studies that bring a range of methods to the customization or tailoring of interventions to a targeted problem and the selection of an innovative design that feature participants' preferences for one or more treatment groups (Song et al., 2010).

Most concepts of central importance to precision health can be described by both their quality and quantity. Precision health places no limit, hierarchy or value judgement on the classifications of type of information used to tailor a treatment approach, arrive at a clinical decision, or provide. If the information leads to the 'right treatment, for the right patient, at the right time', it buys its way into the model (Redekop & Mladsi, 2013). Yet one of the most limiting barriers to the ongoing development of mixed methods integration models has been the pervasive use of the overly simplistic binary of mixed-methods into quantitative and qualitative approaches and data types. As described earlier, more contemporary conceptualizations of mixed-methods research leave behind the uninformative binary of 'something qualitative mixed with something quantitative', and instead bring a focus on the integration of data, method, and design assemblages that most aptly address the research question or hypothesis (Bazeley, 2018b; Sandelowski, 2014). "When data are divided into qualitative and quantitative, it limits the possibility of seeing them and the world they represent through other dimensions, or even as being dimensional at all" (Bazeley, 2018b, p. 334). Mixed-methods have the power to address the complex questions inherent in precision health if researchers leave behind such ineffective binaries and focus on the meaningful dialogue that comes from integrating data types, sources, and analytic strategies.

Despite broad agreement on the theme of integration, or data interdependence, in many definitions of mixed-methods research (Fetters, Curry, & Creswell, 2013; Maxwell, 2013; Onwuegbuzie & Teddlie, 2003; Sandelowski, 2014), studies in the health sciences over the past several decades show a general lack of integration (Bryman, 2007; O'Cathain, Murphy, & Nicholl, 2010). Yet it is this purposeful interdependence (Bazeley, 2018a) between data sources, interrelatedness or degree of mutual illumination between data components (Bryman, 2007), prior to the drawing of final conclusions, that will allow mixed-methods to leverage the complexity needed to harness precision health approaches to care. Various models of data integration strategies have been reported (e.g., Creswell & Plano Clark, 2011; Fetters, et al., 2013; Scherman, Zimmerman, & Smit, 2013) but most simply can be categorized into three types of mixes: use-together, linking, or converting data from one form into another (Bazeley, 2012; Sandelowski, 2014). In the use-together mix, the data types used in a study remain distinct through data through collection, analysis, and results, and may have some level of integration in the discussion section of the research report. In the linking mix, distinct sources of data are collected and analyzed. Placement of the data in juxtaposition to each other allows data comparison, contrast, or extension in relation to each other (Sandelowski, 2014). In the conversion type of mix, sources of data are collected, but then are integrated prior to analysis through conversion or assimilated of the data sources into a new data-type (e.g., Britt & Evans, 2007; Caiola, Barroso, & Docherty, 2017; Docherty, Vorderstrasse, Brandon, & Johnson, 2017).

As nursing science moves to advance the use of precision health concepts and balance our need for both idiographic and nomothetic knowing, mixed methods is a powerful harness for guiding us towards capturing the complexity inherent in human responses to health and illness. Mixed methods can guide the collection of the most relevant information about a phenomenon of interest and the integration, configuration, and synthesis of the information into results that allow targeted, predictive and personalized care.

Discussion

Nursing scientists have long embraced the value of multiple ways of knowing as the basis for our science and practice. In this paper, we focused primarily on empirical ways of knowing and on the advancement of empirical knowledge using new and emerging data sources that hold promise for scientific and clinical advancement. We acknowledge, however, that empirical knowing that does not integrate other aspects of knowing will likely fail in achieving precision health's promise. To that end, we encourage the full scope of scientific approaches by nursing scientists in order to meet human health needs. For some, precision science is perceived as synonymous with genetics and omics – and while these are important ways of knowing that have the potential to dramatically alter disease treatment – this cannot be the sole focus. If we are to improve the health and well-being of all, it is important for nursing scientists to broadly frame precision health beyond just biology and behavior and integrate characteristics of the broader environments in which people are born, live, play, work, learn, and worship. This broad perspective is synchronous with the All of Us study (https://allofus.nih.gov/).

We believe new methods of data collection and analysis hold promise for facilitating the movement toward precision health. We also acknowledge limitations to these data approaches and to precision health initiatives in general. A major concern is that the scientific techniques that have been amazingly successful for a relatively small number of diseases have limited success in improving the health those with common, but chronic conditions (Rothstein, 2016). Other concerns include the cost of access to precision health interventions, especially those with limited health care insurance and potentially discriminating policies about their use. Lack of privacy regarding the collection and use of data is also a concern. There are no clear policies related to data access and control for much of the data that are collected in relationship to omic, sensor, or geospatial data. Protections under the Common Rule and the HIPAA Privacy Rule are applicable to most precision health data. However, policies related to data access and return of data to individuals are not clear, nor is it is clear what limits will be placed on third-party access.

Clearly, there is a need for further research and consideration of concerns around validity, feasibility, ethical, social, and culture concerns around precision health technologies and analytic approaches. The scientific promise of precision health and the role of nurse scientists in the discovery of more precise understanding of health phenomena and in the development and delivery of precision health interventions is exciting. We think that nurse scientists will be integral to the development of precision health science that that they will do so using the best data collection and analytic techniques available and to making sense of precision data in the most ethical ways.

Conclusion

Precision health initiatives hold much promise for improving our understanding of illness and wellness conditions that are integral to nursing science. Researchers still have much to learn before implementing these initiatives into practice to improve lives. Nursing scientists have the potential to contribute to precision health initiatives in many ways including providing the necessary guidance to ensure a broad, integrated focus on the entirety of human experience.

Acknowledgements

Dr. XXX work was supported by the National Institutes of Health under grants P01NR011587, R01-NR014800, and 3 R01NR014800.

References

Abbott SM, Malkani RG, & Zee PC (2018). Circadian disruption and human health: A bidirectional relationship. The European Journal of Neuroscience. doi: 10.1111/ejn.14298.

Andrews PW, Bharwani A, Lee KR, Fox M, & Thomson JA (2015). Is serotonin an upper or a downer? The evolution of the serotonergic system and its role in depression and the antidepressant response. Neuroscience and Biobehavioral Reviews, 51, 164–188. doi: 10.1016/j.neubiorev.2015.01.018. [PubMed: 25625874]

Basta LA, Richmond TS, & Wiebe DJ (2010). Neighborhoods, daily activities, and measuring health risks experienced in urban environments. Social Science & Medicine, 71, 1943–1950. doi: 10.1016/j.socscimed.2010.09.008. [PubMed: 20980088]

Bazeley P (2012). Integrative analysis strategies for mixed data sources. American Behavioral Scientist, 56, 814–828. doi:10.1177/0002764211426330

Bazeley P (2018a). Integrative analysis in mixed methods research. London: Sage.

Bazeley P (2018b). "Mixed methods in my bones": Transcending the qualitative-quantitative divide. International Journal of Multiple Research Approaches, 10, 334–341. 10.29034/ijmra.v10n1a22

Brainard J, Gobel M, Scott B, Koeppen M, & Eckle T (2015). Health implications of disrupted circadian rhythms and the potential for daylight as therapy. Anesthesiology, 122, 1170–1175. doi: 10.1097/ALN.0000000000000596. [PubMed: 25635592]

Branas CC, Nance ML, Elliott MR, Richmond TS & Schwab CW (2004). Urban-rural shifts in intentional firearm death: Different causes, same results. American Journal of Public Health, 94, 1750–1755. [PubMed: 15451745]

Britt DW, & Evans MI (2007). Sometimes doing the right thing sucks: Frame combinations and multi-fetal pregnancy reduction decision difficulty. Social Science & Medicine, 65, 2342–2356. [PubMed: 17698273]

Bryman A (2007). Barriers to integrating quantitative and qualitative research. Journal of Mixed Methods Research, 1, 8–22. 10.1177/2345678906290531

Caiola C, Barroso J, & Docherty SL (2017). Capturing the social location of African American mothers living with HIV: An inquiry into how social determinants of health are framed. Nursing Research, 66, 209–221. doi: 10.1097/NNR.0000000000000213. [PubMed: 28252555]

Carper BA (1978). Fundamental patterns of knowing in nursing. Advances in Nursing Science, 1(1): 13–24. doi:10.1097/00012272-197810000-00004. [PubMed: 110216]

Caspi A, Sugden K, Moffitt TE, Taylor A, Craig IW, Harrington H, … & Poulton R (2003). Influence of life stress on depression: Moderation by a polymorphism in the 5-HTT gene. Science, 301(5631), 386–389. [PubMed: 12869766]

Chambers DA, Feero WG, & Khoury MJ (2016). Convergence of implementation science, precision medicine, and the learning health care system: a new model for biomedical research. Journal of American Medical Association, 315, 1941–1942. doi: 10.1001/jama.2016.3867.

Corwin E, Dunlop AL, Fernandes J, Li S, Pearce B, & Jones DP (2018). Metabolites and metabolic pathways associated with chronic stress exposure in pregnant African American women. Under Review.

Corwin EJ, Hogue CJ, Pearce B, Hill CC, Read TD, Mulle J, & Dunlop AL (2017). BMC Pregnancy Childbirth, 17(1), 395. doi: 10.1186/s12884-017-1550-y. [PubMed: 29179694]

Creswell JW, & Plano Clark VL (2011). Designing and conducting mixed methods research. Thousand Oaks, CA: Sage Publications, Inc.

DeFranco EA, Hall ES, & Muglia LJ (2016). Racial disparity in previable birth. American Journal of Obstetics & Gynecology, 214(3), 394, e391–397. doi: 10.1016/j.ajog.2015.12.034.

Dinan TG, & Cryan JF (2017). The microbiome-gut-brain axis in health and disease. Gastroenterology Clinics of North America, 46, 77–89. doi: 10.2527/jas.2016.1256. [PubMed: 28164854]

Docherty SL, Vorderstrasse A, Brandon D, & Johnson C (2017). Visualization of multidimensional data in nursing science. Western Journal of Nursing Research, 39, 112–126. doi: 10.1177/0193945916672448. [PubMed: 27756850]

Dunbar S, Corwin E, Gary RA, Higgins MK, Smith A, & Butler J (2016). Novel correlates of depressive symptoms in family caregivers of heart failure patients. Circulation, 134, A12706.

Fakhoury M (2016). Revisiting the serotonin hypothesis: Implications for major depressive disorders. Molecular Neurobiology, 53, 2778–2786. doi: 10.1007/s12035-015-9152-z. [PubMed: 25823514]

Fetters MD, Curry LA, & Creswell JW (2013). Achieving integration in mixed methods designs. Health Services Research, 48, 2134–2156. doi: 10.1111/1475-6773.12117. [PubMed: 24279835]

Grey M, & Rechenberg K (2018). Sleep and glycemia in adolescents with type 1 diabetes. Diabetes, 67, A212 10.2337/db18-814-P

Jacoby SF, Tach L, Guerra T, Wiebe DJ, & Richmond TS (2017). The health status and well-being of low-resource, housing-unstable, single-parent families living in violent neighbourhoods in Philadelphia, Pennsylvania. doi: 10.1111/hsc.12345.

Jeon S, Conley S, & Redeker NS (2018). Rest-activity rhythms, sleep disturbance, and functional performance in people with stable heart failure. Under Review.

Jeon S, Conley S, & Redeker NS (2019). Discrepancy between wrist-actigraph and polysomnographic measures of sleep in patients with stable heart failure and a novel approach to evaluating discrepancy. Journal of Sleep Research, 28(2), e12717. doi: 10.1111/jsr.12717 [PubMed: 29943403]

Karg K, Burmeister M, Shedden K, & Sen S (2011). The serotonin transporter promoter variant (5-HTTLPR), stress, and depression meta-analysis revisited: evidence of genetic moderation. Archives of General Psychiatry, 68, 444–454. doi:10.1001/archgenpsychiatry.2010.189. [PubMed: 21199959]

Kohane IS (2009). The twin questions of personalized medicine: who are you and whom do you most resemble? Genome Medicine, 1, 4. doi: 10.1186/gm4. [PubMed: 19348691]

Kondo MC, South EC, Branas CC, Richmond TS, & Wiebe DJ (2017). The association between urban tree cover and gun assault: A case-control and case-crossover study. American Journal of Epidemiology, 186, 289–296. doi:10.1093/aje/kwx096PMID:28481962 [PubMed: 28481962]

Lutz PE (2013). Multiple serotonergic paths to antidepressant efficacy. Journal of Neurophysiology, 109, 2245–2249. doi: 10.1152/jn.01093.2012. [PubMed: 23343901]

Lyles CR, Lunn MR, Obedin-Maliver J, & Bibbins-Domingo K (2018). The new era of precision population health: insights for the All of Us research program and beyond. Journal of Translational Medicine, 16(1) (July 27, 2018) doi: 10.1186/s12967-018-1585-5

Martin JA, Hamilton BE, Osterman MJK, Driscoll AK, & Drake P (2018). Births: Final data for 2016. National Vital Statistical Report, 67, 1–55.

Maxwell JA (2018). The " silo problem" in mixed methods research. International Journal of Multiple Research Approaches, 10(1), 317–327. 10.29034/ijmra.v10n1a20

Mittelstadt B (2017). Ethics of the health-related internet of things: a narrative review. Ethics and Information Technology, 19, 157–175. doi: 10.1007/s10676-017-9426-4

National Institute of Nursing Research (U.S.). (2016). NINR strategic plan. https://www.ninr.nih.gov/sites/files/docs/NINR_StratPlan2016_reduced.pdf. Bethesda, Md: National Institute of Nursing Research.

Oberst MT, Thomas SE, Gass KA, & Ward SE (1989). Caregiving demands and appraisal of stress among family caregivers. Cancer Nursing, 12, 209–215. [PubMed: 2766264]

O'Cathain A, Murphy E, & Nicholl J (2010). Three techniques for integrating data in mixed methods studies. British Medical Journal, 341, c4587. doi: 10.1136/bmj.c4587. [PubMed: 20851841]

Odgerel Z, Talati A, Hamilton SP, Levinson DF, & Weissman MM (2013). Genotyping serotonin transporter polymorphisms 5-HTTLPR and rs25531 in European- and African-American subjects from the National Institute of Mental Health's Collaborative Center for Genomic Studies. Translational Psychiatry, 3:e307. doi: 10.1038/tp.2013.80. [PubMed: 24064711]

Onwuegbuzie AJ, & Teddlie C (2003). A framework for analyzing data in mixed methods research In Tashakkori A, & Teddlie C, C. (Eds.), Handbook of mixed methods in social and behavioral research (pp. 321–350). Thousand Oaks, CA: Sage.

Ordway MR, Sadler LS, Canapari CA, Jeon S, & Redeker NS (2017). Sleep, biological stress, and health among toddlers living in socioeconomically disadvantaged homes: A research protocol. Research in Nursing & Health, 40, 489–500. doi: 10.1002/nur.21832. [PubMed: 29058789]

Radloff LS (1977). A self-report depression scale for research in the general population. Applied Psychological Measurement, 1, 385–401.

Risch N, Herrell R, Lehner T, Liang KY, Eaves L, Hoh J, … & Merikangas KR (2009). Interaction between the serotonin transporter gene (5-HTTLPR), stressful life events, and risk of depression: a meta-analysis. Journal of the American Medical Association, 301, 2462–2471. doi: 10.1038/ng.381. [PubMed: 19531786]

Redeker NS, Mason DJ, Wykpisz E, & Glica B (1995). Women's patterns of activity over 6 months after coronary artery bypass surgery. Heart & Lung, 24, 502–511. [PubMed: 8582826]

Redeker NS, Mason DJ, Wykpisz E, Glica B, & Miner C (1994). First postoperative week activity patterns and recovery in women after coronary artery bypass surgery. Nursing Research, 43, 168–173. [PubMed: 8183659]

Redekop WK, & Mladsi D (2013). The faces of personalized medicine: A framework for understanding its meaning and scope. Value in Health, 16(6), Supplement, S4–S9. doi: 10.1016/j.jval.2013.06.005.

Rothstein MA (2016). Some lingering concerns about the precision medicine initiative. Journal of Law, Medicine & Ethics, 44, 520–525. DOI: 10.1177/1073110516667948

Salvatore S, & Valsiner J (2010). Between the general and the unique. Overcoming the nomothetic versus idiographic opposition. Theory & Psychology, 20, 817–833. 10.1177/0959354310381156

Sandelowski M (2014). Unmixing mixed-methods research. Research in Nursing and Health 37, 3–8. doi: 10.1002/nur.21570. [PubMed: 24307343]

Scherman V, Zimmerman L, & Smit B (2018). Mixed method data analysis: An exploratory approach to strengthening inferences about relationships and affinities. International Journal of Multiple Research Approaches, 10(1), 57–76. 10.29034/ijmra.v10na4

Song M, Sandelowski M, & Happ MB (2010). Current practices and emerging trends in conducting mixed methods intervention studies in the health sciences In Tashakkori A & Teddlie C (Eds.), Sage handbook of mixed methods in social & behavioral research (2nd ed, pp. 725–747). Thousand Oaks, CA: Sage.

Tach L, Jacoby S, Wiebe DJ, Guerra T, & Richmond TS (2016). The effect of microneighborhood conditions on adult educational attainment in a subsidized housing intervention. Housing Policy Debate, 26, 380–397. [PubMed: 27570434]

Wiebe DJ, Richmond TS, Guo W, Allison PD, Hollander JE, Nance MI, & Branas CC (2016). Mapping activity patterns to quantify risk of violent assault in urban environments. Epidemiology, 27, 32–41. doi: 10.1097/EDE.0000000000000395. [PubMed: 26414941]

Yang I, Corwin EJ, Brennan PA, Jordan S, Murphy JR, & Dunlop A (2016). The infant microbiome: Implications for infant health and neurocognitive development. Nursing Research, 65, 76–88. doi: 10.1097/NNR.0000000000000133. [PubMed: 26657483]

Highlights

- Including newer data approaches can improve precision health decisions.
- Omics in research may lead to better assessment and management to improve care.
- Electronic sensors allow real time monitoring of behavior and biology in research.
- Geospatial data provide an important lens to improve precision health approaches.
- Broader understanding of the complexity of human health and illness will inform health care policy.

Table 1.

Potential Strategies for Precision Health Science and Their Strengths and Challenges

	Examples	Strengths	Challenges
Omics	Genomics of risk factors Microbiome	Increased understanding of physiologic processes Aid screening and diagnosis Increased mechanistic understanding	Limitations of single gene exploration Unknown clinical utility Costs
Electronic Sensors	Actigraphy	Increased validity of typically behavioral measures Increased understanding of physiologic changes in relationship to behaviors Allow combination of data from multiple sources	Limited evidence related to outcomes Lack of theoretical underpinning Lack of normal standards Human subjects literacy in use
Geospatial Data	Geomapping	Increased understanding of health risks related to exposures Ability to identify targets of intervention beyond the individual level	Data from multiple sources, some of which have “boundaries” that may not map to actual exposure Sophisticated spatial analytic techniques require expertise