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Use of theory to guide development and application of sensor technologies in Nursing

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ABSTRACT

Sensor technologies for health care, research, and consumers have expanded and evolved rapidly. Many technologies developed in commercial or engineering spaces, lack theoretical grounding and scientific evidence to support their need, safety, and efficacy. Theory is a mechanism for synthesizing and guiding knowledge generation for the discipline of nursing, including the design, implementation, and evaluation of sensors and related technologies such as artificial intelligence and machine learning. In this paper, three nurse scientists summarize their presentations at the Council for the Advancement of Nursing Science 2019 Advanced Methods Conference on Expanding Science of Sensor Technology in Research discussing the theoretical underpinnings of sensor technologies development and use in nursing research and practice. Multiple theories with diverse epistemological roots guide decision-making about whether or not to apply sensors to a given use; development of, components of, and mechanisms by which sensor technologies are expected to work; and possible outcomes.

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The landscape of sensors and related technological applications to health research and clinical practice has grown and changed immensely over recent years. Advances in machine learning and other forms of artificial intelligence (AI), WiFi, and the "internet of things" (IoT), smaller and smaller microchips and power sources, improvements in microfluidic ("lab-on-a-chip") tech and 3-D printing, nanotechnologies, and other recent inventions have largely driven this evolution (Zhu et al., 2020). Sensor technology can be defined as, "a device that responds to a physical stimulus (such as heat, light, sound, pressure, magnetism, or a particular motion) and transmits a resulting impulse (as for measurement or operating a control)" (Merriam-Webster Online Dictionary, 2019). In many cases, introduction of new sensor-based technologies to the marketplace and health systems is out-pacing both scientists' ability to thoroughly evaluate their safety and efficacy, as well as policy-makers such as the United States Food and Drug Administration's (FDA's) ability to regulate their use (McGrath & Scanaill, 2013; United States Food & Drug Administration, 2018). An increasing and larger proportion of these

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sensors advertised with health applications are classified as FDA-cleared class I or II predicate-based devices requiring, effectively, a much lower standard of evaluation than FDA-approved class III medical devices (Mitroff, 2019). Each year, industry events like the mammoth Consumer Electronics Show (CES) unveil another wave of these new sensor-based and AI-driven technologies, each of which may offer opportunities to support health, but also potential pitfalls. Given both the diversity and growth of the sensor and related AI technologies in the community and clinical space, nurses and nurse researchers require frameworks to guide decision-making regarding their use. Theory is a vital tool for guiding nurse decision-making and praxis (Kagan, Smith, Cowling, & Chinn, 2009).

The importance of theory to guide the development, implementation, and evaluation of interventions has been supported by scientists in the social, behavioral, and health fields (Fleury & Sidani, 2018; Gitlin & Czaja, 2016). Yet the role of theory in the development, evaluation, and implementation is not always clearly understood or fully recognized (Gitlin & Czaja, 2016). Theory-based interventions continue to be undervalued and underutilized in planning and publication of intervention research (Glanz & Bishop, 2010). Theory is an explanation of why a phenomenon occurs the way it does. Theory reflects the body of knowledge that organizes, describes, predicts, and explains a phenomenon (Fleury & Sidani, 2018). In intervention research, theory and/or theoretical frameworks provide a representation of the complexity of the problem, context, intervention, and outcomes. Theoretical frameworks clarify the problem providing additional information on potential factors influencing the problem, the population experiencing the problem, specific intervention components to address the problem, intervention processes, and outcomes suggesting effectiveness of the intervention (Fleury & Sidani, 2018).

Theory is a systematic way of understanding the problem of interest including events, behaviors and/or situations. The role of theory may vary depending on the phase of research. In the developmental phase (discovery, feasibility, and proof of concept), theory is useful to determine the possible benefits and selection of treatment components, delivery characteristics, and general approach to the intervention. In the evaluation phase (efficacy, effectiveness), theory is used to understand and identify the mechanisms of action of the intervention and who will benefit from the intervention. During the implementation phase (translation, implementation, and sustainability), theory provides an understanding of processes and guides implementation decision making (Gitlin & Czaja, 2016).

Advances in technology have provided patients with easily accessible and low-cost tools to help manage their health (Institute for Healthcare Informatics, 2015; The Office of the National Coordinator for Health Information Technology, 2016). A wide variety of technology interventions are being developed to provide patients with information and strategies for prevention, detection, and management of disease and symptoms (Institute for Healthcare Informatics, 2015; The Office of the National Coordinator for Health Information Technology, 2016). However, many of these technology interventions are not theory based and lack rigorous scientific development (Hamel, Thompson, Albrecht, & Harper, 2019). A recent review of 599 unique smartphone applications (apps) for cancer patients indicated that less than 20% (n=118) were based upon empiric evidence (Hamel et al., 2019). A recent published review of the effectiveness of behavior change apps reported that six of 23 of the apps reviewed were theory-based (Zhao, Freeman, & Li, 2016). Furthermore, apps designed with a behavioral change theory were more effective in influencing outcomes. The need for theory-based technology intervention based upon the best available evidence hold promise for improving health of many populations.

In this paper, three nurse scientists with differing clinical and content expertise, summarize their presentations at the Council for the Advancement of Nursing Science 2019 Advanced Methods Conference on The Expanding Science of Sensor Technology in Research discussing the theoretical underpinnings of sensor technologies development and use in nursing research and practice. The panel addressed the question, what are examples of theoretical underpinninngs for sensor use in nursing research? Authors provide specific examples of contexts in which theory guided nurse decision-making related to sensor applications, as well as times in which theory led to the decision *not* to apply sensor technologies to an identified health challenge or research question.

For the purposes of this paper, the organizing framework for each of the presentations is the "*who, what, where, why, when, and how*" of theoretical underpinnings of sensor technology in each nurse scientist's respective area of research. This framework highlights the high degree to which nurse scientists are called upon to practice reflexivity at each stage of research and particularly in contexts where both technology and methods are rapidly evolving. The symposium sought to present – not a unified theory to guide nursing research involving sensors – but rather, ontological diversity within the field. The purpose of this manuscript is to summarize both the major content and highlights of each nurse scientist's presentation at the 2019 CANS Advanced Methods Workshop on Sensor Research, as well as critical points raised during the question and answer period that followed.

Theoretical Underpinnings in Use of Sensor Technology: *Focus on Adolescent Driving Behaviors*

Dr. Catherine C. McDonald, PhD, RN, FAAN, University of Pennsylvania & Children's Hospital of Philadelphia

The leading cause of adolescent morbidity and mortality is motor vehicle crashes (Centers for Disease

Control and Prevention, 2017). Over the last few decades, there have been major advances to reduce motor vehicle crashes that have involved improving infrastructure, enacting policies that affect licensure, and advancing vehicle technology to improve safety. However, the rates of adolescent driver crashes remain unacceptably high and a public health concern not just for adolescents, but also for those that share the road with them. Several factors contribute to adolescent driver crashes, including inexperience on the road, lack of driving skill, and risky behaviors (Curry, Hafetz, Kallan, Winston, & Durbin, 2011). Addressing all components that place adolescent drivers at risk is a formidable challenge, yet necessary in order to get to the goals of Vision Zero (Vision Zero Network, 2018).

The use of sensor technology in adolescent driving research is not necessarily new. A number of critical naturalistic and driving simulation studies have used sensors to collect data on driver performance and behavior, laying an important foundation for understanding how to reduce adolescent motor vehicle crashes (Dingus et al., 2006; Fisher et al., 2002; Simons-Morton, Zhang, Jackson, & Albert, 2006). These data have been able to identify skill-based performance deficits, such as elevated g-force events, lack of hazard anticipation or poor speed management, measured through sensors in eye tracking devices, driving simulators, and in-vehicle monitoring devices. This includes some of my research with colleagues comparing adolescent and adult drivers in a driving simulator protocol, which showed that adolescents made more simulated driving performance errors than adults, and for every error made their risk for a simulated crash increased (McDonald et al., 2015). These performance-based measures are necessary as they are key to understanding and promoting the operative skills for vehicle safely on the road. However, there remains areas of opportunities to further explore elements of adolescent driver behavior with sensors that may contribute to motor vehicle crashes, such as distracted driving. Moreover, much of the research in monitoring adolescent driver behavior through sensors has been in isolation of a theoretical foundation that is inherent to nursing science.

Who, What, Where, and When of Sensor Technology in Adolescent Driving Behavior

In my program of research, the "*Who*" is newly licensed adolescent drivers. Newly licensed adolescent drivers are the group at highest risk for a motor vehicle crash and are therefore a critical target population for intervention (Curry, Pfeiffer, Durbin, & Elliott, 2015). Depending on the state in which an adolescent lives and applies to get their license, this can be as early at 14.5 years to 17 years (Governors Highway Safety Association, 2019). With newly licensed adolescents, there is an intersection of normal maturation in all domains of their being that is inherent with human development, the social and familial context of their lives, as well as a general lack of experience on the roadway. Together this intersection creates a "*Who*" that may be vulnerable to involvement in a motor vehicle crash.

Largely, the "*What*" of my focus in motor vehicle crash prevention research has been adolescent driver inattention. Adolescent driver inattention can be defined as eyes on the road, hands on the wheel, and mind on the task of driving (National Highway Traffic Safety Administration, 2019). Often for adolescent drivers, the focus has been on cell phone use while driving (Delgado, Wanner, & McDonald, 2016). However, other factors that place adolescents at risk for motor vehicle crashes can be considered, in particular peer passengers. Peer passengers can have a similar consequence of cell phones related to driver inattention, drawing eyes away from the roadway, hands off the wheel, or mind off the task of driving. Research has shown that peer passengers increase adolescent driver fatality risk (Ouimet et al., 2015; Tefft, Williams, & Grabowski, 2012). Alternatively, peer passengers can have the opportunity to help keep adolescent driver attention on the roadway, by handling the cell phone, giving directions, or even remaining vigilant to potential on-road hazards. The concept of a safe passenger behavior is not new, but with the interplay of real-life and a proxy virtual passenger (i.e., a cell phone), risk reduction efforts need to consider different ways of addressing crash contributing factors.

In my research of addressing the "*What*," the Theory of Planned Behavior (TPB) has provided a theoretical basis for intervention development and attempts at behavior change, targeting the attitudes, perceived behavioral control, and norms about adolescent driver inattention (Ajzen, 1991, 2019; McDonald, Brawner, Fargo, Swope, & Sommers, 2018). Using TPB with adolescent driver inattention draws from the nursing and health literature in behavior change relevant to adolescent health. In the utilization of TBP for behavior change with adolescent driver inattention, reliance of multiple forms of behavioral data was key—whether quantitative self-report, qualitative interviews, or sensor technologies including simulator kinematics data, eye tracking, or in-vehicle monitoring. Sensor technology, however, has an opportunity to provide a window into behaviors that can help us tease apart the effective ingredients needed for interventions.

For example, the use of sensors in the "*Where*" and "*When*" of adolescent driver inattention is key to understanding how to reduce the risky behaviors, but is also well-informed by elicitation research with adolescent on their perceptions. In our focus, group research with adolescent drivers (McDonald & Sommers, 2015), we found that despite recognition that hand-held cell phone engagement, texting, and app use while driving are dangerous activities, they and their peers engaged in it anyway. In addition, adolescent indicated that context mattered as to whether they engaged with their phones or not, as well as spatial and temporal characteristics. For example, adolescents described engaging with cell phones on familiar roads, at lower speed limits, or when stopped at traffic lights. The adolescent self-described spatial-temporal characteristics are important. In addition, adolescents describe that the sender or receiver on the other end of messages with phones influenced their decisions around engagement with the phone. For some of these adolescent drivers it seems, they are cognizant of a decision-making structure to using their cell phone while driving. These self-perceptions are important in the theoretical foundations for the direction of the intervention development, as well as implementation of sensor technology in this line of research.

However, the *"Where"* and *"When"* of data collected with smartphone sensors and in-vehicle monitoring provides another vantage point (McDonald et al., 2019). Using the metric of cell phone "unlock" as a metric for handheld cell phone use, smartphone sensor data from 16 adolescents, ages 16 to 17 years of age, licensed for ≤90 days was examined. These data included over 5,624 miles traveled in 705 trips, in which the adolescents had a mean of 23.96 unlocks/100 miles (SD = 22.97), 1.23 unlocks/trip (SD = 0.96), and 4.87 unlocks/hour driven (SD = 3.93). The speed at unlock ranged from 0 to 87.18 mph, with an average speed at unlock was 25.00 mph (SD 16.63). The *"Where"* and *"When"* of these sensor data indicated varying degrees of risk relative to motor vehicle crashes. In the future, it would be valuable to compare the adolescents' sensor-based data with their perceptions of their behavior and decision-making structure.

In the critical questions of "*Who, What, Where, and When*," there are still gaps to be addressed in the use of sensors with adolescent driver inattention. For example, the *"Who,"* is unclear if a broad population approach is necessary, or if stratified risk groups of high cell phone engagers is now to best approach use of sensors as way to define the scope of the problem or to intervene to reduce known behaviors. In our work with the driving simulator data and self-report of inattention in adolescents (McDonald, Sommers, Fargo, Seacrist, & Power, 2018), we found that increased self-reported symptoms of inattention were associated with increased driving performance errors (as identified by driving simulator data). These data point to the importance of varying degrees of risk in adolescent drivers. The good news is that not every adolescent driver will be involved in a motor vehicle crash. Efforts should be targeted in a way that we get to zero lives lost.

The *"What"* can also become an ever-changing target behavior relative to rapidly advancing technology. For example, can sensor technology identify the most time-relevant risk behaviors relative to cell phone use while driving? The *"What"* may not about texting, messaging, or scrolling through social media—rather any of the behaviors that take eyes off the road, hands off the wheel, and mind off the task of driving. With the increase in advance driver-assisted systems (ADAS), changes in how technology in the vehicle keeps the occupants safe—such as lane keeping assistance and crash collision avoidance—can potentially influence how an adolescent drives and what technology will do for their safety and attention to the roadway (Hannan, Palumbo, Fisher Thiel, Weiss, & Seacrist, 2018; Weiss, Fisher Thiel, Sultana, Hannan, & Seacrist, 2018). More research is needed at the intersection of ADAS, adolescent drivers, and traffic safety.

"When" to use sensors for adolescent driver inattention during the driving trajectory of the adolescent is still unclear. For example, adolescent learner drivers (or those with a learner's permit) have a lower motor vehicle crash rate as compared to licensed adolescents. However, if approaching adolescent driver inattention in a preventive model, establishing norms of safe attentional behaviors in the learner period with measurement and intervention may provide a better dose-response that trying to intervene with adolescents who already have their license. From a temporal-spatial perspective, the *"Where"* of sensors is tightly intertwined with *"When"* they are engaging—such as speeds, weather, roadway characteristics, and time of day. In addition, with increasing use of cell phones in cars, the interaction between adolescent drivers, cell phones as a virtual passenger, and live peer passengers—more research is needed to help identify the risk relationships (McDonald & Sommers, 2017).

Contemplating the "Why" and "Why Not" of Use of Sensor Technology in Adolescent Driver Research

This brings to the major questions of the "*Why*," or more importantly, the times "*Why Not*" to use sensor technology in adolescent driving behavior research. The *Why* should focus on efforts to keep the adolescent driver safe. There are a number of commercial apps that adolescents and families can use to track driving behaviors, using Global Positioning System and gyroscopes in smartphones to establish the kinematic data. A concept behind some of these monitoring apps is to set the opportunity for parents to have knowledge about their adolescent's driving behaviors and to talk with them about high risk events, so as to prevent further—or even better to prevent them from happening at all (Carney, McGehee, Lee, Reyes, & Raby, 2018; McGehee, Raby, Carney, Lee, & Reyes, 2007). As researchers, and as part of the consent and assent process, adolescents and parents are aware of the data being collected in the simulator and on the road. The same bidirectional awareness with the parent-adolescent dyad around use of commercially available apps is needed for trust and open communication that is needed for healthy adolescent development.

Theoretical Underpinnings of Electronic Screening with Clinical Decision Support and Individualized Patient Education

Dr. Bonnie Gance-Cleveland, University of Colorado Anschutz Medical Campus

Patient self-report data, a very basic sensor, combined with algorithms developed from clinical guidelines has the potential to improve clinical decision making and healthcare. Clinical decision support (CDS) is health information technology designed to provide healthcare providers with assistance in decision making. CDS links health observations or self-reported information from patients with health knowledge or evidence for practice to influence health choices for improved health care. CDS applications may also generate individualized patient education materials. CDS is useful for both providers and patient populations.

The "*who, what, how, where, when*, and *why*" of CDS with individualized patient education materials for use in clinical practice are discussed with two exemplars from our work. The "*who*" for CDS includes both the busy clinician who has many barriers to adopting all the practice guidelines and the patient whose care may be impacted by the failure to receive care based upon the latest evidence. There is widespread failure of clinicians to follow guidelines for a variety of conditions (Barlow, 2002; Bauer, 2002). The barriers to implementing guidelines include inadequate tools or resources (Barlow, 2002), insufficient knowledge and skills (Barlow, 2002), lack of self-efficacy (Story, 2002), lack of time (Story, 2002), and insufficient reimbursement (Story, 2002).

The "*what*" is the CDS with individualized patient education materials that has the potential of promoting use of evidence-based guidelines. Provider self-efficacy regarding counseling has been linked to access to CDS (Perrin, 2005). Other studies indicate that patients who received written health information with graphics that depicted their response to therapy improved their motivation to adhere to the treatment plan and were more satisfied with care (Tang, 1998).

Although CDS can be applied in any setting, the "*where and when*" for our exemplars are primary care practices – pediatric primary care well child visits, and prenatal visits for pregnant women.

First, Heart Smart Kids is a pediatric primary care CDS that screens for weight-related risk and protective factors and provides individualized patient education materials for use in motivational interviewing (MI) counseling. Screening and education areas include nutrition including daily breakfast, eating out, milk consumption, fruit and vegetable consumption, junk foods, and sugar sweetened beverages; physical activity, inactivity, and sleep. The CDS system consists of two Web-based applications accessed through standard Web browsers on Internet-connected computers: a bilingual lifestyle interview and a Web page for the entry of measurements and the generation of individualized education materials (Gance-Cleveland, Gilbert, Gilbert, Dandreaux, & Russell, 2014). To facilitate MI counseling, the interview includes three questions on attitudes toward change – the importance of change, confidence in ability to change, and readiness to change. The system algorithm compares patient data with clinical guidelines and generates the individualized education materials including standardized growth charts and recommendations to be used in the MI counseling session between the family and the provider.

The second CDS system, *StartSmart* uses the same platforms and screens pregnant women for risk and protective factors including: anxiety, depression, substance use (tobacco, alcohol, marijuana, and drugs), intimate partner violence, sleep, physical activity, weight status (underweight, overweight, gestational weight gain, and gestational diabetes mellitus), immunizations (influenza, Tdap) and prenatal vitamins (Gance-Cleveland et al., 2019). Using validated instruments (e.g., Generalized Anxiety Disorder, National Institute of Drug Abuse quick screen, Patient Health Questionnaire-9, Abuse Assessment Screen, glucose tolerance test, body mass index, and self-report for physical activity and sleep), patients were placed into risk categories based on established cut-points (Gance-Cleveland et al., 2019). Women complete the screening on an iPad in the waiting room. Each screen has a single forced response question for each of the risk and protective factors including an option to decline to answer.

The clinic staff then enter the height, weight, blood pressure laboratory results, and immunization status into the measurement application. The staff then generate individualized handouts, including graphic depiction of gestational weight gain and a summary of the tailored recommendations, based on the patient's risk category. The education materials are written at the sixth-grade reading level. Individualized patient and provider summaries that include the level of risk for each item based are generated to prompt MI counseling regarding risk and protective factors.

This CDS application has also been translated into Spanish using the Beaton model for translation and cultural adaption that includes a five-stage development process: **Stage I:** Translation into Spanish by two native Spanish speakers, **Stage II:** Synthesis of the translations through discussion with the research team and two translators, **Stage III:** Back translation of the Spanish version by two native English speakers, **Stage IV:** Expert committee review of the English version compared to the original and consensus is reached on final translation, **Stage V:** Pretesting with the target audience.

The "How" of CDS Development was Guided by Theory

The "how" we developed these CDS systems was guided by the Technology Acceptance Model

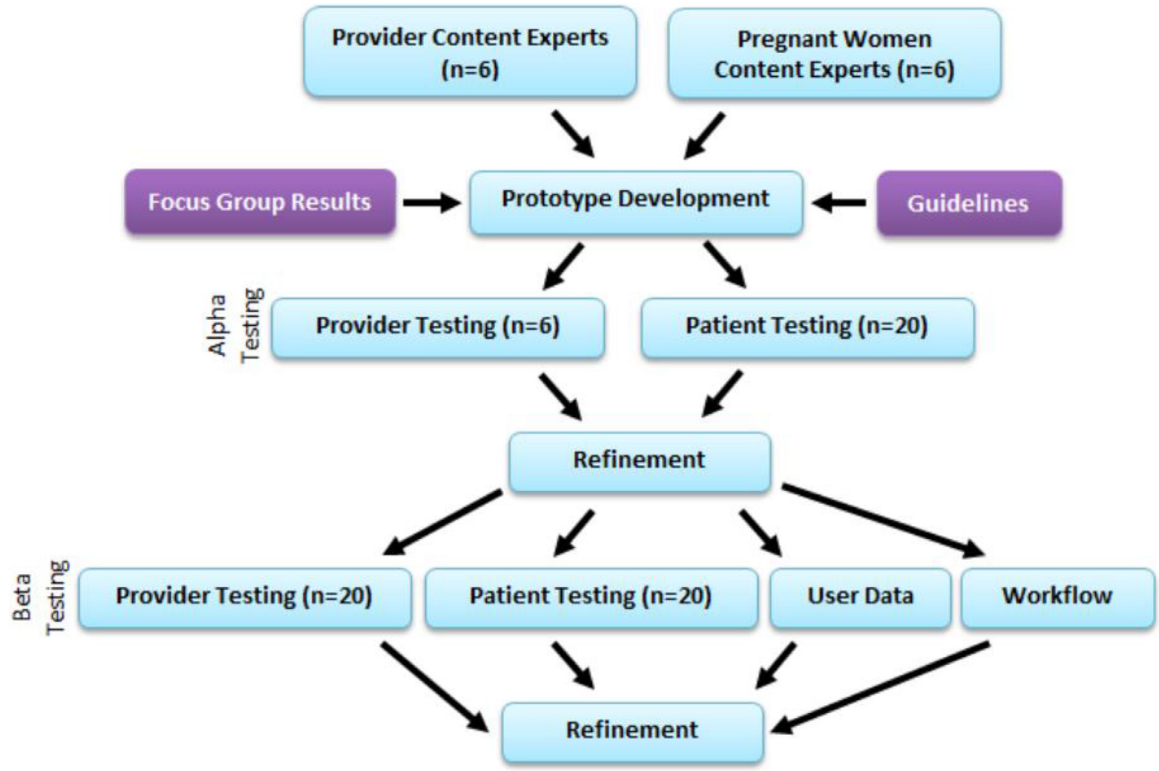

Figure 1 – Iterative development using technology acceptance model.

(Davis, 1989) that included a partnership between clinicians and scientists. We used an iterative development approach that incorporated end users feedback (patients and providers) at each phase (Figure 1) to facilitate ease of use and increase usefulness. The focus is on usability and acceptability from the users' perspectives. The iterative development included prototype development using the published guidelines from professional organization, focus group findings from patients and providers, and consultation with patients and providers who had experience with the conditions in the screening application (i.e., patients and providers who cared for depressed pregnant women, substance use during pregnancy, etc.). The prototype was then alpha tested by clinicians and patients in a faculty practice midwifery clinic and refinements made based upon their feedback. The revised application was beta tested in the same clinic with feedback from patients and providers as well attention to workflow (Gance-Cleveland et al., 2019).

The "How" for the Patient Education Materials

The theoretical underpinnings for both CDS interventions incorporating MI counseling includes self-determination theory (SDT). MI is a client-centered, directive method for enhancing intrinsic motivation to change by exploring and guiding patients toward resolution of ambivalence and inconsistencies between their goals and behavior (Markland, Ryan, Tobin, & Rollnick, 2005; Miller & Rollnick, 2002). SDT posits three fundamental needs as the basis for motivation: competence, autonomy, and relatedness (Ryan & Deci, 2000). There are three dimensions of social environment that promote these fundamental needs including structure, autonomy support, and involvement (Markland et al., 2005). The technology prompts the provider on MI counseling which promotes competence, autonomy, and relatedness or empathetic understanding.

StartSmart also incorporates the Screening, Brief Intervention, Referral to Treatment (SBIRT) framework (Hargraves et al., 2017; Substance Abuse and Mental Health Services Administration, 2011). *StartSmart* uses a comprehensive SBIRT approach with decision support and individualized patient education at the point of care, for the assessment and prioritization of care for pregnant patients (Hargraves et al., 2017). The SBIRT framework has primarily been used for perinatal substance use disorders and to some extent mood disorders (Substance Abuse and Mental Health Services Administration, 2011). An extended SBIRT model was used to develop *StartSmart* in which providers (a) screen for prenatal risk/protective factors, (b) use MI in a brief intervention to improve risk/protective factors, and (c) refer/treat when problems are identified (Substance Abuse and Mental Health Services Administration, 2011). The system algorithm uses the validated assessment tools to place patients in risk categories (low, medium, high) and individualized patient education is based upon risk categories. Low or no risk receives positive reinforcement, medium risk receives a brief intervention, and high risk are referred for specialty care or treatment (Figure 2). The

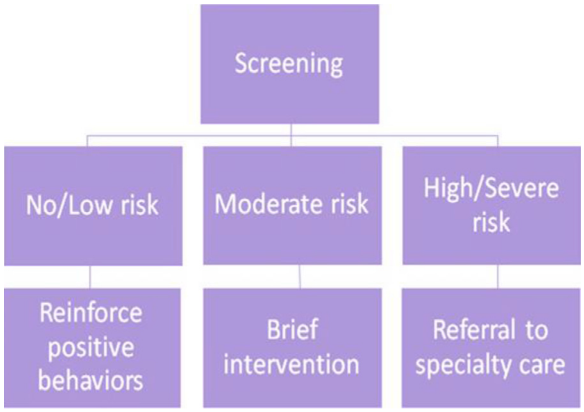

Figure 2 – Screening, brief intervention, referral to treatment.

individualized patient education materials based upon the treatment algorithms are the basis for the MI counseling using the SBIRT framework to increase the patient's understanding of health risks and provide options for brief intervention and referral as needed, along with resources in the community. If screening reveals significant health risks such as intimate partner violence or suicidality, immediate referral and warm handoff to appropriate care is arranged (Gance-Cleveland et al., 2019). In addition, the screening incorporates eligibility for Nurse-Family Partnership, a home visitation program in 42 states with established positive outcomes for women and their babies (Olds et al., 2014).

The questions of "*why or why not*" for CDS depends upon the quality of the intervention which must be used to counsel the patient not instead of counseling the patient. Implementation of the technology requires training providers on the use of the CDS and appropriate clinician interaction with the patient using the education materials to insure understanding of the screening findings, and appropriate counseling regarding treatment.

Ambient Sensing, Wearables and Artificial Intelligence: Emancipatory Nursing Theory for Community Co-Creation, Transformation, and Digital Defense

Rachel K. Walker, PhD, RN, University of Massachusetts-Amherst College of Nursing and IALS Center for Health and Human Performance

As use of medical- and consumer-grade sensors rapidly expands and intensifies (Zhu et al., 2020), nurses and nurse scientists will face myriad decisions with regards to the development, application, evaluation, and regulation of such technologies in both research and clinical practice. Emergent fields such as *augmented intelligence* (Bhandari & Reddiboina, 2019), which involves assistive applications of AI, and *ambient intelligence* (Bravo, Cook, & Riva, 2016), where digital connections between objects and AI-embedded sensors automate activities such as human profiling and environmental modification, herald a world in which individual nurses, patients, and communities have less and less control over care environments and data privacy (Benjamin, 2019). While some of these technologies may offer important benefits to individuals and society, *technochauvinism* – or the belief that more and newer technology is always better (Broussard, 2018) poses an existential dilemma and threats to human dignity and nurses' ability to engage in ethical practice. Philosophy and theory to guide nurses' use of these emergent technologies must be human-centered, community-directed, and account for the known and unknown ways in which forces of oppression and exploitation in society shape and influence health and human experience (Kagan et al., 2009). Therefore, nursing research and practice approaches to sensor use should be guided by critical and emancipatory theories of nursing and design justice (Costanza-Chock, 2018; Kagan et al., 2009).

Understanding the 'What' of Human vs. Technology-Based Sensing

Nursing agendas regarding use of sensors and related technologies should begin with conceptual clarity regarding the very definition of what is a *sensor* in the first place. This author [R.W.] started nursing in Mali, West Africa, learning from midwives who provided care by the light of a kerosene lamp, and who gathered data using their eyes, ears, and hands, working with knowledge retrieved from their own complex neural networks. These Malian midwife colleagues were, and remain, some of the most sophisticated *sensors* in the world. Indeed, this is one of the very first definitions of 'sensor': "…[a] receptor…that responds to sensory stimuli or to other changes in the…environment." ("sensor, n.") (Oxford English Dictionary, 2020). Humans are the original sensors.

Modern sensor technology, including the technology of *surveillance,* unlike more rudimentary nursing tools such as the stethoscope, extends, filters, amplifies, transforms, and archives a digitized version of human sensing in ways unprecedented in both speed and scale (Benjamin, 2019). Sometimes technological sensors support health, sometimes they cause harm – for instance, when sensing in misapplied or inaccurate, and occasionally both effects occur, but to different individuals. Effects of sensor use can also have temporal dynamics – helping at one point, hurting at another –in ways that may remain invisible to the persons who chose to use them in the first place (Benjamin, 2019). As sociologist Dr. Ruha Benjamin has observed, designing such 'benevolent' technology is at its heart "a colonizing project" (Benjamin, 2019, p. 176). No matter how sensors are used with humans- to describe, to self-monitor, or to actually change behavior – emancipatory theories of nursing indicate that sensors are always, *always an* intervention (Walker, 2019).

Emancipatory Approaches to Sensor Use Consider the "How" and the "Who" in Systems

Emancipatory knowing requires reflection on *how* dynamics driving injustice in society inevitably impact sensor design and sensor-related outcomes (Kagan et al., 2009). This includes seeking to understand *who* is involved in design and decision-making processes for sensor use, *who* is currently benefiting from those systems, and *who* is being harmed (Costanza-Chock, 2018). *Emancipatory intent* requires centering the leadership and expertise of those persons and communities at greatest risk of being harmed and silenced by structures of power that operate within the design ecosystem (Costanza-Chock, 2018; Fuller, 2012). Such efforts at consciousness-raising, collective problem-solving, and reflexive practice in the design and use of sensors and other surveillance technologies are known as ***design justice*** (Costanza-Chock, 2018).

MIT professor Dr. Costanza-Chock and members of the recently-founded *Design Justice Network* have collectively defined design justice as "an [emergent] field of theory and practice that is concerned with *how* the design of objects and systems influences the distribution of risks, harms, and benefits among various groups of people. Design justice focuses on [how] design reproduces, is reproduced by, and/or challenges structures of power in society – what scholars of Black feminism have named the matrix of domination" (Collins, 1990; Costanza-Chock, 2018).

There are many examples of Dr. Patricia Hills Collins' "matrix of domination" (Collins, 1990) at work in the world of sensors and related AI-driven research. Centered whiteness and homogeneous design teams in the tech industry have designed sensors which only detect and respond to light-skinned individuals (Breland, 2017). Cisheteropatriarchy (establishment of an exclusionary and false gender binaries in which cisgender male, heterosexual individuals are positioned as both the norm and given power over all others) has led to rampant classification errors in facial recognition software and other forms of racist, misogynistic, homophobic, and transmisic bias embedded so deeply in the software as to cause external observers to openly wonder whether some AI applications should never have been built first place (Samuel, 2019). As cameras and other biometric sensors are increasingly embedded in everything from fitness trackers and smartphone applications to doorbells and refrigerators, invasive, exploitive, and potentially harmful forms of surveillance capitalism are on the rise (Zuboff, 2019). Additionally, leaders of some Native American and Indigenous communities have reported a new form of *biocolonialism*: repeated violations of their sovereignty by U.S. Federal actors such as the NIH and others seeking to collect genetic and "omic" data for use in AI-driven data mining for precision medicine, specifically, the *All of Us* initiative (Hansen & Keeler, 2018).

How can nurses support resilience to such structural and social forces of oppression and exploitation? Emancipatory theory requires nurses build inclusion and accountability systems directly into leadership for sensor use (Costanza-Chock, 2018; Kagan et al., 2009). Good intentions – what AI experts such as Dr. Ruha Benjamin have described as a spirit of "technological benevolence" (Benjamin, 2019) – are not enough. Methodologies grounded in emancipatory knowing, such as the equity-centered community co-design (Creative Reaction Labs, 2018), center the leadership of communities nurses design with and for, and reinforce reflexivity regarding historical, economic, and social forces that will inevitably seek to shape those collaborations (Collins, 1990).

"Where" Matters: Health and the Heuristic of Person-(Techno) Environmental Fit

Technology is an undeniable part of the environments that surround us, from our apparel to the WiFi (Choi, Lazar, Demiris, & Thompson, 2019). Each us exists on a spectrum of capability and health that varies in relation to our environments. With consent, sensors can help optimize the fit between persons and their environments to support a vision of health *as each would uniquely define* it. This represents a heuristic inspired by the scholarship of Lawton and Nahemow (1973), and later Szanton and colleagues (Szanton, Klimmek, Roth, Savage, & Nkimbeng, 2014; Szanton et al., 2016; Szanton et al., 2019), that we refer to here as *person-techno-environmental fit*. Heuristics are methods or processes that aid in learning and problem-solving. When using the heuristic of optimizing person-techno-environmental fit, nurses and nurse scientists seek to improve the fit of an environment through the addition, subtraction, or modification of available technology within that environment, in order to better match an individual's description of what health looks for them. Such functional, person-directed definitions are not restricted by the narrow parameters of biomedicine, which defines health as strictly the absence of disease. This is how our research teams at UMASS Amherst have used emancipatory theory, equity-centered co-design practices, and the heuristic of optimizing person-techno-environmental fit, to discern not only *how* and *where* to address specific challenges with sensors, but to define *what* challenges and *whose* challenges we're addressing in the first place.

Examples of Nursing Applications of Emancipatory Theory to Sensor Use

Emancipatory intent means the design challenge must be defined in the words of those we design with and for. We spent hundreds of hours spent listening to persons managing chronic fatigue, many of them women treated for breast cancer, to understand what health looked like for them. They explained why fatigue was a distressing symptom insofar as it interfered with their ability to do things that were vitally important to them, while remaining invisible to many around them, including their healthcare providers. Clinicians may minimize or dismiss disability related to chronic symptoms when there's no obvious test or clear pharmacological solution. We call this *medical gaslighting* (Walker & Smithline, 2018). So we set out to create a tool that might facilitate capturing aspects of their experiences in a way that would allow individuals living with fatigue to make the invisible impacts of fatigue visible to others – not to prove fatigue for diagnostic purposes, but to allow them to self-monitor, and to be believed. We partnered with patient advocates and computer scientists as we used eye tracking technology to measure parameters of eye movements associated with high and low levels of self-report fatigue – capturing quantifiable functional impacts of this otherwise invisible symptom (Walker & Smithline, 2018).

We also asked what health looked like for persons taking oral chemotherapies at home. Rather than defining health in terms of biomarkers or scans, volunteers often discussed activities such as caring for small children and sexual intimacy – deeply meaningful activities that some had ceased doing completely out of fear of exposing loved ones to toxic byproducts of the drugs they had been prescribed (Walker & Szanton, 2017). There is not great empirical evidence on the clearance rates of some chemotherapies from semen, vaginal fluid, or breastmilk – but the concern was less about pharmacokinetics and more about the perceived threat of harming a loved one, and general lack of control (Houlihan, 2015; Yuki, Ishida, & Sekine, 2015). We partnered again with patient advocates, oncosexologists, and chemical engineers to build the first microfluidic devices – also known as a "lab on a chip" devices that can be read by a smartphone, that can determine when certain common chemotherapies and their metabolites are no longer detectable in body fluids such as urine, semen, and vaginal fluid. We're now on our fourth generation prototypes (Walker, 2019).

Further, many told us about disabling pain and numbness in their fingers, toes, or genital areas resulting from their cancer therapy. There is some evidence that vibrations, tuned to the right frequency, could potentially palliate some peripheral neuropathies (Steckman et al., 2019). So in partnership with the Wearable Electronics lab of chemist Dr. Trisha Andrew, we began exploring ways to optimize the person(techno)environmental fit through use of soft nano-coated fabrics (Anderson, 2019) that might eventually become part of socks, gloves, or underwear capable of being tuned to the particular vibrations.

When to Say No: Emancipatory Nursing Approaches to Digital Defense

Such intimate applications require us to think about applying sensors to humans the same way we would treat physically entering another person's personal space and laying hands on them. Sensing – a digitized form of sensing through touch – requires consent. Framed within design justice (Constanza-Chock, 2019), sensor work involving individuals or whole communities without their affirmative and informed consent is effectively *digital assault*.

Nurses' role in optimizing person-techno-environmental fit, viewed through an emancipatory lens, also means equipping communities against applications of intrusive surveillance, extractive data collection and unsecure data-driven systems we haven't created ourselves. We must be prepared to practice feminist theory-driven *refusal* of some technologies (Cifor & Garcia, 2019) and *digital defense*. Digital defense involves enabling communities to exert greater authority and control over when and how their data are collected and disseminated (Lewis, Gangadharan, Saba, & Petty, 2018). The *Our Data Bodies* project has developed a set of emancipatory theory-guided qualitative methods for facilitating this type of process (Benjamin, 2019). Our lab has participated by helping build controls designed to block wall-mounted radar sensors – radar meaning they can see through walls (such as those increasingly used in home care tech to detect falls) – from seeing through walls they had no right to see through.

The Why: Co-Opting Technology for the Community and Planetary Health

While we hope to generate useful technology, emancipatory theory instructs us that a commercially-viable product is not a definitive measure of success. Co-opting artificial intelligence and other emergent surveillance technologies means unapologetically leveraging sensor tech to raise the visibility and voices of people we design with and for, particularly those pushed to the margins (Costanza-Chock, 2018). For instance – with relation to the global emergency that is climate change and the need for more resilient systems in areas likely to be most affected by the disasters that result (Castner et al., 2019).

Last year our team invented a working prototype for the central component of a portable system designed to generate critical IV fluids such as normal saline from existing water sources at the point of care in the case of disasters. The need that drove this project was the destruction of most of the IV fluid manufacturing capacity for North America in the wake of Hurricane Maria – a weather event that also devastated infrastructure across Puerto Rico (Campbell, 2018; George Washington University & University of Puerto Rico, 2018). While we hope development of this system will progress to the point of viability in disaster prone areas, emancipatory theory reminds us that is not the main point. Every time this project is discussed, including how it may deploy sensors to ensure medical-grade purity and proper concentrations for the IV fluids, we it also forces a discussion about *why* this technology exists in the first place. These conversations force a reckoning with the on-going challenges facing our relentless nurse colleagues around the globe, including on the island of Puerto Rico, and the urgent reality of climate change. We must acknowledge the urgent need for radical solidarity and collective action required to address it (Campbell, 2018). Indeed, this was the focus of our recent feature in the Oncology Nursing Forum, “Climate Change Should Be On Every Nursing Research Agenda” (Walker, Pereira-Morales, Kerr, & Schenk, 2020).

Discussion

Technology has become a way of life in modern health care. As nurse scientists, we focused on the importance of theory to guide decisions around technology, development of technology, mechanisms of action of technology interventions, and evaluation of technology interventions. As we move forward into this high-tech health care world, the importance of maintaining the essence of nursing practice is essential. The American Association of Colleges of Nursing Essentials (American Association of Colleges of Nursing, 2020) and Robert Wood Johnson Foundation Future of Nursing 2030 (American Nurse Association, 2020) report includes an emphasis on the role of technology and sensor technologies and their impact on nursing practice. The importance of technologies supporting the discipline, so nurses are able to maintain the “high touch” and humanistic relationships with individuals and communities they serve, is critically important.

Likewise, the American Nurses Association (ANA) draft position statement on AI (American Nurses Association Center for Ethics and Human Rights Advisory Board, 2019) states that appropriate use of AI in nursing practice would support and enhance the caring and compassion as the central elements in the nurse-patient relationship and should be avoided when it diminishes these core values. The statement emphasizes the need for nurses to ensure advanced technologies do not compromise the nature of human interactions and relationships central to the nursing profession. Exemplars of clinical decision support in this article provides prompts for clinicians to use motivational interviewing to enhance their understanding of the risks of current behavior and options for them to consider to enhance protective factors (Gance-Cleveland et al., 2019). Furthermore, nurses can position and support the bidirectional trust and communication in parent-adolescent dyads around interventions that use sensors in adolescent driver safety.

In addition, the ANA draft position statement suggests that nurses need to be informed about technology to educate their patients and families about the pros and cons of technology and to relieve fears so that technology will be accepted to promote optimal health outcomes. Finally, the draft position statement emphasizes that technology does not replace nursing skills or judgment. Nurses remain accountable for decisions made and actions taken in the course of nursing practice. Technologies that assist in clinical practice are adjunct to, not replacements for, nurses’ knowledge and skills.

Nursing education needs to continue to incorporate theory, models, and frameworks that guide nursing practice including sensor technologies, including decision-making regarding the use of sensors and technology, as well as the perils of technocentrism (relentless centering of technology as the focus of study) and technochauvinism (Broussard, 2018). A better understanding of the history of tech, and nursing ethics governing use of emergent technologies is especially needed. Surveillance technologies such as sensors involve training datasets and design choices that may inadvertently exclude or harm some individuals and communities (Benjamin, 2019; Broussard, 2018). Rather than relying on nurses’ good intentions as a panacea against potential hazards of sensor use, nurses and nurses scientists should build in systems of accountability to the communities they serve through the use of strategies such as digital defense and equity-centered, co-design practices (Creative Reaction Labs, 2018; Lewis et al., 2018). Professional nursing organizations, such as the ANA and the American Academy of Nursing, should also advocate for policy and regulations, that require transparency and auditability of sensors and other AI technologies for use in nursing and healthcare. In addition, the education of future nurse cases for sensor technologies, as well as, the role of theory in the development, implementation, and evaluation of sensor technology interventions (Fleury & Sidani, 2018; Gitlin & Czaja, 2016).

Conclusions

As evidenced by the highlights of each nurse scientist’s presentation at the 2019 CANS Advanced Methods Workshop on Sensor Research described in this manuscript, diverse theories guide the decisions about sensor technologies including: whether to develop, the process of developing, how the technologies work, and what the outcomes of the interventions. The development of theory-guided sensor technologies presents many opportunities for improved health care. However, increasing pressure to rapidly develop and implement these tools without rigorous testing and solid grounding in philosophies and theory of nursing practice, presents challenges for the nursing profession. Nursing practice needs to maintain focus on social justice, equity in health and health care, caring, compassion, and the relationship with the patient using technology to facilitate the interactions not replace them. Nursing education needs to prepare the clinical nurses for ethical use of technology while preserving the essence of nursing. Nursing education also needs to emphasize that technology needs to be theory-based, scientifically rigorously tested, transparent and accountable to the individuals and communities that nurses serve. In some cases, this may entail the use of theory and evidence to guide refusal of some technologies (Cifor & Garcia, 2019). Education of nurse scientists can lead the way in theory-guided technology decisions, development, implementation, and evaluation.

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