REPORT

NSF WORKSHOP ON

Reconfigurable Sensor Systems Integrated with Artificial Intelligence and Data Harnessing to Enable Personalized Medicine*

March 7-8, 2019

Alexandria, VA

Workshop Committee:

Chair: MICHAEL DANIELE, NC State and UNC-Chapel Hill
Co-Chair: EDGAR LOBATON, NC State
Co-Chair: VEENA MISRA, NC State

Organizer: ALPER BOZKURT, NC State
Organizer: OMER ORALKAN, NC State

Administration: C.J. GOSNELL, Center for Advanced Self-Powered Systems of Integrated Sensors and Technologies (ASSIST)

Report Contributors: MICHAEL DANIELE, NC State and UNC-Chapel Hill
EDGAR LOBATON, NC State
ALPER BOZKURT, NC State
JEFFREY DICK, UNC-Chapel Hill
PETER LILLEHOJ, Michigan State
MEHDI JAVANMARD, Rutgers
REZA GHODSSI, Maryland

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EXECUTIVE SUMMARY

This report summarizes the presentations and discussions from a workshop convened at the National Science Foundation (NSF) on March 7-8, 2019 in Alexandria, VA. The focus of this multi-phased workshop was to determine future strategies for advancing the fundamental understanding and engineering of reconfigurable sensor systems by integrating hardware with data harnessing, real-time learning, and artificial intelligence capabilities. Specifically, this workshop addressed the changing application requirements, resources, and future challenges facing the research and development of reconfigurable sensor systems for clinical applications in the fields of medicine, human performance, and behavioral psychology.

The workshop enabled the broader engineering community to discuss and highlight issues confronting the development and application of reconfigurable sensor system for medicine. Through keynote talks, panels, and breakout discussions, researchers, clinicians, and representatives of Government agencies from different disciplines identified challenges and produces a set of recommendations to advance next-generation sensor hardware. The workshop presenters and discussion participants highlighted the shifts in hardware needs to meet the expectation of data scientists in the areas of artificial intelligence and machine learning, with a broad base of applications and resource needs that have more thorough validation and reliability than that provided by current demonstration of reconfigurable sensor system hardware. ***In summary, the healthcare community's needs are evolving rapidly, and advanced data science capabilities are more pervasive, emphasizing the need for researchers to accelerate the development of validated, user-friendly designs and platforms to support wider application of multimodal sensing hardware.***

We summarize the findings by the participants into key aspects as below:

1. *Putting All the Sensors Together:* The advances made in flexible electronics integrating multiple types of substrates (i.e., silicon, flexible electrodes, etc.) have been the greatest breakthrough because of the way in which it has extended the reach of sensor technology, allowing different sensor types to be integrated and to interface with soft or flexible biological systems. The greatest barriers still lie in the available bio-recognition elements; accuracy and reliability; in "real-world" operation; packaging; electrical interconnection between flexible and rigid component. *The application of data analytics techniques may be able to improve accuracy and reliability. The development of hybrid fabrication strategies, combining 3-D printing with standard microfabrication techniques for on-demand material delivery, can be considered as the next-generation approach for building reconfigurable sensors.*

2. *Reliability and Reproducibility of Multimodal Sensing*: With miniaturized and multimodal biosensing systems, lack of accuracy and precision makes quantitative analysis difficult. Sensitivity and reproducibility are multiplied in the multimodal systems. This is often the result of (1) each sensor modality having its own failure modes and limitations; (2) testing or demonstration in non-physiologically relevant experimental conditions. Simulation or actual *in vivo* testing are expensive to conduct and non-standard. We have to understand how sensors will operate in real conditions. *Standardization of sensor testing protocols, both in vitro and in vivo, will enable the use of advanced data analyses and provide for accurate comparisons across sensor modalities.*

3. *Designing for Data:* Machine learning and big data analytics are now an essential part of the scientific discovery process, complementary to and increasingly integrated with hardware

design. *Considerations for the needs of machine learning and big data analytics should be included in the initial design and simulation phased of engineering reconfigurable hardware, i.e. being able to build enough reliable sensors to collect the necessary volume of data for machine learning and artificial intelligence application.* Accordingly, the first identified challenge was the absence of collection of data to train machine-learning algorithms to enable an artificial intelligence approach to identifying digital biomarkers. An important resource to achieve this is the databanks that made available by federal agencies such as National Institute of Health (NIH) and Centers for Disease Control and Prevention (CDC), but they are only available for a limited set of sensor modalities.

4. *Medicine Requires Human-Centered Design:* Reconfigurable sensor technologies are not readily adopted by the end users, including patients, physicians and nurses. For example, wearables tend to suffer from low patient compliance and digital data from new medical technology can be difficult to interpret by clinical staff. *Operator-in-the-loop methods are needed to bridge interface capability gaps, ensure interoperability of the hardware, and reduce hazardous situations.*

Organization. The workshop was held at the NSF Headquarters on March 7-8, 2019 in Alexandria, VA. The workshop included approximately 75 participants, drawn from academia, industry, healthcare systems, Federal laboratories, and other Government agencies. A participant list is provided in Appendix A.

The workshop program was chaired by Michael Daniele (NC State and UNC-Chapel Hill). The technical topics were formulated, and the respective panel sessions were chaired by Veena Misra, Edgar Lobaton, Omer Oralkan, and Alper Bozkurt (NC State). The program is provided in Appendix B.

Three invited, keynote presentations spanned and highlighted the workshop. The first talk, presented by Aydogan Ozcan (UCLA), presented recent efforts in computer vision and machine learning research to replace conventional clinical practice, *e.g.* histological staining of biopsies. Dr. Ozcan's presentation highlighted a clear need to identify clinical practices that can be automated. The second talk, presented by Ieuan Clay (Novartis), illustrated the use of wearable sensor systems in clinical trials to define new digital biomarkers, and he stressed how the integration of hardware and software innovation is needed to better validate clinical outcomes. Specifically, Dr. Clay addressed the need to produce hardware that is user-friendly, whether that be the clinician or patient. This ensures the reliability of data to be analyzed and converted into validated digital biomarkers. The third talk, presented by Julian Goldman (Massachusetts General Hospital), described the experiences of clinicians using multimodal sensor systems in the healthcare environments. Specifically, Dr. Goldman suggests the Medical Internet-of-Things may be outlining the necessary roadmap that needs to be followed in designing new sensor hardware. Overall, the invited, keynote presentations addressed hardware, computational, and clinical challenges faced by researchers trying to develop sensors to enable personalized medicine.

Panel and Breakout Sessions followed the keynote presentations. Session chairs presented a brief overview of the challenges and future research direction in their respective fields. Each panel comprised of short presentations by panelists, followed by an extended forum for discussion. Research challenges and solutions from each area were discussed (Section II) to provide a series of suggestions that outline a roadmap for the future research landscape in reconfigurable sensor systems (Section III).

I. Background in Integrated Systems for Personalized Medicine

Intelligent, interactive, and networked sensor systems are a growing part of the biotechnological landscape, especially in the area of wearable, implantable, and point-of-use biomedical devices.[1-4] Consequently, as biological, behavioral, and psychological monitoring moves from the laboratory to the point-of-care, data analytics and real-time intelligence will need to adapt to the requirements of the healthcare system. [5-10] Advances in sensing and data capture allows a coupling between sensing, actuation and control to close the loop in real-time and invoke the need for various flexible (reconfigurable) hardware technologies. In addition, these closed- or human-in-the-loop solutions will require real-time decision making to realize individualized and personalized interaction and interventions.[11-16] These feedback loops go well beyond classic supervisory control and can build upon new technologies in artificial intelligence.

Hardware for sensor systems have largely followed a "*1 sensor : 1 analyte"* architecture and relied on remote data processing and decision making, but the development of large-scale, reconfigurable, multi-functional systems is in its initial stages.[17-27] When discussing sensor networks, most of the focus is usually on systems consisting of many small, inexpensive, battery-powered sensor nodes with limited capabilities. This is not the interest of the proposed workshop. This workshop is interested in the next-generation of sensor nodes that can and should have multiple different sensor front-ends (e.g. electrochemical, optical, acoustic, etc.) and can be attached to different platforms (e.g. mobile, wearable, and implantable). Combining different sensor modes into a single package has an immense potential to improve the reliability and validation of measurements made by improving data compatibility and consistency.

Multiple configurations of sensors or their technical characteristics can be required for different operations (e.g. detection, classification, etc.), for different applications (e.g. diagnosis, prognosis, behavior identification, modification, recognition, etc.), and in different scenarios (e.g. hospital, emergency care, at-home, etc.). To achieve reconfigurable capabilities from current sensor systems will require reduction in cost, reduction in time to adaptation, and the recognition and integration of new data and computer science capabilities. For example, during operation, a continuous blood glucose monitoring system that observes a specific chemical concentration may be required to quickly switch to surveillance mode to detect alternative metabolites post-meal, or maybe the system is needed to close the loop and deliver insulin based on available learning models, which integrated a patient's medical history as well as their current physiological status. At this moment sensor, systems are relatively inflexible to cope with such different operational demands.

Designing reconfigurable hardware to take advantage of next-generation machine learning and artificial intelligence is both a minimally explored [28, 29], yet clearly challenging, area of research. Challenges for designing and engineering reconfigurable sensor systems to leverage capabilities in machine learning and artificial intelligence include: balancing computing among local, edge or cloud; meeting latency and liability requirements; privacy and security of personal health data; understanding role of personalized vs. aggregate data; correlation of heterogeneous data streams; and building predictive and personal health models for individuals using longitudinal and continuous data sets.

The emerging hardware implementations for such machine learning and artificial intelligence for on-node processing and edge computing need to consider the associated computational and application-driven issues to overcome these challenges. In recent years, the hardware community

has been overcoming many of these major technology gaps, such as sensing modalities [30-37], power requirements of computation and communication [38-42], and flexible and wearable materials [43-48]. Accordingly, the landscape is primed to define the scientific roadmap and necessary sensor technologies that can enable artificial intelligence and machine learning tools [49-54] for improved healthcare outcomes.

Lastly, personalized medicine is the tailoring of medical treatment to the individual characteristics of each patient. The approach relies on scientific breakthroughs in our understanding of how unique molecular and genetic profile makes a person become susceptible to certain diseases, and this new knowledge can only be acquired *via* new analytical tools and methods. Moreover, while the term "Personalized Medicine" has been used to describe medicine based on –omics, *i.e.* genome and proteome, there is a more encompassing view: personalized medicine also includes the "phenome," which is the set of all phenotypes expressed by an organism, the "exposome", which is the set of environmental conditions experiences by and organism, [55-57] and even the "activiome" which is to integrate the impact of everyday activities. Such a vision requires an acceleration of development in both multifunctional analytical hardware and data analytics. Many biomarkers are patient specific, which will require personalized sensor systems, while remote detection technologies (e.g., camera based photoplethysmography, temperature, activity, respiration, etc.) can be generalized and be used to assess environmental and behavioral conditions for all persons. Machine learning and artificial intelligence can be used to integrate these heterogeneous data streams to identify personal health status, personal experience, and any actionable abnormalities.

II. Summary of Panel Discussions and Breakout Sessions

Framing Questions for Panelists

1. *What are the challenges and opportunities that exists in integrating Reconfigurable Sensor Systems hardware with data harnessing, machine learning and artificial intelligence in order to bridge the existing gaps?*
2. *What are the barriers for making a paradigm shift in Personalized Medicine?*
3. ***Panel 1:*** *What are the barriers in developing sensing approaches as well as in the translation of approaches that are reliably demonstrated in the lab? What science or engineering is missing for a breakthrough?*
4. ***Panel 2:*** *Most commercial and research progress in hardware for personalized medicine has been in smart adaptation of existing electrical, optical and mechanical methods to probe the body. This adaptation has involved innovations in miniaturization of sensing hardware, making rigid electronics more conformal and flexible, and embedded systems hardware that increases the value of the measured data. What do you think the biggest hardware breakthrough so far in general and in your prospective research fields and what has been the greatest barriers?*
5. ***Panel 3:*** *What challenges are associated with data fusion and model transfer in reconfigurable sensory systems? What are the challenges with ensuring reliability / verifiability of the sensor measurements and AI for reconfigurable sensor systems?*
6. ***Panel 4:*** *In comparison to the translation of medical devices, how can the utility of new data science techniques become accepted in the clinic? What types of data interface do you foresee being needed for practitioners to adopt new data / "metrics" for diagnosis and prognosis?*

PANEL 1
Point-of-Care, Wearable, and Implantable Sensors: Modalities and Diagnostics to Supplement Offline-Data with Point-Of-Action Intelligence

Panel 1 and Breakout Session participants focused on identifying the state-of-the-art in sensor science and technologies, where current sensors are limited, and how the needs of reconfigurable sensor systems should guide future sensor design and research.

The goal of sensor system development is always to create a compact system that integrates all required process steps and improves the key performance parameters of sensitivity, specificity, speed, accuracy, dynamic range, robustness, ease of use, and costs. Figure 1. Illustrates the key performance parameters of any sensor system, as well as classification of different sensor applications in personalized medicine based on their portability and intervention time. Figures are derived from presentation by Shantanu Chakrabartty (University of Washington, St. Louis).

During discussion, there was clear consensus regarding the breakthroughs and challenges for developing reconfigurable sensor systems, viewed from the perspective of sensor design. These conclusions can be organized into three categories: (1) Sensor and Systems Materials, or (2) Accuracy Issues, and (3) Application Improvements. Herein, we will summarize the recent breakthroughs and upcoming challenges in both these categories, as determined by Panel 1 and the Breakout Session participants.

A. New Sensor and Systems Materials

The first breakthrough in developing personalized biosensor systems has been the advances made in flexible electronics and electronics manufacturing. Integrating multiple types of substrates (*e.g* silicon, flexible electrodes, organic electronics, textiles, etc.) have been the greatest breakthrough because of the way in which it has extended the reach of sensor technology, allowing different sensor types to be integrated and to interface with soft, deformable biological systems. The greatest barriers to integration still lie in the electronic packaging; electrical interconnection between sensing systems and flexible materials and rigid CMOS components for example, continues to be a major issue. 3-D printing technologies (*e.g.* polyjet, stereolithography, two-photon lithography) can be also considered as another major technological breakthrough in manufacturing for creating/prototyping miniature sensors displaying complex shapes in 3-D. The capability to print bio- or biocompatible materials extends to potential use for developing bioelectronics or biological hardware. However, the limitation in printing conductive or dielectric/high-K materials with on demand resolutions - essential for creating integrated circuit components - is a key challenge, and the development of hybrid fabrication strategies, combining 3-D printing with standard microfabrication techniques, can be considered as the next-generation approach. With that said, it was not clear whether flexible electronics is truly necessary for wearable electronic systems given the fact that complicated circuitry can be miniaturized sub-square centimeter sized chip using traditional microfabrication techniques.

In addition to performance, it is important that the sensors dedicated to personalized medicine still need to be application specific. Personalized health monitors, *e.g.* wearables, need to be portable, lightweight, unobtrusive and inexpensive, offer high sensitivity and reproducibility, be validated in clinical settings, and be approved by the FDA. Without meeting these goals to date, the value of these devices and analytes is not clear.

A recent report by (Gao et al. (Nature 2015) [58] on *in situ* sweat monitoring was probably the most highly cited report in wearable continuous monitoring over the last decade, and resulted in a flood of research in wearable biosensing systems. Nevertheless, biomarkers in sweat, saliva, and exhaled breath condensate are not well known or correlated to the gold standard of blood tests. For example, In-situ continuous monitoring of protein is a dream that still has not been fulfilled, despite the immense use. This will require biorecognition elements that can be reset on demand dozens, if not hundreds or thousands of times, before fouling. More importantly, continuous or long-term monitoring with long lifetime is a challenge due to sensor saturation and degradation; any solution to this will require new bio-recognition strategies. One of the main barriers in implantable sensors is limited biocompatibility and short operating life. There needs to be new biocompatible

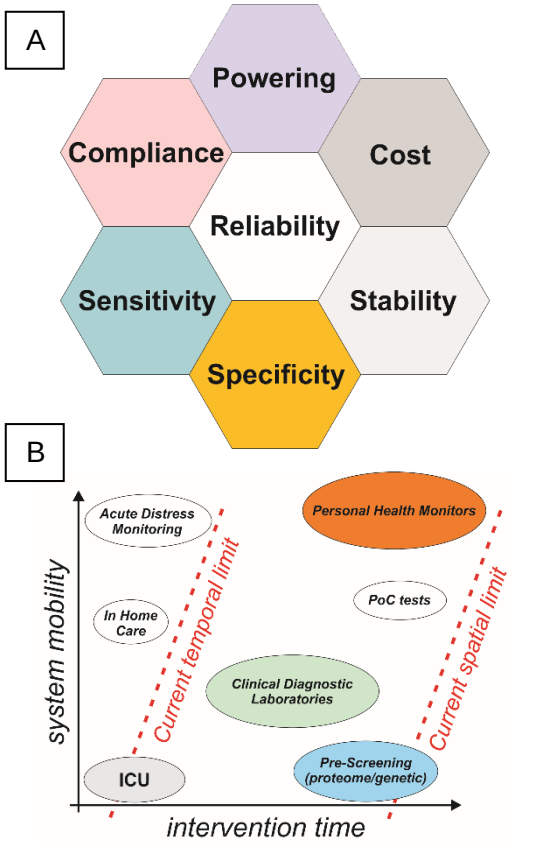

Figure 1. **(A) P**arameters for successful sensor design will revolve around reliability. **(B)** Unique considerations for personalized medicine systems include system mobility and applications specific intervention time.

materials and/or coatings, which can enable sensors to remain operational, *in vivo* for several months. In addition, biosensors that can detect proteins without any probe capture molecule will be necessary to enable truly reconfigurable personalized medical systems.

B. Accuracy Issues

Multiple participants echoed the fact that miniaturized biosensing systems lack accuracy and precision, which make quantitative analysis difficult. Lab-on-chip technologies, while performing well at the bench, have difficulty making it out of the lab and into the clinic. Regarding complex matrices and analytes, after 30 years ELISA is still gold standard. There is an assumption that if a biosensor is good enough to be published, it probably already should be accurate. However, this is not the case, and we still rely on ELISAs. Dr. Javanmard (Rutgers University) summarized a key issue in translating miniaturized sensor systems, "One can call this, the Elizabeth Holmes problem. With minimal analyte, you get close to the Poisson limit. How can one creatively leverage sensing systems to solve this?"

With this challenge in mind, the Panel 1 and Breakout Session participants identified a potential for machine learning and artificial intelligence as a means to use the generated sensor data to aid in the design and "correction" of reconfigurable sensor systems. Machine learning and artificial intelligence account for data heterogeneity, missing data, and person-to-person variability. Multi-modal sensing platforms and data analytics can provide reliability and accuracy estimate of the measurement. While hardware innovation is on the horizon, it is not clear how machine learning and artificial intelligence can improve the hardware development, not only use the data from the hardware to improve clinical outcomes. The use of machine learning and artificial intelligence could improve the analytical performance, reliability and reproducibility of low cost sensors, such as those fabricated on paper in addition, textile. Using machine learning and artificial intelligence to analyze biosensing data could minimize human error for improved accuracy. The algorithm requirements can also help determine the necessary sampling frequencies. Low sampling rates could diminish the sensitivity; however, high sampling rates consume more power and generate large amounts of data, which require expensive storage.

C. Applicability Improvements

Any personalized technology needs to be easily adopted by the end users, including patients, physicians and nurses. Device adoptability, specifically user/patient compliance needs to be improved. For example, wearables tend to suffer from low patient compliance because they are uncomfortable or complicated. It is necessary for developers to consider the following: how long do specific sensors need to be worn? Can compliance be monitored and validated? Compliance may be achieved by designing wearables to be as small and lightweight as possible, and improving the usability of medical devices through applying human-centered design principles. In particular, human factor needs to be considered and panelist J.C. Chiao (Southern Methodist University) suggested a collaboration with Art School in order to build interfaces. Ubiquitous sensing is promising, but must reduce costs per nodes. Obtaining Food and Drug Andministration (FDA) approval and Clinical Laboratory Improvement Amendments (CLIA) waiver for diagnostic device can require > $10 million in capital. Nevertheless, it is obvious that cheap sensors are ***cheap***. They may require calibration, more expensive quality assurance and quality control (QA/QC), processing.

Poor compliance issues also compound missing data and data interpretation problems. Digital data from new medical technology can be difficult to interpret by clinical staff. Real-time sensors

are *real-time*. Large volumes of data, potentially not relevant timescale. This leads to a necessity to incorporate data quality metrics in models. Aaron Mazzeo (Rutgers University) considered that too much data is not good, so active learning schemes may be useful, as well as explainable AI.

Lastly, if all the hardware and software efforts are successful, for translation we much recognize personal monitoring is *personal, leading to* Privacy/Ethics issues: GPS trajectories, heart rate, etc. and feedback to user can influence behavior.

In conclusion, it is the Panel 1 and Breakout sessions participants assessment that there needs to be a *science* dedicated to take existing sensors technologies, and utilize multi-modal sensing, data analytics to fully solve the accuracy problem. The NSF can play an important role in getting researchers to turn their attention to generating new methods for sensor system validation and reliability improvement. In other words, do not worry about building new fancy sensors, but innovate in the areas of sensor redundancy and reliability by using *in vitro* or simulated biomarker analyses and developing benchmarks and testbeds for a broader range of analytes (ranging from biochemical to biophysical markers) and standard protocols to generate data for downstream processing. Perhaps some more translational and convergent efforts can be supported. This may inform future requirements for accuracy and fidelity of real-time physiological monitoring data. A comparison of data quality between current commercial-off-the-shelf (COTS) devices and clinical monitoring devices may further inform the state of the field and may help identify the utility of "disposable" devices in low resource environments.

PANEL 2

Hardware Form Factors/System Design for Sustained Usage and Data Gathering: Wireless Devices, Body Area networks, Online Services

In Panel 2 and Breakout session, the participants started with the discussion of the reconfiguration of sensor parameters by artificial intelligence in real time to improve system materials and enable power-reduction to extend battery lifetime or self-powered operation. Current energy harvesting devices and self-powered systems are large and bulky; therefore, there needs to be advancements in materials and designs to miniaturize energy harvesters, making them suitable for wearable and implantable applications.

The first identified challenge towards this was the absence of collection of data to train machine learning algorithms to enable such an artificial intelligence approach. An important resource to achieve this is the databanks that made available by federal agencies such as NIH and CDC. This could also be achieved with the design of wearable sensors that would be accepted by majority of the population to gather large volumes of data. It was agreed by the participants that early versions of such design should focus on reliability and ergonomic robustness more than the efficiency of other sensor specs (e.g. sensitivity, specificity). Scalability is an important barrier both in terms of achieving sufficient sensor systems actively used by the population to generate such large-scale (big) data. Especially a need for user interaction with the device either for device maintenance or data entry is a hindrance towards large-scale patient/user compliance.

In in the next generations of reconfigurable hardware, the connection between reliability versus predictability could be investigated. From this point of view, commercial off the shelf subsystem components would be more efficient for a higher impact during earlier stages, which could be replaced by application specific integrated circuits in the future. Any such system design should keep intraoperability in mind and be compatible with and adaptable to various use case scenarios

related to activities of daily life. Implementation of edge processing more and more would not only lower down the dimensions of such devices but also reduce the computation power and help machine learning to be more reliable.

In such a reconfigurability effort, sensors should be tasked and controlled, come in a library of sensors where a selection can be made and be software defined. Reconfigurability would allow sensors to learn/know how to and when to increase the sampling rate.

Current day medical practice uses biomedical devices for diagnosis, treatment and prevention. While the classical statistical approaches would help with the former two, the prevention is where the artificial intelligence would have the most impact. The prediction speed versus accuracy will play an important role in reliability and use of feedback provided by the artificial intelligence for prediction. In this, the artificial intelligence would need to create updatable, multiscale and end-to-end models that also would consider environmental, behavioral or sometimes psychological context during the collection of data in a holistic way. Such models would also enable model based bio- and biomedical system engineering to design next generation of reconfigurability of these sensors systems.

Among all the needs of the medical field, the rare conditions affecting the majority of population (such as Alzheimer's or autism) would benefit most from an artificial intelligence based predictability with respect to other more commonly occurring conditions with established statistical framework. NSF was recommended to define new grand challenges or design new solicitations to target such rare conditions more and enable joint programs with NIH on generation the relevant data using reconfigurable systems on these conditions. A longitudinal and population wide data collection would help artificial intelligence to figure out what goes wrong in the body, how it goes wrong and identify the sensors that provides highest predictability for such future failures and even come up with actionable feedback to avoid/prevent these.

Several stakeholders of reconfigurable sensor systems should be considered when shaping the future of this area. It should be noted that use of such systems in medicine would alter the decision-making mechanism as well as the workflow in current day medical practice. It would be unrealistic to expect a revolutionary change, where a potential entry point of such systems would be radiology. This field relies on technology both to generate objective input (such as medical imaging) during their decision-making in addition to supporting this decision-making (e.g. by marking the suspicious lesions on such images). Design of domain specific artificial intelligence that will support the sensors to be reconfigured to improve the outcomes of this decision-making and predictive accuracy would make a major contribution to this field. This in turns also affects another stakeholder, insurance companies, which values any prediction about the deterioration of health conditions. However, it is also a fact that the current day medical practice misses a roadmap how to provide actionable feedback based on the data collected using these reconfigurable sensor systems in connection with these stakeholders.

It should be noted that both FDA and IEC works on standardizing patients' interaction with medical devices, software and algorithms. Therefore, such agencies working on standards and approvals should be an essential part of any conversation about reconfigurable sensor systems from the beginning where NSF could facilitate the organization of future workshop bringing industry, academia, NIH and such standardization/approval institutions together. The reconfigurability of sensor system by artificial intelligence also would help these agencies for the analysis, standardization and approval of all modes of operation of such devices and algorithms.

Machine intelligence connected to reconfigurability of sensor systems could easily figure out what would go wrong and how it would go wrong in a device or algorithm using a model-based analysis before such failures occur in the real life.

The interdisciplinary aspect of the entire concept of reconfigurable sensor systems (which needs various expertise from hardware engineering to data sciences, from applied math to ergonomic design, sociology and clinical medicine) requires next generation work force to be trained in a way that encourages curiosity in all of these disciplines while providing easy access to informative educational resources. Innovation at all fronts should be encouraged by NSF through initiating focused interdisciplinary Integrative Graduate Education and Research Traineeship (IGERT) programs, allocating funds for creating relevant curriculum as well as encouraging high schools and undergraduate institutions to organize hackathons on topics related to reconfigurable sensor systems supported by artificial intelligence. This is the only way to ensure enough number of trained individuals and interest will exist in the US during next 5 to 20 years to bridge the gap between various subfields and lead the field.

Ultimately, the panel arrived at similar conclusions to Panel 1. Panel 2 also identified other technical challenges and barriers regarding sensor and data development:

1. Sensor technology fouls with time, implying time-course measurements are not reliable and sensor use is limited to one or few individual measurements. In itself, this represents an opportunity to develop new electrochemical sensors, and study how artificial intelligence and machine learning training sets can be used to correct such issues.
2. Barriers to advancement include the investment put into amperometric sensors. Selectivity is still gained by specific molecular interactions – as we all know, electrochemistry is rather poor in terms of speciation but cannot be beat in terms of spatial and temporal resolution (i.e., electrochemistry resolution is not limited by the diffraction limit of light; rather, it depends only on the fabrication of the electrode). The smallest electrodes to date are single atoms.
3. Labs are cleaner than the field – to test efficacy for the field, one should perform experiments in the field or simulate the field in the laboratory. Device testing is most relevant when these fields and errors associated with field measurements are taken into account.
4. Dimensionality reduction is important. Handling high-dimensional data dramatically increases power consumption. Need to adaptively learn low-dimensional structures from data (that are critical to the machine learning pipeline) to be measured and transmitted by the device.

PANEL 3.

Sensor Fusion with Machine Learning and Artificial Intelligence: Challenges of Integration and Informatics

Recent advancements in wearable technologies provide an opportunity to evaluate the utility of physiological monitoring data to provide early indications of health status changes and generate new decision-making capabilities. An earlier warning of negative health outcomes (*e.g.* infection) could allow for an earlier treatment regimen and higher likelihood of positive outcomes. Panel 3

and Breakout Sessions participants addressed the barriers and opportunities to expand on the utility of physiological monitoring technologies by developing algorithms to improve the performance and utility of physiological health monitors.

The principal suggestions from Panel 3 and the Breakout Session participants are (1) algorithms should address baseline data or groundtruthing, which is often hard to obtain; (2) validation of the algorithms is vital; (3) there needs to be more efforts for creating data sets that can be used by the machine learning community; (4) incentives may be needed in order to overcome language and knowledge barrier between data science and hardware experts, and promote integrated collaborations.

With that said, it was repeatedly highlighted by all members of the panels and participants: More data and better data is required! Both data scarcity and label scarcity are the preeminent challenges in using the next-generation of machine learning and artificial intelligence to improve healthcare outcomes. In addition to a dearth of data, there are general data collection issues that need to be corrected across the board, including missing data, irregular sampling, poor signal-to-noise ratio, temporal imprecision, and data heterogeneity.

The following characteristics should guide acquisition of data:

1. Data analytics require clean/parsed data to combine disparate data streams and identify relevant data and data correlations;
2. Data sources should be unobtrusive, persistent, broadly distributable sensors. This is important to ensure the sensors are not influencing the data. Ideal data streams will also include proxy data sources (e.g. environmental conditions or activity status);
3. Data collection should be longitudinal, contextual (e.g. heart rate elevation in traffic), and correlated with health outcomes.

While some data acquisition issues can be ascribed to interpersonal variability, many of these challenges can be directly overcome by better hardware design with input from data scientists. Improvements to new acquisition methods, devices and technological tools, include the following:

1. Development and adoption of acquisition methods for data in more physiological conditions such as standing, moving, exercising; new (wearable, multimodal) sensors and sensor data analysis to obtain functional data, also during daily life;
2. Acquisition of data independent from the acquisition system, the acquisition method, or the acquisition source;
3. New developments in data formatting and data processing, which automatically collect, format the data, provide it to the end-user for assessment, and sharing. This may include de-noising and dimensionality reduction of the raw data and of the extracted feature space;
4. Data formatted in a predefined standardized and certified way for clinical purposes.

The group also identified non-technical avenues of success that would support the acceleration of hardware solutions into clinical outcomes:

1. Engaging all groups (medical, engineering, data and patients) in a collaborative manner is essential;
2. The collaborations between the machine learning/artificial intelligence community must be viewed as specific to the sensor / clinical challenge;

3. It would benefit the community to go beyond sequential development, *i.e.* the engineer developing the sensor, contacting the clinician for validation, and then having the data person doing machine learning or statistical analysis. It would be good to overlap efforts;
4. It would be good to have a two-way interaction between hardware and software. Not just having hardware providing data, but the analysis guiding the hardware design (for example);
5. Creating a shared dataset and library;
6. For reconfigurable system, it would be beneficial to determine how to combine multimodal sources (coming from maybe even similar modalities but different locations - i.e., same underlying process). This could benefit from physical computational models, machine learning, and sensors people working together.

Lastly, Panel 3 and Breakout Session participants identified unique issues in the culture difference between hardware and software developers. This requires new cooperation and culture changing efforts. The groups will need to start getting over Language, Style and Knowledge Barriers. Many participants asked how do we find the people that are willing to learn (from each other's); including funding for teams that include sensor, data and clinical and human/factors; equivalent funding levels across the fields; seeding EAGER or planning grants, or pre-planning to search for collaborators.

Based on this discussion, the following recommendations can be made to (1) Generate a community and shared resources; (2) Enable cooperation and changing culture. We must identify ways to create a community for wearables; have centralized resources for prototype scale-up (GitHub for circuits / Open source designs); standardized validation protocols.

PANEL 4

Difficulties and Barriers in Making a Paradigm Shift in the Clinic

With the advances in analytical test equipment, analyses protocols, and in understanding how the biomolecular compositions or their intermolecular or environmental interactions affects human health, we are closer to realizing viable application of personalized medicine.

Panel 4 and Breakout Session participants considered the barriers to translation of sensor systems for personalize medicine. Major barriers in realizing the paradigm shift toward personalized medical data acquisition go back to the hardware design strategies. Barriers include, making sensor systems available to a broader range of population, include 1) lack of cost-effective analytical systems utilizing streamlined fabrication processes, 2) complexity in defining clear problems and determining potential solutions, requiring more communication between practitioners and engineers, and most importantly 3) identifying personalized markers that will predict disease susceptibilities and treatment responses.

A first major step for designing new reconfigurable sensor systems is the identification of these markers, followed by creating adaptable sensing technologies capable of detecting patient-specific markers at a low enough cost to be applied to more diseases or risk factors. Adaptable manufacturing processes then come into play with development of distributable sensor systems. Thus, the key to personalized medicine is both the creation of sensing systems that accurately and inexpensively operate, and creating properly instrumented manufacturing systems to ensure a robust product, leading to improved data acquisition and ultimately better patient outcomes.

The participants also noted that more data/information is not always better for the end-user or clinician, *i.e.* quality is preferred over quantity. If the data is not properly curated and delivered, it can have detrimental effects. One major step in utilizing these advances will be to incorporate hardware and software in a systematic way into the clinical decision-making process, where the ultimate information delivery is concise, palatable, and validated. There are multiple strategies necessary to collect and curate useful data into actionable information. Modified from the presentation by Dr. James Weimer (University of Pennsylvania), we may consider the following progression of questions in designing intraoperable, reconfigurable sensor systems that can be translated into the clinic:

1. Use a Clinical Decision Support (CDS) design methodology
    a. How to identify, collect and label (if necessary) clinically relevant data?
    b. How to monitor CDS systems while minimizing clinical overhead?
2. Understand the Caregiver-in-the-loop paradigm
    a. How to model caregiver-automation interactions? How to adapt?
    b. How to monitor/quantify clinical cognitive load without increasing workflow overhead?
    c. How to tune/adapt system to improve patient safety?
    d. How to adjust workflow to make all the above feasible?
    e. Safety and assurance
    f. How to best adjust workflow to make CDS systems viable?
    g. If you are using machine learning, what guarantees can you REALLY make?
    h. How to formalize system assumptions and designing corresponding monitors?
3. Designing for Assured Autonomous Medical Systems
    a. How do we design systems when physiological models are uncertain?
    b. How do we learn in the presence of inter/intra-patient variability?
    c. How do we verify system performance at design time?
    d. Monitoring and Control of Autonomous Medical Systems
    e. How do we monitor the system for anomalous behavior?
    f. How can controller LECs be personalized to the patient?
    g. How can we dynamically generate evidence for assurance?
    h. Dynamic assurance for Autonomous Medical systems?
    i. How can we assure the safety of systems with dynamic evidence?
    j. How can this information be conveyed to caregivers?

By answering the aforementioned question, we can generate evidence for improving efficacy.

To date, few preliminary projects using wearable sensors and point-of-care diagnostics for personalized health applications have been undertaken, of these, only some were able to model a significant number of real patients and demonstrate a concrete improvement in health outcome measures. Regarding the future design of reconfigurable sensor systems for personalized medicine and the validation of their efficacy in improving healthcare, we recommend the following distinct types of new projects:

1. Engineering the large-scale deployment of established sensing methods paired with novel deep learning or AI to conduct clinical assessment studies to determine the safety, efficacy, efficiency and benefits of incorporating deep learning and AI into such tools;

2. Modelling methods and the further development of integrative models, including targeting their pre-clinical or retrospective validation;
3. Integrating electronic health record standards into new device and sensor use protocols.

Lastly, both hardware and software developers must strongly consider putting the clinician-in-the-loop. Sensor and personalized health solutions were designed to return to the clinician a neatly package answer intended to be immediately used to make a clinical decision. In reality, because of their inherent complexity, many predictive models require support from an experienced clinician. Medical input is necessary, not only to preprocess the data, but also to provide essential quality assurance checks. Clinicians are trained to aggregate heterogeneous information and extract patterns even when information is very noisy or incomplete; computers find such tasks very difficult to complete.

III. Roadmap and Suggestions from Sensor Hardware, Data Science, and Medicine

Reconfigurable sensor systems will provide the necessary intelligence needed to migrate from population-based prediction towards truly personalized medicine, which emphasizes the acquisition, integration, processing and application of patient-specific information. Personalized health models will allow patients and clinicians to become more pro-active in instituting lifestyle modifications and clinical surveillance for the prevention of diseases.

The workshop presenters and discussion participants highlighted the shifts in sensor system needs and expectations, with the clear identification of needs that are much more transdisciplinary and translational than that traditionally supported. A breakthrough in the science and engineering of reconfigurable sensor systems for personalized medicine requires convergent instrument, data management, and computational capabilities to address the enormous complexity of the biological and behavioral differences between every patient and every disease. Improvement of health outcomes will only be achieved by combining technological advancement with deep clinical, molecular and contextual analyses.

Simulation and modeling, measurement and instrumentation, and data analysis are interdependent, as an integral part of the scientific discovery and engineering development processes. Machine learning and big data analytics are now becoming an essential part of these processes, complementary to and increasingly integrated with the starting design. Accordingly, future research efforts must prioritize:

1. New self-powered families of sensors for truly personalized health care based on energy efficient approaches and heterogeneous integration solutions in biocompatible form factors to extend the intervention window and to support specific prevention strategies.
    a. Provide a new generation of frictionless autonomous smart sensors at all levels required by health care data collection: implantable, wearable, environmental.
    b. Develop new user interfaces for life-style feedback loops and related diseases.
    c. Accepted protocols to support evaluations of sensor technologies, including formal processes for verification, sensitivity analysis, validation (including clinical trials), risk-benefit, and cost-benefit analyses, and ultimate product certification.
2. The extension of existing data tools to support time-varying, dynamic data, and support multiscale interactive visualization for data defined at different time scales (data defined across different spatial scales); Extensions to support novel human computer interaction and interactive visualization that allow the usage of large-scale data from heterogeneous sources for knowledge discovery.
    a. Acquire, store and redistribute the ever-accumulating amounts of data per patient required to fulfil this goal, within a strong governance framework, which protects personal data from misuse and ensures privacy.
    b. Self-learning mechanistic/machine learning models translating information into predictions on the future development of diseases for prevention and the likely response to specific therapies.
    c. Approaches to analyzing disparate datasets to include data standardization and storage and possible identification of unique predictive parameters.

d. Ability to download data from many individuals in an automated, centralized, and timely manner.

e. Data security and availability, including hardware to software solutions specific for personalized medicine data.

3. At the clinical level, methodologies must be adapted and adopted to compare solutions with current standard of care. It is unlikely that current conceptual prototypes, developed as proofs of concept, can be effective for direct clinical translation. It will be necessary to re-engineer current prototypes for each specific clinical task, reengineering the user interface to prevention, diagnosis, prognosis, treatment planning, or monitoring.

    a. Cohort studies evaluating the correlations between physiological monitoring data and health record information focusing on known exposure or illness events.

    b. Evaluating the predictive performance of the models with multiple time points along the patient's health record timeline.

    c. Assessing the requirement for individual baseline data versus group/no baseline information. Additionally, the usefulness of using "near neighbor" data to improve predictive capability.

    d. Evaluation of the minimum frequency of physiological monitoring data needed for strong correlations to health effects and optimization of the algorithm's predictive power.

In turn, these research focuses suggest several potential directions for Research Infrastructure and Research Support:

Specific areas that need to be understood and addressed include integration, heterogeneity, and sustainability, as well as diversity and broader impact from a user and community perspective.

1. Clearly and unambiguously delineate solicitations and investments in sensor phenomena research and sensor system innovation, while recognizing the former ultimately informs the latter.

2. Interoperability and Reliability – across scientific instruments and domains – remain elusive goals, limiting opportunities for reproducibility, collaboration, and discovery. Consider a funding model that requires collaboration across projects to drive interoperability and includes an evaluation of reproducibility.

3. Researchers need to have access to all resources and capabilities required by a modern workflow. The community must create a formalized approach to data and data sharing. This could be tied to existing resources, but data need to be accessible. Centers can provide storage in short term, but the long-term need is for a model to store data in perpetuity. NSF should explore both medium and long-term approaches. This is possible with commercial cloud services, but not on current academic systems.

4. Support for effective management of individualized data, including support interfacing with the existing healthcare systems under the criteria of clinical adaptability.

5. New and creative kinds of partnerships, *e.g.* academic and clinical, are necessary to sustain national research competitiveness and NSF leadership. NSF cannot do this by

itself but should not try to replicate NIH efforts. The demand for clinical testing capabilities is dramatically expanding and exceeds what NSF currently supports.

Broader Impacts: We foresee and advocate for both research and development innovation via a multidisciplinary and convergent community of healthcare providers, technologists, scientists, mathematicians and engineers. Three general recommendations to support such a vision are presented below:

1. *Reconfigurable Hardware and Wetware as a Grand Challenge:* adaptable biosensing, *in silico* medicine, and the development of the digital biomarkers, must be recognized as a Grand Challenge, where fundamental research in biomedical science, mathematical and computational methods, biomedical engineering, and computer science must coexist with more applied and translational research.
2. *Academic-Industry-Clinical Partnership:* Academic researchers should closely collaborate with industry to broaden applications, *e.g.*, amendments to current diagnostic test kits. Industry should invest in databases to support knowledge and document sharing, and to contribute to "translational ready" design tools. Clinicians should be incorporated as a necessary focus group to guide systems design. The research community should widen their efforts and participation through providing open-source testbeds and hardware platforms.
3. *Education and Training:* Workforce training and availability remain challenges in biomedical microdevice design and translation. This should incorporate NSF's unique role in broadening participation. We need clearer career paths in medical device engineering, as well as pipelines that lead to leadership. Specifically, these pipelines should permit and encourage the participation of non-educational institutions such as national laboratories, federal agencies, and hospitals/clinics. This will attract talented students to actively study engage in interdisciplinary activities.
    a. System reliability, validation, and performance analysis courses and programs must be developed in universities and incorporated into the undergraduate and graduate curricula. Such courses should educate students on how to think of system reliability as a design parameter and goal rather than strictly aiming for optimization or peak performance.
    b. Publication avenues must increase for reliability, replication testing and validation for researchers that are actively engaged in studying the translation potential for sensor systems.

IV. CONCLUSION

This workshop used personalized medicine as a prime example of how the sensor and sensor system community can think about the concept of "reconfigurability" from a secure design of hardware, systems, and application perspective by utilizing the rapidly evolving data science and artificial intelligence capabilities. The workshop presented the potential to look across the traditional barriers to personalized medicine and discuss how the design and performance of reconfigurable sensor systems should be guided and improved by both hardware considerations and learning/AI capabilities. The workshop participants stressed the need for having data-aware and robust design as an important component of hardware design, as well as a skillset of future workforce development and as an educational need in academic courses.

For many years, advanced data analytics has been treated an afterthought of sensor design and multiplexed or reconfigurable sensing has been considered merely one of the possible applications for sensor hardware. Typically, biosensors were designed and validated to execute as isolated, physically secure and well-defined conditions. This paradigm has been proven limited in value for the translation to next-generation healthcare, such as predictive population health and personalized medicine. It is thus essential to make serious efforts to bridge gaps between participating engineers/scientists, which will help overcome a variety of physical and technological challenges, including the following:

1. Design of sensors with respect to form factor (size/shape), power/energy requirement, working environment compatibility, performance requirement (sensitivity, selectivity, detection limit), manufacturing cost, etc.
2. Determining key data characteristics from the various types sensing results for more effective machine learning and optimization of artificial intelligence.
3. Different types of data measured by the device require different levels of robustness, privacy, and accuracy in their analysis, and the outcome of the analysis by the machine learning pipeline should inform the device to adapt and to re-allocate its resources for future measurements.

The presented talks and panel discussions during the workshop recognized the importance of need for increased collaboration between the hardware, data science, and clinical communities. For example, a single sensing system could include a transducer and a designated application specific integrated circuit (hardware) with machine learning algorithms (data/computer science) reporting results to a cardiologist (clinical). Each of these parties has a unique design language and need for the capabilities of each system components. When operating exclusively, the final system has poor intraoperability and reliability, leading to poor reliability and efficacy. Better communication pipelines, education, and standardized protocols may help overcome these issues. In addition, there were suggestions to engage other research communities, such as human-factors scientists, communications, and more broadly, social and behavioral scientists to generate user feedback groups to provide their objectives and constraints and to better interpret and understand feedback from those devices.

In conclusion, medicine and prevention have historically operated on heterogeneous, statistical groups. To switch focus from the "statistically best" therapy to an "individually best" therapy requires much more information on every patient. This will include terabytes of data, from –omics characterization and imaging to environmental and lifestyle recording. This healthcare revolution

will require acceleration of two technical developments: (1) We need to distribute many more sensor systems across the population, deployed in various form factors—with a particular focus on the development of highly reliable, autonomous, multi-modal platform and power-efficient computing. (2) Data generation is however not everything. We also need concepts to integrate and transform this data into information to predict future health and quantify the effects and side effects of possible therapies (or preventive measures) on every individual.

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APPENDIX A. Registered Workshop Speakers & Participants

1. Mohamad Al-Kalaa (Food & Drug Administration)
2. Radhakisan Baheti (National Science Foundation)
3. Filbert Bartoli (National Science Foundation)
4. Rashid Bashir (University of Illinois, Urbana-Champaign)
5. Mitra Basu (National Science Foundation)
6. Sankar Basu (National Science Foundation)
7. Shekhar Bhansali (Florida International University)
8. Linda Blevins (National Science Foundation)
9. Olga Boric-Lubecke (University of Hawaii)
10. Alper Bozkurt (NC State University)
11. Shantanu Chakrabartty (University of Washington-St. Louis)
12. Krishnendu Chakrabarty (Duke University)
13. Junhong Chen (National Science Foundation)
14. J.C. Chiao (Southern Methodist University)
15. Ieuan Clay (Novartis)
16. Michael Daniele (NC State University; University of North Carolina at Chapel Hill)
17. Jeffery Dick (University of North Carolina at Chapel Hill)
18. Sandy Eckel (University of Southern California)
19. Deniz Erdogmus (Northeastern University)
20. Shubhra Gagopadhyay (National Science Foundation)
21. Reza Ghodssi (University of Maryland, College Park)
22. Lawrence Goldberg (National Science Foundation)
23. Julian Goldman (Massachusetts General Hospital)
24. Giovanna Guidoboni (University of Missouri, Columbia)
25. Subhanshu Gupta (Washington State University)
26. Chris Hartshorn (National Institutes of Health)
27. Mehdi Javanmard (Rutgers University, New Brunswick)
28. Steve Kim (Air Force Research Lab)
29. Anthony Kuh (National Science Foundation)
30. Katsuo Kurabayashi (University of Michigan)
31. Rebecca Law (Defense Threat Reduction Agency)
32. Drummy Lawrence (Air Force Research Lab)
33. Insup Lee (University of Pennsylvania)
34. Chenzhong Li (National Science Foundation)
35. Peter Lillehoj (Michigan State University)
36. Jenshan Lin (National Science Foundation)

37. Edgar Lobaton (NC State University)
38. Carmina Londono (National Science Foundation)
39. Clare Mahoney (National Nanotechnology Coordination Office)
40. Ben Marlin (University of Massachusetts, Amherst)
41. Aaron Mazzeo (Rutgers University, New Brunswick)
42. James McKnight (United States Army Medical Research and Materiel Command)
43. Veena Misra (NC State University)
44. Linda Molnar (National Science Foundation)
45. Brian Montgomery (National Institute of Justice)
46. Lee Moores (U.S. Army Engineer Research and Development Center)
47. Vladimir Murashov (National Institute of Occupational Safety and Health)
48. Babak Nikoobackt (National Institute of Standards and Technology)
49. Wendy Nilsen (National Science Foundation)
50. Shahriar Nirjon (University of North Carolina at Chapel Hill)
51. Omer Oralkan (NC State University)
52. Aydogan Ozcan (University of California, Los Angeles)
53. Anil Pahwa (National Science Foundation)
54. Dinesh Patwardhan (Food & Drug Administration)
55. Giorgio Quer (Scripps Institute)
56. Eric Rhodes (Defense Threat Reduction Agency)
57. Jeff Rogers (IBM)
58. Shad Roundy (Utah Univeristy)
59. Praveen Sekhar (Washington State University)
60. Seila Selimovic (National Institutes of Health)
61. Nirmish Shah (Duke University)
62. Dan Siegal (Defense Advanced Research Projects Agency)
63. Siddhartha Sikdar (George Mason University)
64. Gymama Slaughter (Old Dominion University)
65. Stacey Standridge (National Nanotechnology Coordination Office)
66. Payam Taheri (National Aeronautics and Space Administration)
67. Pavan Turaga (Arizona State Univeristy)
68. Usha Varshney (National Science Foundation)
69. Roy Vigneulle (United States Army Medical Research and Materiel Command)
70. James Weimer (University of Pennsylvania)
71. Fokko Wieringa (IMEC)
72. Zhang Yi (University of Missouri, Columbia)
73. Qingxue Zhang (Indiana University - Purdue University Indianapolis)

APPENDIX B. WORKSHOP AGENDA

Day 1: March 7, 2019	
8:00 – 9:00 am	**Registration and Breakfast** *Note: Please arrive by 8:00 AM to pass through visitor security at NSF*
9:00 – 9:15 am	**Opening and Introductions:** *Shubhra Gangopadhyay and Usha Varshney, NSF* **Welcome:** *Linda Blevins and Filbert Bartoli, NSF*
9:15 – 9:45 am	**Workshop Logistics:** *Michael Daniele, NCSU/UNC-Chapel Hill* **Vision, Capabilities and Value Proposition for Workshop:** *Veena Misra, NCSU*
9:45 – 10:15 am	**Invited Talk (Hardware / Systems):** *Aydogan Ozcan, UCLA*
10:15 – 10:45 am	**Invited Talk (Data / Personalized Med):** *Ieuan Clay, Novartis*
10:45 – 11:00 am	BREAK
11:00 -12:30pm	**Panel: Point-of-Care, Wearable, and Implantable Sensors: Modalities and diagnostics to supplement offline-data with point-of-action intelligence** (Moderator: Omer Oralkan) *JC Chiao, SMU* *Gymama Slaughter, ODU* *Jeffrey Dick, UNC-Chapel Hill* *Peter Lillehoj, Michigan State* *Aaron Mazzeo, Rutgers* Presentation by each panelists (7 min each + 3 min Q&A). Open the forum to attendees for discussion (40 Min).
12:30 - 2:00 pm	LUNCH
2:00 - 3:30 pm	**Panel: Hardware Form Factors/System Design for Sustained Usage and Data Gathering: Wireless devices, body area networks, online services** (Moderator: Alper Bozkurt**)** *Olga Boric Lubecke, Hawaii* *Shantanu Chakrabartty, Washington U, St. Louis* *Krishnendu Chakrabarty, Duke* *Mehdi Javanmard, Rutgers* *Reza Ghodssi, Maryland* Presentation by each panelists (7 min each + 3 min Q&A). Open the forum to attendees for discussion (40 Min).
3:30 - 3:45 pm	BREAK

3:45 - 5:45 pm	**Panel: Sensor Fusion with Machine Learning and Artificial Intelligence: Challenges of integration and informatics** (Moderator: Edgar Lobaton) *Deniz Erdogmus, Northeastern* *Sandy Eckel, USC* *Giorgio Quer, Scripps* *Shekhar Bhansali, FIU* *Rashid Bashir, UIUC (Call-In)* Presentation by each panelists (7 min each + 3 min Q&A). Open the forum to attendees for discussion (40 Min).
5:45 pm	ADJOURN Note: Those invitees not attending Day 2 need to create responses to questions provided for Report.
6:30 pm	**Dinner:** Embassy Suites Alexandria Hotel, 1900 Diagonal Rd, Alexandria, VA
Day 2: March 8, 2019	
8:00 – 9:00 am	Arrival and Breakfast
9:00 - 9:15 am	**Welcome Back and Start of Day 2:** *Michael Daniele, NCSU/UNC-Chapel Hill*
9:15 – 9:45am	**Invited Talk (Technology in Clinic):** Julian Goldman, Mass. General Hospital
9:45 - 10:00 am	BREAK
10:00 - 11:30 am	**Panel: Difficulties and Barriers in Making a Paradigm Shift in the Clinic.** (Moderator: Veena Misra) *Nirmish Shah, Duke* *Jeff Rogers, IBM* *Foko Wieringa, IMEC* *James Weimer, Penn* *Ben Marlin, UMass* *Giovanna Guidoboni, Mizzou* Presentation by each panelists (7 min each + 3 min Q&A). Open the forum to attendees for discussion (40 Min).
11:30 - 12:00 pm	Action Items for Working Groups
12:00 - 1:30 pm	LUNCH
1:30 - 3:00 pm	Working Group Discussions
3:00 - 4:00 pm	Presentations by Scribes to Summarize Outcomes of Discussions
4:00 - 4:15 pm	**Closing Remarks:** *Shubhra Gangopadhyay, NSF*
4:15 pm	ADJOURN

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