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Sensor Reproducibility Analysis: Challenges and Potential Solutions

Praveen Kumar Sekhar,[1,*,z] Wayant Billey,[2,] Makeiyla Begay,[2,**] Bradley Thomas,[2,**] Clarencia Woody,[2,**] and Thiagarajan Soundappan[2,*,z]**

[1]*Nanomaterials and Sensors Laboratory, School for Engineering and Computer Science, Washington State University Vancouver, Vancouver, Washington 98686, United States of America*
[2]*Nanoelectrochemical Analysis and Energy Storage Laboratory (NEST LAB), Department of Chemistry, School of Science, Navajo Technical University, Crownpoint, New Mexico 87313, United States of America*

The ability to repeat research is vital in confirming the validity of scientific discovery and is relevant to ubiquitous sensor research. Investigation of novel sensors and sensing mechanisms intersect several Federal and non-Federal agencies. Despite numerous studies on sensors at different stages of development, the absence of new field-ready or commercial sensors seems limited by reproducibility. Current research practices in sensors needs sustainable transformations. The scientific community seeks ways to incorporate reproducibility and repeatability to validate published results. A case study on the reproducibility of low-cost air quality sensors is presented. In this context, the article discusses (a) open source data management frameworks in alignment with findability, accessibility, interoperability, and reuse (FAIR) principles to facilitate sensor reproducibility; (b) suggestions for journals focused on sensors to incorporate a reproducibility editorial board and incentivization for data sharing; (c) practice of reproducibility by targeted focus issues; and (d) education of current and the next generation of diverse student and faculty community on FAIR principles. The existence of different types of sensors such as physical, chemical, biological, and magnetic (to name a few) and the fact that the sensing field spans multiple disciplines (electrical engineering, mechanical engineering, physics, chemistry, and electrochemistry) call for a generic model for reproducibility. Considering the available metrics, the authors propose eight FAIR metric standards to that transcend disciplines: citation standards, design and analysis transparency, data transparency, analytical methods transparency, research materials transparency, hardware transparency, preregistration of studies, and replication.
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Ubiquitous sensors are integral to Internet of Things (IoT) applications.[1,2] The promise that everyone and everything will be connected wirelessly and services like healthcare will be brought to everyone, everywhere, anytime, for virtually any need highlights the omnipresence of sensors.[3–5] These devices sense the environment and provide applications for home automation, safety, comfort, personal healthcare, etc.[6–8] At a macro level, they provide data for smart cities, smart agriculture, water conservation, energy efficiency, environment management, industry 4.0, and society 5.0, to name a few complex microcosms.[9–12]

In addition, the latest review articles indicate the surge in sensor research for monitoring pathogens, sustainability, and in quantum devices.[13–16] The design and operation of these complex systems require methods for policymakers to evaluate the relative merit of alternative options and the implications that choosing one of those options will have. For a decision maker to make an informed choice, accurate data, and meaningful metrics are essential for understanding and assessing the state of the system. Technological improvements in sensors have enabled facile integration into a wide range of systems to provide quantitative feedback about the state of the system. The field of sensors is a common thread that connects many engineering and science disciplines. Further, various Federal agencies have specific programs and call for sensor-related research.[17–19]

Despite the diverse application space, reproducibility is a long-standing challenge plaguing the field of sensors.[20,21] "Reproducibility" refers to independent researchers using the original researcher's data to regenerate the results. "Replicability" refers to when a researcher collects new data to arrive at the same scientific findings as a previous study. "Interoperability" indicates data and metadata are conceptualized, expressed, and structured using common published standards. Figure 1 shows a schematic highlighting the above concepts. Despite innovations and the breadth of research in sensors, extremely limited devices have come into use in the field, and commercialization is primarily attributed to reproducibility issues.

Inappropriate research practices such as HARKing (Hypothesizing After the Results are Known),[23] p-hacking,[24] selective reporting of positive results, and poor research design[25–28] have been proposed to be a cause of irreproducibility. Other factors contributing to the irreproducibility are inadequate training of researchers in experimental design and methodology, such as randomization, bias, replication, statistical analysis, variations in sophisticated techniques, and variability in instrumentation and materials. Additionally, the insufficient time used for research, the bureaucracy and pressure to publish in high-impact journals to compete for research grants and positions, and the lack of proper supervision and mentorship further exacerbate the reproducibility crisis.[29–43] Figure 2 shows critical factors influencing barriers in reproducing results.

The facts mentioned above may lead to researchers taking shortcuts, not transparently reporting their work, or even indulging in questionable research practices. Factors related to costs, lack of infrastructure, disciplinary culture, and weak incentives are barriers to reproducing research.[44,45] Over-reliance on publication in high-impact journals to grant tenure or promotion to researchers makes the crisis even worse. Likewise, publishing novel results rapidly increases the impact factor of journals while ignoring negative or unimpressive results is a worrying factor. Compounding this problem, different researchers in resource-constrained institutions (minority institutions) may not have equal access to the use of the same level of repositories or the skills to share their data properly. These institutions also need more training and teaching resources on the scientific research process, including the experimental design and methods. Initiatives from Federal agencies, institutions, publishing venues, funding agencies, and professional societies are underway to overcome the technological, structural, and infrastructure barriers hindering reproducibility.[46–48] Figure 3 shows the

*Electrochemical Society Member.
**Electrochemical Society Student Member.
zE-mail: praveen.sekhar@wsu.edu; tsoundappan@navajotech.edu

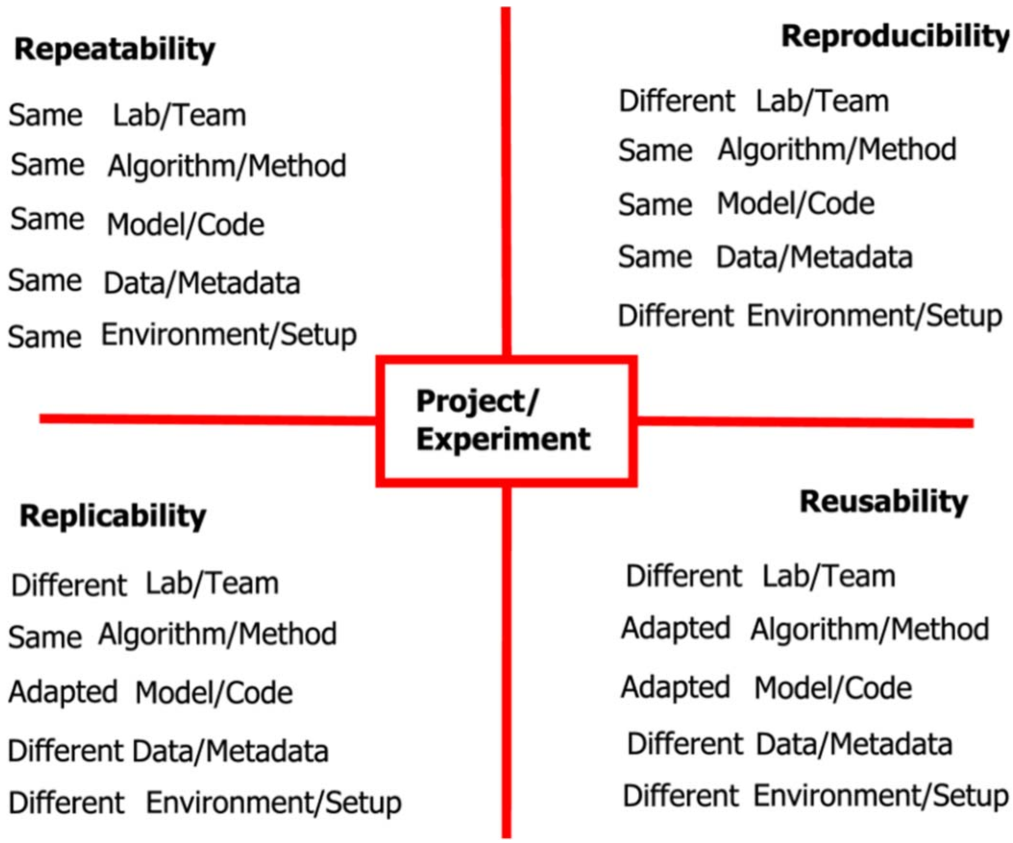

Figure 1. A classification of Repeatability, Reproducibility, Replicability, and Reusability according to the characteristics of a project or experiment.[22]

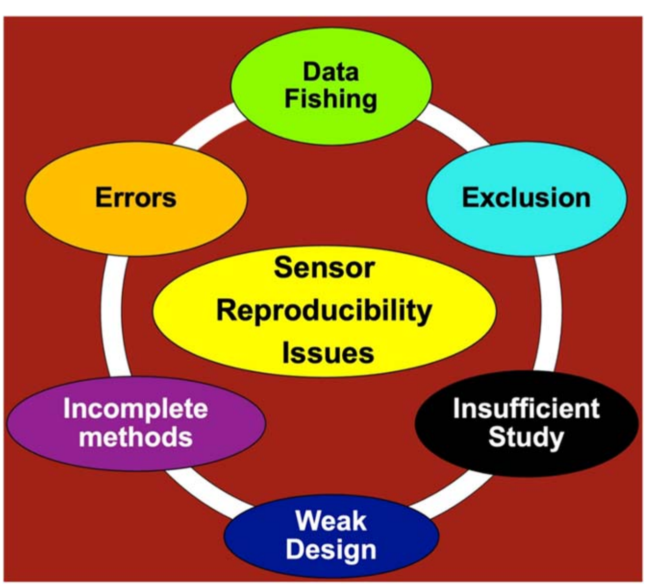

Figure 2. Factors affecting sensors reproducibility.

results of a survey from an open data source regarding reproducibility in remote sensing.

FAIR Background

Federal agencies like the National Science Foundation (NSF) have funded open science efforts in specific disciplines. In Earth sciences, The Magnetics Information Consortium (MagIC) provides a data archive that allows the discovery and reuse of data for the broader Earth sciences community.[50] NSF has also supported the

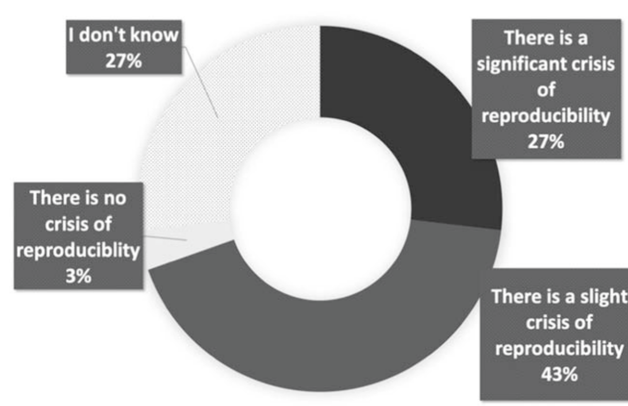

Figure 3. A survey on the state of reproducibility in remote sensing. This survey was conducted as an online survey from 230 investigators involved in remote sensing.[49]

Paleo Perspectives on Climate Change (P2C2) Program,[51] which provides comprehensive paleoclimate data sets that can serve as model test data sets analogous to instrumental observations. Further, the Galaxy Project funded by NSF[52] provides a web-based platform for "data-intensive" biomedical research, including biosensors. For managing bioinformatics and phylogenetic research on plants, NSF has funded the iPlant Collaborative.[53] Further, NSF is partnering with Amazon[54] to support FAIRness in Artificial Intelligence (AI) projects by understanding how AI systems designed on fairness, transparency, and trustworthiness will advance the boundaries of AI applications.

The Office of Data Science Strategy (ODSS) has hosted multiple workshops to ensure National Institutes of Health (NIH) funded research data follows FAIR principles. These workshops bring together stakeholders to discuss ways to enhance a FAIR biomedical data ecosystem. To help researchers find, use, and share data more efficiently, the ODSS is working with technical leaders across the NIH's 27 institutes and centers to modernize the data repository ecosystem, support the storage and sharing of data, and standardize data and adopt common data elements.[55,56] The NIH provided the "Rigor and Reproducibility" guidelines to support reproducibility in biomedical research. Knudtson et al.[57] surveyed the factors to perform rigorous and reproducible research. Sandve et al.[58] provided ten simple rules to conduct reproducible computational research. Many approaches have been reported to ensure the quality of research data for reproducibility.[59–62]

Apart from Federal agencies, the scientific community has suggested several guidelines and recommendations to conduct reproducible research.[63–66] Journals like Nature ask the authors to provide the data used for experiments mentioned in the publications as a mandatory requirement. Nature introduced a reporting checklist in 2014 requiring the authors to make materials, data, code, and associated protocols promptly available to readers without undue qualifications. Cambridge University Press has launched a new open-access journal to help address science's reproducibility issues and glacial peer-review timelines. The journal titled "Experimental Results" gives researchers a place to publish valid, standalone experimental results, regardless of whether those results are novel, inconclusive, negative, or supplementary to other published work.[67] The journal also publishes work about attempts to reproduce previously published experiments.

In addition to publishing venues, the public data repositories like Figshare (2021), Zenodo (2021), Dryad (2021), re3data (2021), etc, are used by the scientists to deposit their datasets, results and code.[68–72] The Digital Biomarker Discovery Pipeline (DBDP)[73] computes feature and provides statistical and machine learning analysis modules to predict health outcomes from wearable and mobile devices. The "Health Outcomes through Positive Engagement and Self-Empowerment" (HOPES) platform extended the Beiwe ecosystem.[74] It can process Android, iOS, and Fitbit data collected with their platform, but it is not publicly available yet. Further, the Ripeta Framework[75] uses over 100 variables to characterize research publications in bibliography, databases and data collection, data mining and cleaning, data analysis, and data sharing and documentation.

Other FAIR initiatives across the world include the Global and Open FAIR (http://go-fair.org), the European Open Science Cloud (EOSC; https://eoscpilot.eu), working groups of the Research Data Alliance (RDA; https://www.rd-alliance.org) and Force11 (https://www.force11.org), the Data Seal of Approval, Nodes of the European ELIXIR infrastructure (https://www.elixir-europe.org), projects under NIH's Big Data to Knowledge Initiative (BD2K) and its new Data Commons Pilots.[76] In addition, the FAIRsharing network and advisory board (https://fairsharing.org) connects open standards-developing communities and data policy leaders, and editors and publishers such as Springer Nature's Scientific Data, Nature Genetics, and BioMedCentral, PloS Biology, The BMJ, Oxford University Press's GigaScience, F1000Research, Wellcome Open Research, Elsevier, EMBO Press and Ubiquity Press.

Hardware and software framework as it relates to sensors research have different creation pipelines. Further, fabrication requires standardization. The challenge that unifies software and hardware as it pertains to reproducibility is the lack of intricate details and nuances though variations in hardware or fabrication quality could be corrected for via error analysis. Recording workflow details, adequately commenting code, containerizing, preserving, and sharing research artifacts, and running internal reproducibility checks all take time, but are often met with little direct reward. In the context of sensors research, the FAIR datasets differ from other investigations due to the data quality, data unavailability, data non-uniformity, and data semantics.[77]

Knowledge Gap

While progress is being made on the incorporation of FAIR principles across the scientific enterprise, as inferred from the previous section, there are yet to be widely adopted standards of FAIR practices prevalent in the sensor community. Further, early and budding engineers need to gain awareness of making their data findable, reproducible, interoperable, and reusable. Moreover, not every institution has the capacity, know-how and infrastructure to support FAIR practices, especially relevant in minority institutions. The current knowledge gap presents an opportunity to develop an ecosystem centered on reproducibility and interoperability in the field of sensors by (a) establishing community standards and standardizing disciplinary practice by achieving consensus and implementation of recommendations of reproducibility across engineering disciplines, (b) deriving a generic metrics reproducibility model that be extended and applied to other disciplines as sensors research spans broad disciplines, (c) training student and experienced researchers via exploring FAIR curriculum and subsequent course integration, and (d) arming minority institutions with adequate resources and knowledge for hindrance free practice of FAIR principles, in particular, reproducibility and interoperability.

Potential Solutions

Conduct a workshop for the sensor reproducibility challenges.—The objective of the workshop is to bring researchers together from diverse fields of science and engineering and related disciplines at all levels (BS, MS/PhD, students, post-docs, early career, mid-career, and senior researchers) to participate, discuss, and formulate action items and frame a roadmap to address sensor reproducibility and interoperability challenges from multiple perspectives. The overarching goal of the workshop would be to standardize research practice and establish a community standard to augment the reproducibility and interoperability of sensor data within the disciplinary framework. In particular, the workshop could emphasize (a) the participation of students and faculty from minority-serving institutions to build capacity and have agency in the roadmap exercise, (b) ingraining students in a sense of FAIR practices at the early stages of their professional career, (c) derivation of a generic reproducibility and interoperability model that can be adopted in other disciplines, and (d) community building through formal and informal alliances. The workshop could be advertised through the Electrochemical Society, American Chemical Society, IEEE Sensors Council, National Society for Black Engineers, Society of Hispanic Professional Engineers, Society of Women Engineers, Materials Research Society, American Ceramic Society, IEEE Women in Engineering, Biomedical Engineering Society, American Society for Civil Engineers, National Postdoc Association, and NSF ASSIST Center. Workshop pre- and post-survey will be designed based on the ten rules to assess the impact of workshops by Sufi et al.[78]

Structured virtual teleconference meetings: journal leadership.—The structured teleconference could happen for one hour every quarter of the year. The participants must be editors and associate editors from various sensor-related journals. The teleconference meeting could be conducted via Zoom. Registration will be required for the teleconference and completion of the meeting pre-survey. Editors and Associate Editors of the Journal of Electrochemical Society, IEEE Sensors and IEEE Sensor Letters, Sensors and Actuators A and B, American Chemical Society Publications, Biosensors and Bioelectronics, Biomedical Microdevices, and Nature Publishing group, to name a few, could find a common time to meet. The topics of discussion could include but are not limited to Author Incentive Mechanism, Reproducibility Badges, Reproducibility Board, Credit to Data Producers, Waiver of Open Access Fees, Pre-publication Reproducibility Check, External Reproducibility Board, Publication of

Negative Results, Reproducibility Editorial Board and Establishment of Community Standards.

Effective use of data management systems.—Significant variability in sensor data generation across teams, individuals, institutions, infrastructure, methodologies, and time results in reproducibility challenges. Further, varying data formats in low-cost sensors compound this problem. However, several data management systems exist to facilitate data reuse and reproducibility. Many of the current ones tend to be tied to specific scientific domains, are often challenging to deploy, and use non-scalable technologies that limit the pervasiveness and widespread acceptance of such services resulting in disjoint data silos. For reproducing sensor data, federating heterogeneous scientific frameworks into a shared data network that enables the data access needs of complex cross-facility collaborations and workflows is vital.

Individual facilities or institutions may house one or more local data repositories or rely on remote data repositories. Data management systems that can be integrated into experimental facilities or data pipelines across institutions to automate data management will increase the use of data sharing. Features such as unique data identification and tracking, abstraction of physical data storage, metadata, and provenance capture, data organization and search capabilities, and data sharing with fine-grained access controls will facilitate ease of reproducibility.

Existing and developing portals like Figshare, Dataverse, Zenodo, Dryad, re3data, RAPIDS,[79] and DataFed[80] can be explored. Sensor reproducibility can be examined using these data management systems across different institutions and investigators. The data management systems facilitating sensor reproducibility can be evaluated against various metrics such as ease of submission, ease of use, integration with existing institutional repositories and experimental infrastructure/facilities, dynamic views of data, query-able structured metadata, extent of workflow support, data analytics, data tagging, schema support and availability of common standards such as number of downloads, subscribers, ratings, and documentation support. The results of the metrics comparison of the various data management systems could be disseminated to a broader audience. The expected outcomes of this solution are (a) awareness of different data management platforms for depositing and retrieving data of different formats, (b) knowledge of metrics and assessment of various data repositories enabling establishment of community standards for reproducibility, (c) advancement in reproducibility by increasing the amount of information available on a scientific topic and reducing the bias favoring the publication of positive effects, and (d) confidence enhancement in authors to practice openness and sharing raw data.

Exploring FAIR framework in teaching.—The implementation of the FAIR principles entails a wide range of skillset that need to be employed by individuals working in many different roles and disciplines. Training will need to be delivered to individuals, referred to as data stewards, who are involved in making data FAIR and keeping it FAIR. Data stewards may be researchers, students, data scientists, data curators, librarians, and data and repository managers, to name a few. Various educational frameworks are developing to teach and train data stewards in these areas. A more recently developed educational framework, the FAIR4S framework (Framework for FAIR Data Stewardship Skills in Science and Scholarship), targets data stewards wishing to acquire FAIR skills.[81] In addition, there exist isolated FAIR training resources such as the Belmont Forum Data Management Toolkit, the DataONE Skillbuilding Hub, ELIXIR (European data infrastructure for the life sciences), FOSTER (Facilitate Open Science Training for European Research) portal, EOSC training portal, and FAIRplus framework.[82–84] The articles recommend seamlessly integrating the training sources on FAIR and mapping them to existing educational curriculum that meets accreditation standards and, in turn, applying the curriculum or curricular materials in existing courses.

Investigating closed loop automation.—An alternative approach[85] recommended by Miles and Lee would be to establish a system where protocols are encoded and shared as open-source software that could be modified collaboratively by scientific peers and run on automated laboratory platforms. Such a system would minimize sources of irreproducibility, allow protocols to be compared, and create an authority chain between a protocol and the data it collects. Cloud computing combined with the Internet of Things (IoT) offers an opportunity to leapfrog the standards-setting debate and create more precise and reproducible research without adding human capital or increasing process time. An automated, programmatic laboratory eliminates much of the risk of error by relying on hands-free experiments that follow coded research protocols. As experiments become more complex, datasets larger, and phenotypes more nuanced, transformative technologies like a programmatic robotic cloud lab will be necessary to ensure that these high-value experiments are reproducible, the results can be trusted, and the protocols producing these experiments can be compared.

Deriving a generic reproducibility model and model adaptability to other disciplines.—The authors recommend creating a generic FAIR metrics model that can be utilized across disciplines. Rather than imposing a "tick box" exercise with which researchers reluctantly comply to the minimum level required, it is preferred to encourage genuine progress towards all the FAIR principles with a model that recognizes and rewards different degrees of FAIR compliance. It is critical that the assessment frameworks for FAIR data suit differences in disciplinary practice. While Open data are preferable, FAIR does not necessarily mean open. Openness is not a requirement of FAIRness since data cannot be made public for privacy or confidentiality reasons. A one-size-fits-all approach that ignores differences between research communities will be counterproductive and unhelpful. Further, what is considered FAIR in one scientific community may differ from the FAIRness requirements or expectations in another community due to norms, standards, and practice.

Hence, the proposed metric FAIR model could address the multidimensionality of the FAIR principles and accommodate all disciplines. The FAIR data metric model should contain (across all research areas) a basic minimum standard of FAIR, such as discoverable metadata, persistent identifiers, and access to the data or metadata. FAIR metrics are available for public discussion at the FAIR Metrics GitHub, with suggestions and comments made through the GitHub comment submission system (https://github.com/FAIRMetrics). Considering the above facts and available metrics, the authors propose eight FAIR metric standards that transcend disciplines: Citation Standards, Design and Analysis transparency, Data Transparency, Analytical Methods Transparency, Research Materials Transparency, Hardware Transparency, Preregistration of Studies, and Replication. The metric model encompassing these standards will be assessed through numeric levels (from 0 to 5), "0" indicating no compliance and "5" indicating the maximum level of FAIR compliance.

Building capacity at diverse institutions.—The authors strongly advocate for enhancing the FAIR (Findability, Accessibility, Interoperability, and Reusability) capabilities at minority-serving institutions (MSIs). This enhancement is crucial for advancing FAIR principles and building human and infrastructural capacities at institutions often facing significant resource constraints. The success of the STEM research enterprise in the USA hinges on the ability to draw from a diverse pool of scientists and engineers who are well-trained and capable of addressing the complex research challenges of the 21st century. By providing the necessary knowledge, oversight, and infrastructure, MSIs can be empowered to adopt FAIR principles, ensuring that their contributions to scientific research are transparent, rigorous, and reproducible.

The workshop, strategically designed to foster diversity among participants, will play a pivotal role in this endeavor. It aims to establish a synergistic community of researchers, educators, and administrators who share a common vision to address scientific challenges. This approach goes beyond impacting individual researchers; it aspires to catalyze institutional and organizational changes that embed rigorous research practices across these universities, ultimately leading to sustainable improvements in transparency and reproducibility.

One of the critical aspects of promoting FAIR capabilities at MSIs is addressing the training and management of responsibilities in work, education, and time allocation within their academic environments. These institutions often face unique challenges, including limited financial resources, infrastructure, and access to advanced scientific tools and methodologies. Consequently, students and researchers at MSIs may need more exposure to informal and formal training opportunities, creating uncertainties in research processes and standards. This lack of exposure hinders the transition from theoretical knowledge to practical applications, such as sensor fabrication, a vital component of STEM education and research.

Sensor fabrication and testing at MSIs often encounter specific challenges due to limited access to cutting-edge scientific practices and advanced instrumentation. Many students and researchers come from core science and educational backgrounds, with less emphasis on interdisciplinary approaches essential for sensor development. These inconsistencies impede progress and highlight the need for more comprehensive training and infrastructural support to enhance technical skills and methodological rigor. Moreover, the time required to produce testable sensors is another limiting factor hindering the advancement of research. Often, fabricating a batch of testable sensors takes an entire day, slowing down the research cycle and limiting the number of experiments that can be conducted. This time-consuming process, combined with the limited laboratory space and equipment, underscores the importance of improving infrastructure and training to enable more efficient research practices at MSIs.

Despite these challenges, researchers at minority-serving universities have demonstrated remarkable success in sensor research. These successes testify to these institutions' resilience, creativity, and innovation potential. They showcase that, with a suitable investment in human capital and infrastructure, MSIs can significantly contribute to scientific knowledge and practical solutions to societal challenges, instilling a sense of hope and optimism in the audience.

Enhancing FAIR principles at these institutions fosters a culture of transparent, rigorous, and reproducible research. It ensures that researchers' diverse perspectives and talents from underrepresented communities are effectively integrated into the broader STEM enterprise. By developing comprehensive training programs, workshops, and infrastructure improvements, MSIs can better prepare their students and researchers to meet the demands of modern scientific challenges. This holistic approach will ensure that these minority universities become integral contributors to the scientific community, driving innovation and diversity in research essential for tackling the complex and multifaceted problems of the 21st century.

Increasing the FAIR capabilities of minority-serving institutions is essential for building a more inclusive, equitable, and effective STEM research ecosystem. Through deliberate efforts to provide training, resources, and infrastructure, these institutions can overcome existing barriers and contribute to high-quality, impactful research. The successes already achieved in sensor fabrication are just the beginning of what is possible when MSIs are empowered to reach their full potential. As they continue to build capacity and expertise, minority-serving universities will play an increasingly prominent role in advancing scientific research and addressing critical challenges nationally and globally.

Future Outlook

Furthermore, reproducibility is the cornerstone of science, so it is critical to improve the quality and reliability of publications by going beyond disseminating results by providing raw data. Incorporating these changes in a competitive scientific enterprise requires broad cultural shifts that extend beyond disciplinary boundaries. The article addresses this complexity by organically nudging scientific practices toward greater openness via complementary and coordinated efforts from all stakeholders. Solving the reproducibility challenge will benefit scientific advancement by promoting transparency, encouraging collaboration, accelerating research, and driving better decision-making. Achieving sensor reproducibility impacts many disciplines and applications, ranging from healthcare to aerospace. For example, air quality sensors for pollutant measurement across urban and industrial areas entail numerous benefits as they provide policymakers and air quality researchers with sound solutions to fill knowledge gaps that are impossible by regulatory monitors and satellite data. Consensus via achieving reproducibility establishes a sense of reliability for policymakers and the public, as these sensors can overestimate or underestimate pollutant concentrations, which can hamper meaningful interventions. Policy decisions based on inaccurate sensor data can be devastating, especially to minority populations facing environmental and health disparities. The authors present a case study on sensor reproducibility using air quality sensors.

Case study.—The goal of this article is to describe reproducibility challenges in sensors research in a generic way that resonates with a wider audience. Subsequent submissions are planned that will focus on chemical sensors, biosensors, and physical sensors.

A low-cost air pollution monitor is a device that uses one or more than one sensor and other components to detect, monitor and report on specific air pollutants. They provide policymakers and air quality researchers with sound solutions to fill knowledge gaps. Sensor data reproducibility is used to quantify the data quality achieved by low-cost gas sensors as part of the monitoring system. Typically, the consensus for sensor data reproducibility is achieved by close examination of the device. For example, on exposure to a target gas with zero concentration, the sensor should provide the same reading with multiple measurements. These measurements recorded in the laboratory, as well as the site of the final installation, ensure robust calibration along with higher accuracy. The sensor performance is influenced by several factors such as where the monitor is placed in the indoor space, time in use, methods of processing the data, data collection procedure, sensor fabrication, hardware, and external environmental factors. The use of multiple identical devices provides reliable insights into the extent of repeatability and variability. A critical test of sensor reproducibility is collocation.

Collocation refers to the process of operating a regulatory grade reference monitor (FRM/FEM)/commercial sensor and a non-reference device (air quality sensor) at the same time and location under real-world conditions for a defined evaluation period. Collocating air sensors with regulatory monitors can help users evaluate the accuracy of their sensors by comparison of the two data sets. Using such a technique, the sensor performance can be benchmarked, and data accuracy improved by data comparison. At least 3 units of the same sensor (from different batch of fabrication) can be used for this exercise. For accurate measurements, the sensor or the array and reference monitor will be placed within 10 meters of each other, and the gas inlet/outlet will be maintained at about the same height. The data collection frequency of the sensor and the reference will be matched by averaging the readings. Apart from the sensing parameters, three important characteristics are also recorded. They are intra-model variability, data recovery, and linear correlation coefficient. Intra-model variability estimates the closeness of measurement values from three units of the same sensor type. Data recovery is calculated using a percentage ratio of the number of valid sensor data points over the total number of data points collected during the testing period. Linear correlation coefficient expresses the strength of the linear relationship between the average measurements from the three-sensor tested and the reference values.

While many variety of gas sensors or sensing mechanisms are investigated for a multitude of applications for air quality, one of the barriers to field testing and subsequent sensor commercialization is reproducibility. Through this article, the authors intend to advocate collocation as one of the studies that need to report in manuscripts via recommendation to the different journal board with sensors as the technical interest area. The following checklist serves as a tool to help researchers think about the reproducibility of the experiment and data analysis. Many of the questions can be thought of as having a yes/no answer or open ended for improvement. (Derived from Neon, The National Ecological Observatory Network is a major facility fully funded by the U.S. National Science Foundation)

Documentation

1. Is there a README file that indicates the purpose of the project, who to contact with questions, a map of the directory structure, and a description of what software and hardware is needed to reproduce your experiment/workflow?
2. Are there README files in each folder describing the contents of the folder, how they were acquired/generated?
3. Is there a CITATION file that tells users how to site the project, data, and code?
4. Are there instructions on how to obtain the raw data and citations for those data?
5. Is there a list of dependencies with the exact version number of every external application used in the process?
6. Are there appropriate LICENSE files that specify the license under which you are distributing your content, data, and code? Have you edited them to include information pertinent to your project?
7. Have you noted the license(s) for other peoples' content, data, and code used in your analysis?
8. For analyses that utilize a random number generator, have you noted the underlying random seed(s)? Do you state the other seeds that you have tested the results with?
9. Is your code well documented?
10. Is there data on experiment repetitions?
11. Do each of your scripts have a header indicating the inputs, outputs, and dependencies?
12. Is it documented how files relate to each other?

Organization

1. Are all data, code, results, and documentation housed within a monophyletic folder structure?
2. Is this folder structure under version control?
3. Is the project's repository publicly available?
4. Are there assurances that this repository will remain accessible?
5. Is your project folder structured to separate your data, code, documentation, and results?
6. Are your raw and processed data files separated?
7. Is your raw data truly raw or has it been manipulated?
8. Are files that store manually entered data structured to be easily read by a computer?
9. Do files use a consistent naming scheme that indicates what they contain?
10. Is there a mechanism in place to archive large files?

Automation

1. Does data processing make use of open software code?
2. Is code written to be flexible enough to the addition of new data?
3. Does your repository make use of continuous integration tools to ensure internal reproducibility?

Publication

1. Are papers and reports from the project generated using literate programming tools so that results are not hard-coded?
2. Did you include a reproducibility statement or declaration at the end of your paper(s)?
3. Did you archive preprints of resulting papers in a public repository?
4. Did you release the underlying code and new data at the time of submitting a paper?
5. What mechanisms are in place to ensure your project remains accessible and reproducible in 5 years?

Conclusions

To progress and improve public trust, science needs innovation and self-correction. Reproducibility and replication offer opportunities for self-correction. In an alternate sense, the article views reproducibility as a measure to examine a research result from the perspective of one's confidence in the components of the study by acknowledging sources of uncertainty in a research study. Establishing community standards for open data practices aiding reproducibility nationwide will translate scientific norms and values into concrete actions and change the current incentive structures to drive researchers' behavior towards more transparency. Intentional focus journal "focus issues" validating existing sensor data is poised to transform the current practices in external verification and sensor commercialization. The article recommendations aim to facilitate the gradual adoption of best practices and standardize reward system for academics irrespective of discipline practicing openness in sensors research. The article suggests centralizing means of aligning individual and communal incentives to practice openness via acceptable scientific policies and procedures. Further, the article recommends increasing FAIR capabilities at minority-serving institutions while providing the required knowledge and oversight to advance FAIR. The knowledge transfer of FAIR principles through the communities of practice approach will prepare buddy scientists for a systemic culture of a transparent research enterprise.

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ORCID

Praveen Kumar Sekhar https://orcid.org/0000-0002-4669-535X
Thiagarajan Soundappan https://orcid.org/0000-0003-0871-1301

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