Analysis of AI/ML Consortium to Advance Health Equity and Researcher Diversity (AIM-AHEAD) Request for Information Responses: Full Report

Authors:

Russ Mardon
Maurice Johnson
Susan Hassell
Sushama Rajapaksa
Nathan Botts

Final – November 5, 2021

Prepared for:
National Heart, Lung, and Blood Institute
Prime Contract Number: GS00F009DA
Subcontractor Number: HHSN268201700020B
Customer PO Number: 75N92020F00001

Prepared by:
Westat
An Employee-Owned Research Corporation®
1600 Research Boulevard
Rockville, Maryland 20850-3129
(301) 251-1500

Contents

Executive Summary

In June 2021, the National Institutes of Health (NIH) released a Request for Information (RFI) to better understand the needs, interests, and opportunities for building and advancing Artificial Intelligence/Machine Learning (AI/ML) approaches using electronic health record (EHR) and other types of data (e.g., genomics, imaging, social determinants of health) to redress health disparities and advance health equity. The NIH received 76 responses to the RFI, of which 2 are considered not responsive to the RFI. In addition, NIH conducted a stakeholder engagement forum (SEF) that included academia, federal agencies, healthcare providers, and the data science/technology industry in order to provide an overview of the NIH AI/ML for health disparities research initiative and engage attendees in listening sessions. As part of the registration process, attendees were offered the opportunity to provide input on essential research, infrastructure, training, and partnership needs to advance the field. Westat conducted a qualitative analysis that highlighted key themes in the responses to the RFI and SEF.

Key findings include the following:

1. **Research** - Respondents suggested a wide variety of research topics in the areas of health disparities, improving data usefulness, and improving AI/ML methodologies to mitigate bias in data sources and models. Respondents suggested ways to link and use a variety of data sources (e.g., EHR, self-reported patient information, genomics, social determinants of health (SDoH), biomarker, wearable sensor, geospatial, and mobile health data) to study a variety of diseases and conditions (e.g., cancer, mental health, infectious diseases [e.g., Covid-19, HIV, and Ebola], dementia and neurological disorders, maternal health, pediatric health, heart disease, and diabetes).

2. **Infrastructure** - While some organizations in academia and industry have invested heavily in AI/ML and can marshal robust infrastructure and resources, other respondents indicated minimal current infrastructure for AI/ML. Respondents indicated a priority need for access to high-quality, federated data integrated across organizations, cloud computing resources, and data management platforms.

3. **Partnerships** - Respondents expressed readiness to partner in both multi-organizational and multi-disciplinary partnerships. Particularly strong is the need for partnerships that span data science, clinical research and health care delivery, and community-based organizations that serve minority or underrepresented populations. Respondents stressed the importance of community engagement in building trust and reducing harm and bias.

4. **Training** - A small number of RFI respondents noted training resources or opportunities currently available, while many more indicated training needs at all levels. Specific training needs include: AI/ML methods and data science, statistical methods to reduce bias, health disparities, ethics in the use of AI/ML, uses of AI/ML in healthcare, and training to increase the diversity of the AI/ML workforce.

5. **Opportunities and Challenges** - RFI respondents expressed various options for using or improving the usability of AI/ML, including bias detection methods, use of natural language processing, and creating open-source AI systems. However, respondents also identified many challenges or limitations to the use of AI/ML in healthcare including privacy concerns, equitable access to data and technology, data completeness and data biases, model biases, barriers to data sharing, and

financial sustainability. There was also concern about applying AI/ML methods to rare outcomes or to ration the availability of health care services due to its limitations.

6. **Prioritizing Under-resourced Institutions** - Several respondents specifically suggested that NIH prioritize under-resourced or minority-serving institutions in funding decisions.

The remainder of this report is organized as follows:

- Introduction
- Part 1: Narrative Analysis
- Part 2: Chartbook
- Appendix A: RFI Questions
- Appendix B: Qualitative Analysis Methodology
- Appendix C: Codebook

Introduction

The Artificial Intelligence/Machine Learning (AI/ML) field currently lacks diversity in its researchers, data, and workforce. These gaps can lead to continued health disparities and inequities for underrepresented communities, which have untapped potential to contribute new expertise, data, recruitment strategies, and cutting-edge science to the field. The National Institutes of Health (NIH) has launched the AI/ML Consortium to Advance Health Equity and Researcher Diversity (AIM-AHEAD) program to close diversity gaps in the field and better engage underrepresented communities (https://datascience.nih.gov/artificial-intelligence/aim-ahead).

On June 21, 2021, the NIH released a Request for Information (RFI) to better understand the needs, interests, and opportunities for building and advancing AI/ML approaches using electronic health record (EHR) and other types of data (e.g., genomics, imaging, social determinants of health) to redress health disparities and advance health equity. The RFI was organized around the four key AIM-AHEAD program areas as shown in Appendix A. The NIH received 76 responses to the RFI by the due date of July 9, 2021.

In addition, on June 25, 2021, NIH conducted a stakeholder engagement forum (SEF) to bring together academia, federal agencies, the data science/technology industry, and health care systems and centers. The purpose of this meeting was to provide an overview of the NIH AI/ML for health disparities research initiatives and then engage attendees in listening sessions. There were 600 registrants. As part of the registration process attendees were offered the opportunity to provide input to the four questions shown below. Westat analyzed these responses in conjunction with the RFI responses since the questions were similar:

1. What are some of the opportunities to use AI/ML in biomedical research (i.e., use cases) that are of interest?
2. What kind(s) of computing resources or infrastructure do you need to build a successful AI/ML research program?
3. What special aspects for training should be considered for this initiative?
4. What partnerships are needed to achieve the goals of this initiative?

Westat conducted a qualitative analysis that highlighted key themes in the responses. The approach included the development of a structured set of codes that parallel the concepts in the RFI, application of the codes across both RFI and stakeholder engagement forum data, and analysis of the codes to identify consistent themes across respondents, as well as specific examples and quotations highlighting the main ideas. Details on the methodology can be found in Appendix B. The complete set of codes and definitions can be found in Appendix C.

Fifty of the most frequently used words in the RFI and stakeholder engagement forum feedback.

This body of this report contains two parts: a narrative analysis of the data organized according to the topics in the RFI, and a chartbook illustrating the frequencies and patterns in the codes as applied to the data.

Part 1: Narrative Analysis

RFI Topic 1 - Use of AI/ML for health disparities and inequities research:

Knowledge, experience, and interest in using AI/ML for health disparities and inequities research

Despite the range of responses to the RFI suggesting research topics of interest for AI/ML, only a few respondents directly articulated their level of knowledge, experience, or interest in conducting AI/ML research to address health disparities. Those that directly indicated this information were typically from academic institutions, research firms, or for-profit organizations. The level of knowledge and experience was typically expressed through their previous publications, development of technologies, or work with clients. Very few respondents expressed a lack of knowledge, experience, or interest. The two major areas discussed were:

1. **Designing and developing AI/ML platforms and statistical analysis plans** – Respondents discussed their knowledge, experience, and interest using AI/ML for medical informatics including building, testing, and monitoring clinical decision support algorithms, phenotyping conditions for clinical epidemiologic studies, detecting training set outliers, and ensuring reproducibility of EHR-based analytics. Respondents also noted developing sophisticated statistical analyses techniques for large data platforms.

2. **Disparities research** – Respondent's knowledge, experience, and interests included studying disparities related to prediction modeling, development of a framework for integrating health equity and racial justice into the AI development lifecycle, and evaluating the performance of AI/ML algorithms with a health equity lens.

High priority research topics of interest and types of pilot studies that could inform future health disparities research

A variety of research topics were suggested in response to the RFI, as well as suggestions for using different forms of data, and focusing on specific diseases of interest. Feedback from the stakeholder engagement forum aligned with the research topics suggested by RFI respondents. Overall, respondents discussed strategies for improving AI/ML by focusing on health disparities, leveraging data sources, and improving upon AI/ML methodologies.

1. **Health disparities** – Most respondents suggested using AI/ML to address health disparities and target interventions toward minority populations. Furthermore, respondents indicated opportunities to promote health equity by addressing the inequities in current AI/ML models and data. This included more active integration of data from minority populations, researching potential biases in AI/ML models, and developing models specifically for minority populations. Specific comments included:

    > "Re-defining fairness for population subgroups...use of AI/ML models can identify small, unique subpopulations that suffer from inequity, not defined by a single attribute. Further research is needed to develop metrics of fairness that can be adapted to broader populations." [Industry/Data Platform and Computational Service Company]

    > "There must be an added focus on examining bias and racism and the ways they are reproduced within AI/ML technology, especially if NIH seeks to advance their recently stated aims around structural racism." [Academic Researcher]

While many of the respondents broadly discussed AI/ML for health disparities and inequities research, some respondents discussed them in the context of specific diseases and health conditions such as cancer, mental health, infectious diseases (e.g., Covid-19, HIV, and Ebola), dementia and neurological disorders, maternal health, pediatric health, heart disease, and diabetes.

2. **Leveraging data sources** – Many of the respondents referred to EHR data when discussing opportunities for using AI/ML for health disparities and inequities research. Respondents indicated that EHRs currently contain a wealth of patient data that could be analyzed and mined using AI/ML. However, they also noted that the EHR data would be more informative if linked to other forms of data, including self-reported patient information, genomics, social determinants of health (SDoH), geospatial, and mobile health data. Some respondents indicated that current EHR systems lack enough information about patients from underserved communities and that there are opportunities to improve AI/ML data mining techniques for these communities.

   Respondents specifically articulated the need to integrate more data about socioeconomic factors to improve upon AI/ML. Respondents discussed partnering with community organizations, using community-level measures, and applying geospatial data and techniques as some strategies for linking social determinant data to individual-level data. A few respondents also recommended using AI/ML to improve upon the prediction of SDoH. Examples of related comments include:

   > "Among the many research opportunities for AI/ML is the potential to combine EHR data with other datasets which reflect external factors related to health. These include data types such as those included in the SVI index, documentation of transportation and recreation of options, and the impact of food deserts." [Academic Researcher]
   >
   > "Combining large EHR datasets, combining biomedical datasets (e.g., EHR clinical data with wearable data, or biomarker datasets, or geolocation datasets), also linking EHR data to community resource datasets to facilitate public health interventions to reduce health disparities." [Academic Researcher]
   >
   > "The recent COVID-19 pandemic has further highlighted the impact of disease on these communities and the need for a holistic data repository focusing on minority health, one which captures not only traditional health information, but also takes into account tangential factors such as socioeconomic status, diet, access to healthcare, health practices and other aspects associated with social determinants of health." [Health Research Firm]

   Another data source commonly noted by respondents was medical imaging data. Respondents suggested that AI/ML provides an opportunity to improve how medical imaging is used and interpreted, including x-rays, CT scans, MRI scans, and images of hand-written notes. A few respondents also suggested using AI/ML to assess images of skin, particularly among those of different races/ethnicities, to help assess certain cancers.

3. **Improving upon AI/ML methodologies** – One of the most noted applications of AI/ML among respondents was its use for predictive modeling of health conditions and outcomes, including

cancer, mental health and substance abuse, and infectious diseases. Predictive modeling was mentioned frequently as a useful tool for predicting both common and rare diseases. However, respondents indicated there needs to be greater emphasis on better predicting conditions and health outcomes among minority populations and underserved communities across a range of conditions.

Some respondents articulated needing to apply AI/ML models in real-world settings across diverse populations to help validate them. Training datasets may be biased, and more research is required in order to validate the predictions AI/ML models, particularly among different racial and ethnic groups. An exemplary quote highlighting this theme was:

> "Research emphasis area for AI/ML should be studies designed to mitigate bias in our numerical models. Bias can arise from many sources in AI/ML including the analysis design phase (e.g., selection of features and choice of ML algorithms), the training phase due to imbalance in the amount of training data for machine learning such that specific populations of patients are underrepresented or misrepresented." [Hospital Health System]

RFI Topic 2 - Infrastructure and resources for AI/ML application and research:

AI/ML is a resource-intensive field, and consequently, there were many vital areas related to infrastructure and resources, both available and needed, shared by RFI respondents and stakeholder engagement forum participants.

Current infrastructure available (e.g., local network drive, cloud access)

Academia and industry have invested heavily in AI/ML. New tools and methods for increasing processing sophistication and training of complex models are under active development. Current architectures described by RFI respondents had a heavy focus on federated systems that provide opportunities for data exchange. Cloud-based systems and services were often leveraged due to qualities of distribution, scalability, and elasticity (i.e., being able to scale and implement resources/services as needed). Infrastructure topics include the following:

1. **Computational Tools, AI or ML Capabilities** – Respondents described several types of expertise in use at their institutions. For example:

    > "One tool that can assist in these research efforts is automatic stratification (AI/ML based) of health outcomes by relevant social determinants. For instance, in analyzing COVID disparities, [the institution] is applying automatic stratification to identify subpopulations with outcomes that significantly diverge from the overall population (e.g., older men with diabetes)."

2. **Cloud Access** – Several respondents described university-based or proprietary cloud computing platforms such as Amazon Web Services (AWS). Cloud-based resources are also available as a NIH funded infrastructure, e.g., NIAGADS, which enables access to existing big clinical and genomic data as well as data management platforms under cloud computing.

3. **Architecture governance** – One industry representative suggested that a unified cloud architecture provides governance advantages as it enables better model management, versioning, deployment, monitoring, and iterative model-prediction enhancement.

Other respondents indicated minimal current infrastructure for AI/ML.

Resources available (e.g., staffing, data management platforms, access to EHR and other types of biomedical research and clinical data, access to existing study populations)

Many respondents come from institutions with ongoing funding or investment in AI/ML that includes staffing, expertise, tools, education and technical assistance, and, critically, access to existing data sets that can help create better AI training and analysis models. Comments related to these aspects were as follows:

1. **AI/ML Expertise/Staffing** – The descriptions of current projects and practices in response to RFI Topic 1 demonstrated a high level of expertise at some academic institutions and in industry. Institutions noted that they actively staff data scientists with significant experience in the healthcare industry and advanced skills in applying AI/ML to solve unique trials and analyses.

> "(The institution) employs more than 40 data scientists with extensive health care industry experience and knowledge coupled with senior operational and clinical industry executives with more than 200 years of collective health care experience." [Industry Representative]

2. **Data Management Platforms that Ensure Privacy** – Several academic and industry representatives discussed multi-institutional collaborative platforms for data sharing to support research and care delivery. Some of these are government-funded while others are proprietary. Robust data integration capabilities and management infrastructure are needed to maintain these centralized data sources and ensure privacy.

> "(Our) platform provides the opportunity for data to be appropriately anonymized according to HIPAA Safe Harbor rules and tokenized at the patient level, encompassing a comprehensive source for NIH to leverage for greater public health." [Industry representative]

3. **Access to EHR data, other biomedical research or clinical data, or existing populations** – The data management platforms described in the previous item offer members access to extensive clinical datasets. For example:

> "The [institution] has research-ready, longitudinal electronic health record (EHR) data on more than 6 million patients (41 percent below federal poverty level, 42 percent racially diverse), more than 858,000 social determinants of health (SDH) screenings across a growing geographically diverse network of FQHCs, and a team of 40 researchers focused on health equity. We will bring this expertise to partner in accessing AI/ML technology and expertise." [Clinical Researcher]

Infrastructure and/or resources needed (federated data, cloud computing, etc.)

Access to high-quality federated data is a high priority for respondents. Equally, cloud-based access would increase opportunities for diverse and dispersed researchers and AI/ML developers to innovate and explore health disparities and inequity factors and dimensions. Responses received from the RFI were highly aligned with the stakeholder engagement forum comments. A high need for increased processing power (via graphics processing units (GPU)), cloud-based resources, and AI/ML models that could be easily federated were all topics frequently mentioned in both cases. Comments across key domains included:

1. **Availability of Data** – Robust data integration and management infrastructure is needed to centralize sources, sample training data, transmit scoring data, and receive scores from AI systems. Specifically, respondents commented on:

    > "In translational research and implementation science, AI/ML can efficiently collect, integrate, and synthesize complex data representing the patient's holistic experience of health, from multiple sources. Sources include payers, providers, employers, and patients themselves, such as those collected from medical devices and IoT. However, data comprising social determinants are lacking for AI/ML use in health disparities research, specifically at the level of individual persons." [Scientific/Computing Industry Representative]

    > **"**Currently, there is a problem with different payer organizations (commercial, public) housing medical records and the lack of coordination across healthcare systems. It is to be assumed that individuals will change jobs or geographies, and there must be an infrastructure to allow for appropriate crosstalk between systems to have a more comprehensive view of the patient journey over time." [Biomedical Sciences Industry Representative]

2. **Cloud Computing** – Some respondents indicated a lack of access to affordable cloud computing resources. Cloud technology inherently brings scalable computation and distributed training, which can support researchers in optimizing algorithms and systems more frequently to improve performance, increase accuracy, and scale to larger input data sizes while developing solutions on top of an infrastructure built around patient data protection ensuring healthcare industry compliance.

    > "From the AI/ML development perspective, cloud computing within a computational enclave is optimal since the data itself can then be safeguarded and will never leave the repository. The requirements for a computational enclave are obviously much more extensive than the requirements for a simple data repository. A computational enclave involves CPUs, GPUs, containerization capabilities (such as Docker), system security requirements, and, ideally, availability of many common AI/ML libraries and visualization software." [Health System Researcher]

3. **Data Management Platforms** – Deploying useful and accurate AI/ML requires a secure, trustworthy data management platform that can provide transparent, generalizable data with a

lack of bias. Such a platform is needed to develop and deploy models on production data and continuously improve them based on user feedback.

4. **Funding** – Many respondents applauded NIH's efforts to support the development of the infrastructure needed to advance the use of AI/ML research into health disparities reduction. For example:

> **"**To facilitate adoption, infrastructure grants and support are needed for community hospitals, critical access hospitals, standalone urgent care centers, particularly in rural and underserved locations. The risk arises that without supportive funding for infrastructure, these essential healthcare providers won't be able to use these tools and customize them to their patient base." [Academic Researcher]

RFI Topic 3 - Partnerships approaches for AI/ML application:

Interest in establishing multi-disciplinary partnerships and networks

Respondents expressed readiness to partner in both multi-organizational and multi-disciplinary partnerships.

1. **Multi-Organizational Partnerships** – Of the types of multi-organizational partnerships needed, academia, industry, government, and clinical and healthcare organizations were most frequently mentioned as possible partners. Comments included:

> "We see the necessity of partnerships across organizations to reduce health inequities and diversify the AI/ML workforce. We are interested in such partnerships as a means to better represent historically under-represented patients in AI/ML, and to broaden the benefits of AI/ML, particularly to inform policies and practices to support health equity." [Federally Qualified Health Center]

> "I am very interested in connecting with multi-disciplinary partners and networks for building ML solutions. As an employee of a small business, we often work with partners to deliver solutions for our customers. Partnerships with academia, clinical researchers, and healthcare researchers at hospitals are of interest." [Industry/Data Platform and Computational Service Companies]

2. **Multi-disciplinary Partnerships** – Respondents also expressed interest in establishing multi-disciplinary partnerships, both within and across organizations. Some examples of respondents being interested in bringing people together from different areas of expertise are:

> "Multi-disciplinary research and training partnerships among investigators in computer science, biostatistics, and epidemiology are needed. Also, consider permitting international partnerships with low- and middle-income countries." [Academic Institution]

> "We are interested in establishing multi-disciplinary partnerships (including industrial ones) and networks, and we are willing to share data and resources." [Academic Institution]

> “We are an open-science network facilitates multi-institutional, multi-disciplinary coordination through domain specific work groups that bring together physicians, epidemiological researchers, healthcare IT experts, academics, health network administrators, bioinformaticians, pharmaceutical leaders, machine learning researchers, members of other open-science initiatives such as N3C, and more.” [Scientific Organization]

Current partnerships, networks, or initiatives that could be leveraged

Current partnerships, networks, and or initiatives mentioned by the respondents can be broken down into the following categories:

1. **Multi-disciplinary partnerships** – Current multi-disciplinary partnerships across academia, industry, government and healthcare systems.

2. **Federated learning** – Collaborations between many organizations to develop, test and implement unbiased and fair AI/ML algorithms.

3. **Industry** – Partnerships with cloud platform providers and AI/ML libraries.

4. **Academia** – Alliances with university data scientists and AI/ML researchers.

5. **Clinics, hospitals or healthcare systems** – Networks of healthcare providers doing clinical AI/ML research.

6. **Government** – Provides funding and networking for AI/ML research, as well as intramural research.

7. **Institutions serving minorities or underrepresented populations** – Minority disadvantaged partners that can be leveraged to add diverse positions and inputs.

Types of partners needed

Both RFI respondents and stakeholder workshop respondents mentioned the need for partnerships for their AI/ML applications to have a substantial and sustained impact. Both types of respondents need partnerships with other organizations and experts in various fields such as AI/ML, Data Science, Bioinformatics, and Epidemiology.

1. **Multi-disciplinary partnerships** – Partnerships between academia, clinical researchers, healthcare researchers at hospitals for improving the development and implementation of AI/ML.

2. **Industry** – Respondents mentioned the need for partnerships with cloud platform providers, imaging equipment manufacturers, pharmaceutical companies, etc.

3. **Academia** – Research and training partnerships among investigators in computer science, biostatistics, and epidemiology, etc. are mentioned as needed.

4. **Clinics, hospitals or healthcare systems** – Respondents require partnerships for clinical trials, de-identified electronic health records, and other large patient datasets for research.

5. **Community programs** – Partnerships with community organizations are mentioned as needed to ensure oversight, engagement, and allowing for the rejection of proposed ideas which could result in harm or misuse.

6. **Patients or patient advocacy groups** – Partnerships with patients and patient advocacy groups are needed to determine how to implement prediction models, and to provide training datasets.

7. **Government** – Respondents require government partners to gain access to data networks, funding sources, and a conducive regulatory environment.

8. **Institutions serving minorities or underrepresented populations** – Partnerships with HBCUs, racially and ethnically diverse, lower-income, and un- or under-insured populations are needed to develop and deploy accurate AI/ML prediction models.

Strategies to ensure and build trust

1. **Community Engagement** – Several respondents stressed the importance of community engagement in building trust and reducing harm and bias. Engaging with stakeholders early and often is key to having substantial and sustaining impact. Comments included:

    > "Partnerships with community organizations and with patients are needed to ensure oversight, engagement, and allowing for the rejection of proposed ideas which could result in harm or misuse." [Academic Researcher]

    > "There must be an added focus on examining bias and racism and the ways they are reproduced within AI/ML technology, especially if NIH seeks to advance their recently stated aims around structural racism. Adopting community-engaged and mixed-methods studies are two ways to ensure a positive response to these problems." [Academic Researcher]

    > "A primary component of the developed program should be engagement of stakeholders (e.g., representatives of community-based organizations, key community leaders) to inform and guide research priorities using AI/ML to address complex health disparity issues in their communities." [Academic Researcher]

2. **Other Trust-building Strategies** – Other strategies to ensure and build trust in their AI/ML applications as noted by the respondents are open-source software development and independent review of research and algorithms. In open-source development, the code is available for review and enhancement by a larger community, resulting in a more inclusive and widely accepted application. Some examples mentioned by the respondents include:

    > "Open source software development is an inclusive format that makes its code available publicly for modification and enhancement by anyone. Collaboratively, the community

> works to improve the algorithms to create a result that is better than a single developer's efforts with the expectation that the result of the community will be shared with all and appropriate attribution will be made to the primary developers." [Academic/Industry Collaborative]

> "Independent ethical review (e.g., IRB review) can facilitate exploration of research questions that are prohibited or unpopular in general public domains that are commonly used in machine learning." [Academic/Industry Collaborative]

Willingness, interest, or concerns to sharing data and resources

Of the respondents currently in partnerships, some showed a willingness to share data and resources to enhance collaboration. Specifically, there were references to sharing electronic health record data, as well as predictive algorithms. However, this was mentioned only a few times, and respondents also had security and privacy concerns about sharing electronic health record data across institutions.

RFI Topic 4 - Training for AI/ML approaches and health disparities and inequities:

Training and type of training resources currently available or accessible

A small number of RFI respondents noted training resources or opportunities that are currently available from specific academic institutions or private industry.

1. **Training programs in AI/ML offered by academia** – Universities and training centers offer certificate programs for early and mid-career training (e.g., George Washington University); Duke University offers a 2-year training program in data science (AI Health Fellows Program).

2. **AI/ML education and training programs offered by private industry** – A few RFI responses described educational offerings from private companies:
   - One company offers AI education through workshops, online media, and a "*Deep Learning Institute*" curriculum spanning backgrounds from novice through experienced AI participants.
   - Another company offers a curriculum-based program for varying AI/ML skill levels (from PhD-level data scientists to data analysts who have never performed machine learning) and is complemented by customized programs delivered by data scientists, engineers, and consultants in workshops.
   - Continuing education training opportunities are available via conferences and webinar series for late-career training (e.g., FedScoop and the Project Management Institute).

Level of training needed (e.g., students, early career, late-career)

RFI responses supported a general theme that training in AI/ML is needed across a range of levels.

> "Investment is needed to accelerate education and awareness from secondary to continued professional development. Priorities include working with universities and professional associations to teach AI skills ranging from foundational (introductory courses, terminology and applications of AI/ML) through advanced application (project development, working with data scientists, effectively applying AI insights into workflow)." [Academic/Industry Collaborative]

Stakeholder engagement forum participants commented specifically about training priorities by academic level:

1. **High school** – Engage minority high school students in AI/ML and biomedical problem training

2. **Undergraduate** – Develop AI/ML modules that could be used by faculty in undergraduate institutions; use community colleges and regional state schools as trainee sources; offer on-the-job training for techs to build mature researchers

3. **Medical and graduate school** – Medical schools should offer educational opportunities in health analytics, machine learning/ AI computing expertise, and training in research and clinical informatics; graduate programs should offer data science training for master's level and PhD students in public health

4. **Post-doctoral** – Train PhDs to create a pool of expertise necessary to kick-start research

Types of training needed

RFI and stakeholder engagement forum respondents expressed a range of training needs related to AI/ML and its applicability to health disparities research. Responses included general commentaries on the importance of training and considerations for developing training programs, as well as specific topic areas of focus. The following general themes were identified across both RFI and stakeholder engagement forum responses:

1. **There is a significant need for training about AI/ML in the healthcare field.** Respondents noted gaps in the availability of trained professionals capable of conducting AI/ML research in healthcare and noted a general lack of existing training resources or competency frameworks related to the use of AI in clinical education programs.

2. **Training programs and educational resources must be accessible, promote a diversified AI/ML workforce, and address health disparities.** RFI comments included recommendations for providing financial support for HSIs, HBCUs, and other minority-serving institutions; incentives for the development of training programs aimed at expanding AI/ML workforce diversity; outreach to underrepresented communities; support for training and open educational resources for resource-limited health care organizations (e.g., in rural and underserved locations); and AI/ML capacity building in underserved communities to reduce bias in current technology development and solutions.

    > "[….] believes that providing support for academic programs focused on equity, social determinants, disparities and related areas, combined with scholarship and internship opportunities within health care organizations is a way to promote both greater interest and greater diversity in the workforce that will use and develop even more advanced AI/ML tools in the future." [Health System Representative]

    Both RFI respondents and stakeholder forum respondents emphasized the need for training in health disparities and social determinants of health. Comments also mentioned the importance of ensuring that training sets include data needed for health disparities research and the risks of AI/ML perpetuating and contributing to structural racism and inequities.

> "Training can mitigate the risk that health disparities and inequities creep into research and health studies with two discrete focus areas in mind: increased awareness/education for researchers to identify and avoid risk areas for disparities and inequities; and improved data set access for more effective model construction and training." [Academic/Industry Collaborative]

3. **AI/ML training needs vary based on professional role.** Both RFI and stakeholder forum respondents commented regarding different training needs for various roles. For example, *programmers* require training in computer science and coding for AI analyses; *AI practitioners/data scientists* who build, interpret, and manage models require training on bias and model implementation to achieve desired outcomes; *clinicians, researchers,* and *end users* need training on interpreting AI-informed recommendations and using AI feedback mechanisms; *decisionmakers* need training on interpreting AI systems and their potential impact when deployed in the real world. Several respondents emphasized the importance of interdisciplinary training to "help clinicians and data scientists understand each other."

Specific Training Topics

Specific training areas of need mentioned by RFI and stakeholder respondents include:

1. **AI/ML methods and data science,** e.g.:
   - Foundations of AI/ML, including methods, applications, and limitations
   - Applied AI, including uses of AI in healthcare, public health/epidemiology, genomics, and biomedical research and development
   - Development and evaluation of AI/ML models, selection of training sets
   - Training in basic data science and big data management
   - AI/ML model deployment in learning health systems
   - Deep machine learning/deep learning algorithms
   - Predictive analytics
2. **Statistics and bias,** e.g.:
   - Basic statistical methods
   - Evaluation of data bias
   - Bias in development of AI/ML algorithms
   - Limitations of training and testing data
   - Mixed-methods and other research methodologies capable of understanding and addressing technological bias
3. **Health disparities or health disparities research,** e.g.:
   - Historical context of underserved communities
   - Health equity and personalization of precision medicine
   - Intersection of informatics and disparities research
   - Aggregating robust populations with sufficient representation of minority populations
   - Screening for inadvertent confounding by race for algorithm development

In addition, stakeholder forum respondents noted training needs in the following specific topic areas:

4. **Ethics**:

- Ethical, legal, and regulatory frameworks for AI/ML
- Handling and ethical use of big data
- Risks and benefits of AI/ML in health care
- Ethical aspects of AI/ML research among underrepresented groups

5. **Computer science**:
   - Coding
   - Programming relevant to medical informatics
   - Computational infrastructure, programs, and databases
   - Software training and program file development
   - Cloud computing

Novel approaches to facilitate training

Overall, RFI and stakeholder engagement forum respondents did not provide many responses on novel approaches to facilitate training. However, one RFI response described a new competency framework developed to guide AI curricula in clinical education.

> "The team partnered with university medical educators to develop six core competencies that include: 1) demonstrate knowledge of AI and its subcomponents applied in healthcare; 2) demonstrate awareness of how AI tools are part of social, economic, and political systems and therefore can impact justice, fairness, equity, and ethics for individual and population health outcomes; 3) determine, clearly communicate and adapt to the changes in team functions and workflows that will results from the implementation of AI tools, and clearly define new roles and responsibilities; 4) demonstrate the ability to navigate AI-enhanced patient encounters that might include non-traditional roles and workflows and an influx of AI-driven data inputs from both the clinical setting and the patient; 5) participate in continuing education and improvement activities involving the uses of AI in healthcare; and 6) critically assess and continuously evaluate the quality, accuracy, safety, contextual appropriateness, and clinical biases of AI tools and their associated datasets in patient care, practice settings, and healthcare administration." [Technology Company]

RFI Topic 5 - Opportunities, challenges, and considerations with using AI/ML to study health disparities and inequities:

Opportunities for using AI/ML

RFI respondents expressed many opportunities for using or improving the usability of AI/ML. In addition to the specific research opportunities and topics described in the summary of topic 1, options include:

1. **Prioritizing Under-resourced Institutions** – NIH was particularly interested in responses that emphasized the need to prioritize under-resourced Institutions or MSIs. Several respondents explicitly mentioned this need. Comments included:

> "To improve training for AI/ML, we recommend supporting development by HSIs, HBCUs, and other minority-serving institutions, and the inclusion of financial incentives for businesses and healthcare partners to develop programs aimed at expanding workforce diversity through paid work experiences." [Academic Researcher]

> "NIH has done a great job of creating research networks, but not necessarily at building ties between those networks, or of helping other institutions (e.g., HBCUs) crack into the ranks of those networks. NIH could continue to increase efforts to make data sharing and other plans reflect openness to harmonization with other institutions and networks." [Academic Researcher]

> "Our vision is to create a robust data repository that brings together HBCU/MSI undergraduate, graduate and professional schools encompassing a wide variety of health related fields – pharmacology, medical, nursing and dental schools and their respective clinical training sites, leveraging a wealth of patient clinical records in a centralized secure repository allowing researchers focus on minority health. Governed by the contributing MSIs, the data repository will focus on the best interests of the communities they serve." [Health System representative]

2. **Improving Bias Detection Methods** – Developing methods that have reasonable computational complexity for assessing potential biases in AI/ML data and algorithms.

3. **Using Natural Language Processing** – Identifying best practices in applying Natural Language Processing (NLP) to EHR notes without risk of exposing protected personal health information.

4. **Creating Open Source AI Systems** – Open source development is a key component of robust clinical solutions as diverse ideas and concerns about the software can be put forward in public forums and improvements can be immediately tested by the community.

Challenges or limitations to using AI/ML

Respondents raised many challenges and limitations. The responses fell into the following general areas:

1. **Privacy Concerns** – Linkages of more information about more people may make it possible to identify some individual with high levels of confidence. There needs to be a policy framework that limits the use of AI/ML for identifying individuals. One respondent offered an innovative way to address privacy concerns:

   > "Synthetic data generated from EHRs is feasible at a large scale to stand in for real data in a way that protects patient privacy and should be fully explored. To be representative, care must be taken to include members of underrepresented groups; although in cases where the N is small it may not be possible to include them without violating privacy guidelines." [Clinical Researcher]

2. **Equitable Access to Data and Technology** – Additional protections and regulatory mechanisms should be established to facilitate equitable access across communities to novel technologies and implementation of AI/ML solutions.

3. **Data Completeness and Data Biases** – Many respondents commented on the problems of missing data and biased data in the types of large-scale clinical datasets needed for AI/ML research into

health disparities. For example, pediatric studies about inherited risk factors require multi-generational and multi-site data that don't currently exist in order to make the use of large-scale AI/ML a reality. Representative quotes include:

> "there is a need for multi-selection and real-world representation in race/ethnicity categories to allow for expanded self-identification." [Academic Researcher]

> **"**Algorithms reflect current and historical biases in ways that can harden inequities by race and ethnicity, gender identity, sexual orientation, disability, age, social class, and geography." [Industry/Data Services Company]

> "Data biases can produce new health disparities as data-driven, algorithm-based biomedical research and clinical decisions become increasingly common." [Academic Researcher]

4. **Model Biases** – Existing statistical methods for estimating prediction models are not designed to address poor predictive performance in minority or health disparities populations. This is a separate issue from biases in the datasets. For example, one respondent reported alarming disparities in the performance of suicide prediction models across racial and ethnic groups:

> "Performance for smaller minority or health disparities populations suffers when associations between predictors and the outcome in those groups diverge from population-level trends"[Health System Researcher]

5. **Barriers to Data Sharing** – There are legitimate concerns regarding EHR data sharing within and across collaborative networks, including 1) privacy concerns; 2) losing control over the data and how it is used; and 3) for those who sell access to their data, loss of profit.

6. **Impartial Evaluations** – Independent evaluations can ensure that known limitations or biases in AI/ML data and methods are disclosed.

7. **Financial Sustainability** – The need for a sustainable business model for non-profit consortia using AI/ML to address health disparities.

8. **Lack of Understanding about Health Disparities Among Health Care Providers** – One commenter pointed to recent evidence indicates a disconnect between the reality of health disparities and the belief by the majority of health care providers that the health care system does not discriminate.

9. **Limitations of AI/ML in Addressing Health Disparities** – Without addressing the social determinants of health directly, no AI/ML research will bend healthcare disparities.

10. **Complexity of Interpreting AI/ML Models** – There is a need to develop simpler models that include only features that will inform the model will be intuitive to end-users.

Concerns or needs of special or unique populations

Respondents highlighted several concerns or needs of special or unique populations such as:

1. **Rare Outcomes** – Poor performance of prediction models in minority and health disparities populations can be exacerbated when trying to predict rare outcomes like suicide attempts and death, or a psychosis disorder.

2. **Populations to Consider** – In addition to more commonly considered underrepresented communities, some specific communities that should be actively considered and engaged in AI/ML health projects include:

    > "…those with disabilities, those who are not English proficient, those of gender and sexual minorities, and patients with chronic conditions such as auto-immune disease." [Academic Researcher]

3. **Rationing of Health Care Services** – The inherent harm of limiting health care on algorithms based on biased or limited datasets impose significant challenges. It is important for systems to incentivize treatment of rare diseases and improve outcomes for small sub-populations of patients.

Considerations for using AI/ML (e.g., overall purpose, future uses, consent)

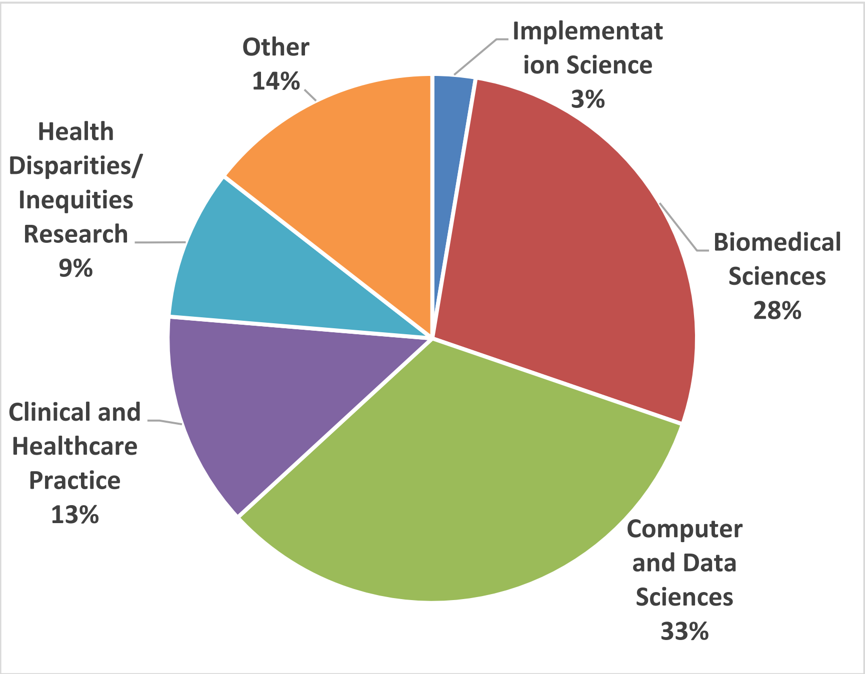
One respondent submitted a general concern about the ownership and use of data and tools by commercial entities that receive public funds. These proprietary entities may limit availability to other users.

Part 2: Chartbook

This section presents a series of illustrative exhibits (e.g., figures, tables, and charts) summarizing Westat's analysis of the RFI and stakeholder engagement forum (SEF) data. The exhibits are based on Westat's coding of key concepts across the 76 RFI responses and 359 SEF registration responses. Details on the methodology can be found in Appendix B. The complete set of codes and definitions can be found in Appendix C.

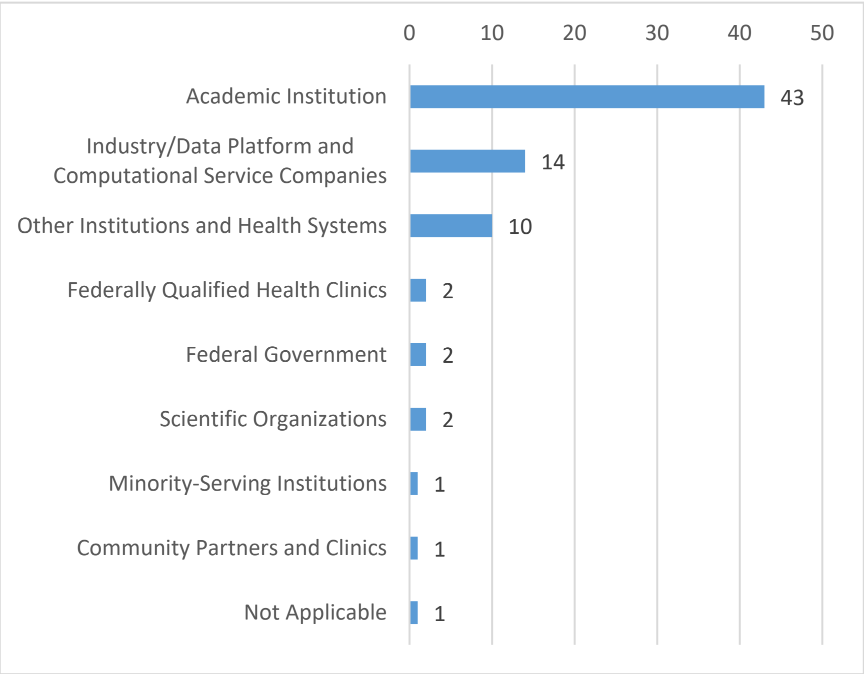
Exhibits 1 and 2 present the areas of discipline and organization types of the RFI respondents. Most of the RFI respondents represented academic institutions and the most reported disciplines were computer and data sciences and biomedical sciences.

Exhibit 1: Areas of discipline across RFI respondents (N=76)*



*Discipline categories are self-identified and mutually exclusive

Exhibit 2: Frequency of organization types across RFI respondents (N=76)*



*Organization type categories are self-identified and mutually exclusive

Exhibit 3 presents the frequency of the structured codes assigned by Westat to the RFI and SEF submissions and supporting documents by code category. The most commonly used categories for the RFI respondents were topics of research interest (Code Category C), types of data interest (Code Category D), and interest in establishing partnerships (Code Category J). Similar to the RFI respondents, many of the SEF respondents provided feedback related to topics of research interest and types of partners needed (Code Category L). Unlike RFI respondents, however, only a few of the SEF respondents discussed prioritization of under-resourced institutions (Code Category A) or expressed interest, experience, or knowledge in AI/ML for HD research (Code Category B). SEF respondents were more often coded for discussing topics of need (e.g., resources, partners, and trainings), but were less frequently coded for discussing current conditions.

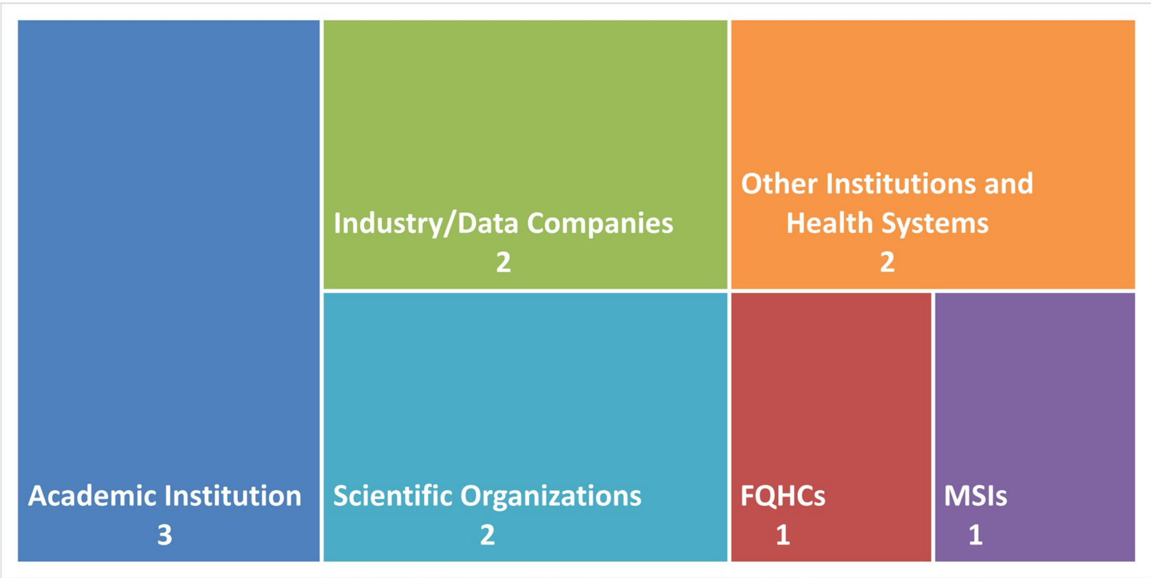
Exhibit 3: Frequency of responses by code category, RFI and SEF respondents*

Code Category	Number of RFI Responses that include the category (% of 76 Total RFI Responses)	Number of SEF Responses that include the category (% of Total 359 SEF Responses)
A. Emphasized need to prioritize on under-resourced institutions or MSIs	11 (14.5)	5 (1.4)
B. AI or ML for HD Research	25 (32.9)	1 (0.3)
C. Topics of research interest	56 (73.7)	159 (44.3)
D. Types of data interested	39 (51.3)	57 (15.9)
E. Interested disease areas	17 (22.4)	53 (14.8)
F. Current infrastructure level	20 (26.3)	2 (0.6)
G. Resources available	18 (23.7)	0 (0.0)
H. Infrastructure needed	27 (35.5)	82 (22.8)
I. Resources needed	26 (34.2)	18 (5.0)
J. Interest in establishing partnerships	38 (50.0)	6 (1.7)
K. Current partnerships	22 (28.9)	3 (0.8)
L. Types of partners needed	37 (48.7)	211 (58.8)
M. Strategies to build trust	7 (9.2)	1 (0.3)
N. Sharing data and resources	10 (13.2)	0 (0.0)
O. Training level needed	7 (9.2)	14 (3.9)
P. Training available	5 (6.6)	0 (0.0)
Q. Training needed	14 (18.4)	95 (26.5)
R. Training topics	19 (25.0)	108 (30.1)
S. Novel approaches to training	3 (3.9)	8 (2.2)
T. Opportunities for using AI or ML NOS	15 (19.7)	0 (0.0)
U. Challenges or limitations to using AI or ML	20 (26.3)	1 (0.3)
V. Other concerns or needs of special populations	4 (5.3)	0 (0.0)
W. Other considerations for using AI or ML	5 (6.6)	0 (0.0)

*Multiple code categories could be coded for each RFI and SEF response. Percentages reflect number of responses with the code category coded divided by total RFI respondents (N=76) and total SEF respondents (N=359)

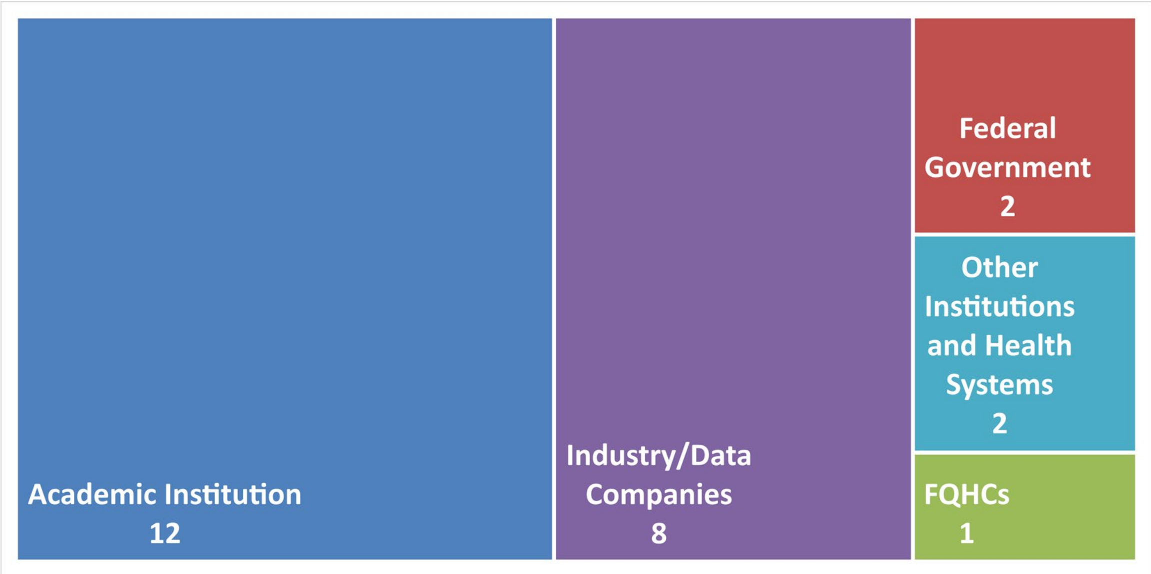
Exhibits 4 presents the number of RFI respondents emphasizing the need to prioritize under-resourced institutions (Code Category A) and **Exhibit 5** presents the number of RFI respondents expressing knowledge, experience, or interest in AI/ML for health disparity research (Code Category B). For both code categories, academic institutions were the most frequent types of organizations that provided this feedback, followed by industry/data companies.

Exhibit 4: Number of RFI respondents emphasizing the need to prioritize under-resourced institutions or MSIs (Code Category A), by type of organization *



*Organization types are self-reported and are mutually exclusive. Total RFI respondents N=76

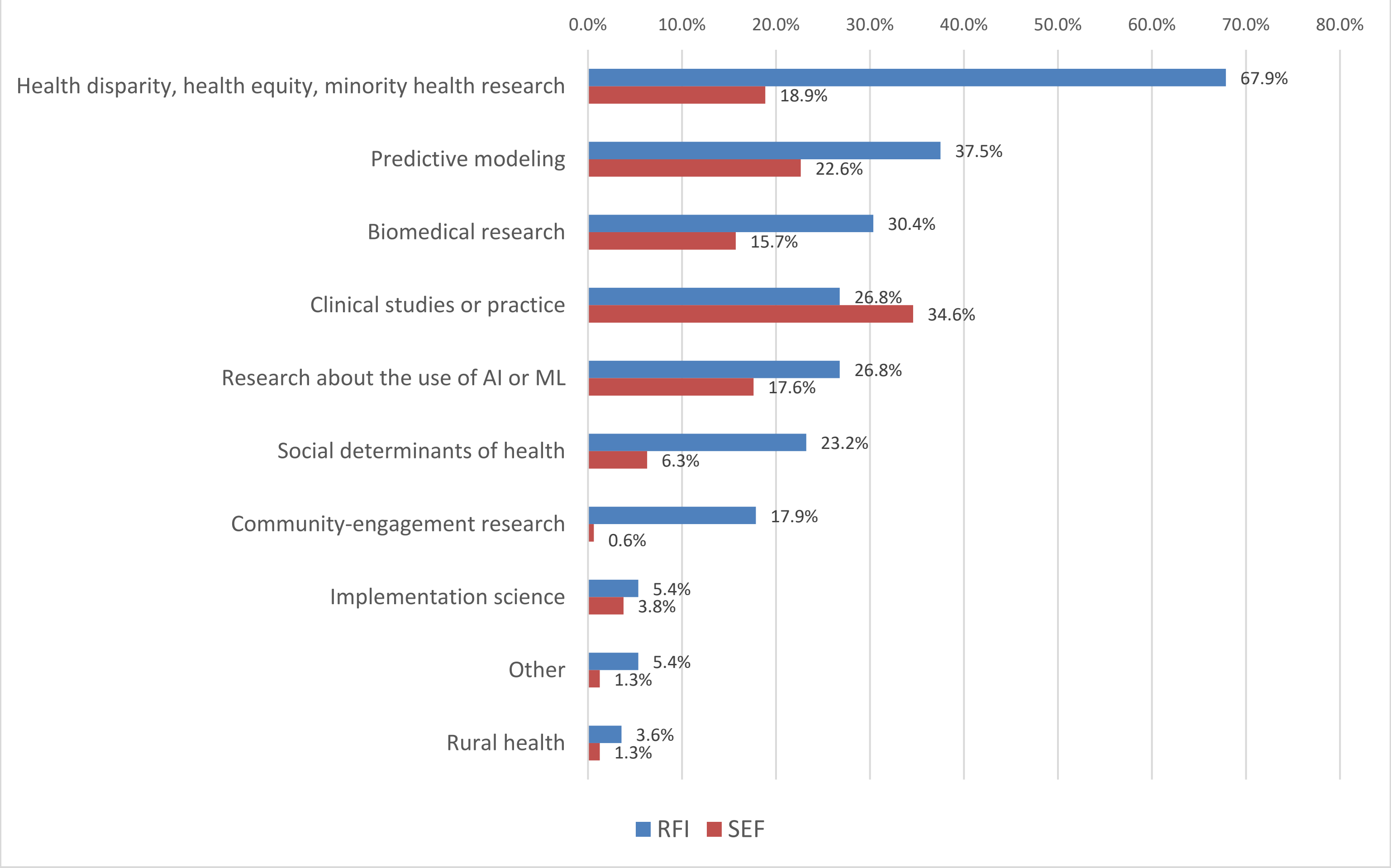
Exhibit 5: Number of RFI respondents expressing knowledge, experience, or interest in AI/ML for health disparity research (Code Category B) by type of organization *



*Organization types are self-reported and are mutually exclusive. Total RFI respondents N=76

Exhibits 6 presents the research topics (Code Category C), suggested by the RFI and SEF respondents. Among both RFI and SEF respondents, health disparity, health equity, and minority health research and predictive modeling were among the top 3 areas of interest expressed. Few RFI and SEF respondents indicated implementation science as an area of interest.

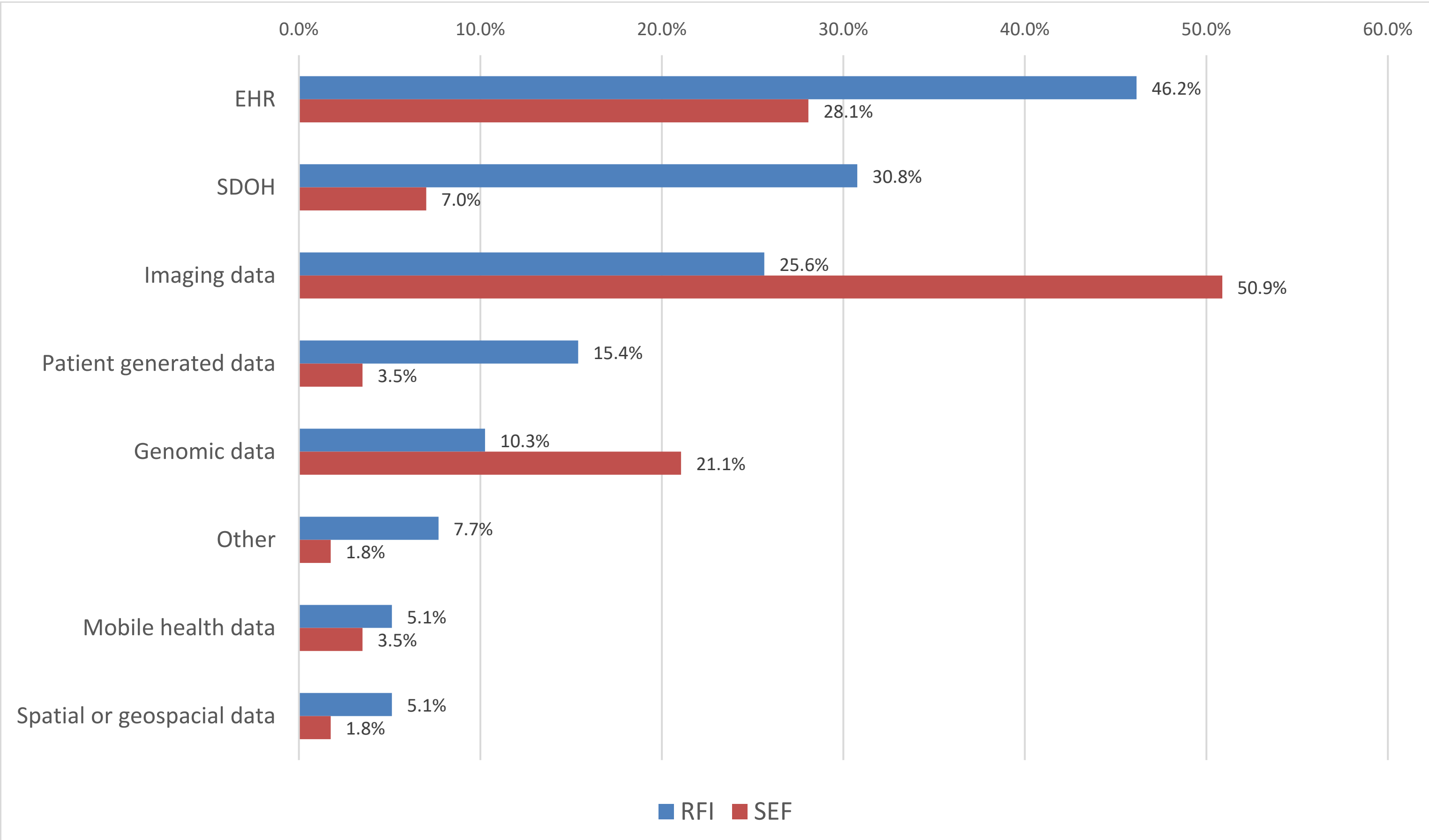
Exhibit 6: Research topics of interest (Code Category C) among those discussing the topic in the RFI (N=56) and SEF (N=159)*



*Multiple Code Categories could be captured per individual RFI or SEF respondent

Exhibits 7 presents the data sources of interest (Code Category D) represented within the RFI and SEF respondents. Among RFI respondents, nearly half of them indicated electronic health records (EHR) as a data source of interest, while for SEF respondents, nearly half of them indicated imaging data. Nearly a third of RFI respondents expressed interest in social determinants of health (SDOH) data, while less than 10 percent of SEF respondents indicated interest. Nearly 20 percent of SEF respondents expressed interest in genomic data, while only about 10 percent of RFI respondents indicated their interest.

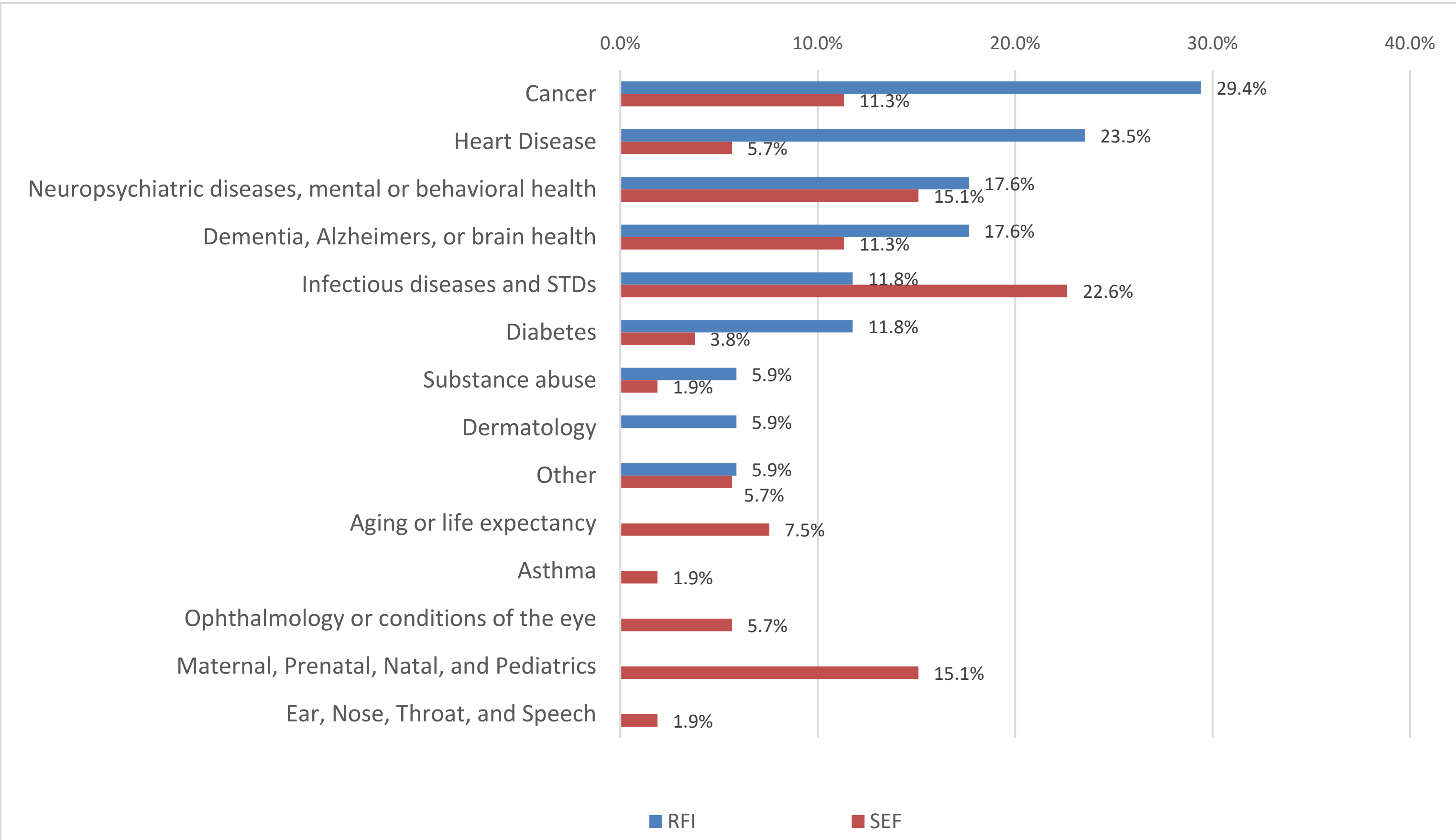
Exhibit 7: Data sources of interest (Code Category D) among those discussing the topic in the RFI (N=39) and SEF (N=57)*



*Multiple code categories could be captured per individual RFI or SEF respondent

Exhibits 8 presents the disease/condition areas of interest (Code Category E) in the feedback provided by the RFI and SEF respondents. Cancer was the most noted disease/condition among RFI respondents, while infectious diseases and STDs were the most noted among SEF respondents. Neuropsychiatric diseases and mental health were among the top 3 indicated conditions for both RFI and SEF respondents. Nearly 15 percent of SEF respondents indicated interest in maternal, prenatal, natal, and pediatric care while none of the RFI respondents expressed interest in those areas.

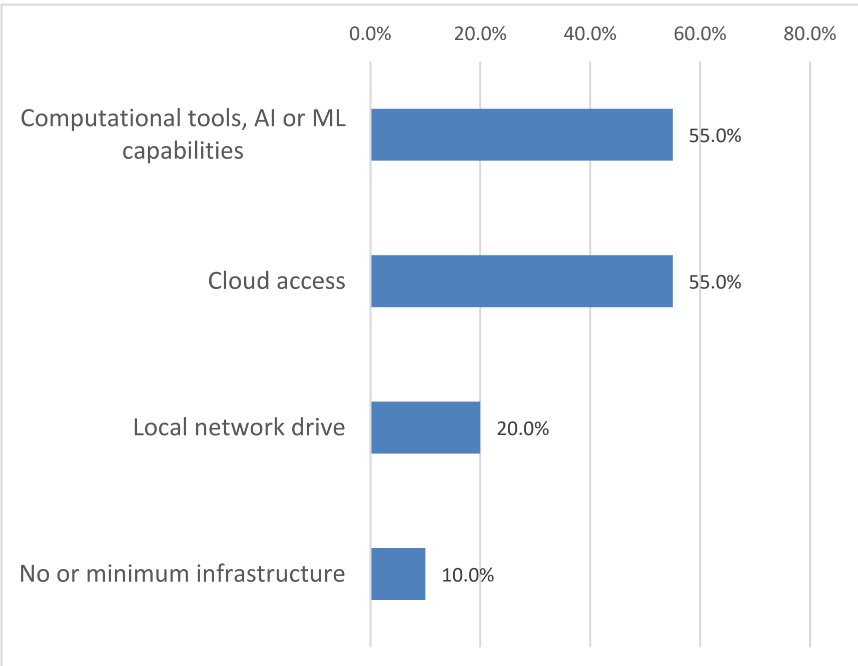
Exhibit 8: Disease/condition areas of interest (Code Category E) among those discussing the topic in the RFI (N=17) and SEF (N=53)*



*Multiple code categories could be captured per individual RFI or SEF respondent

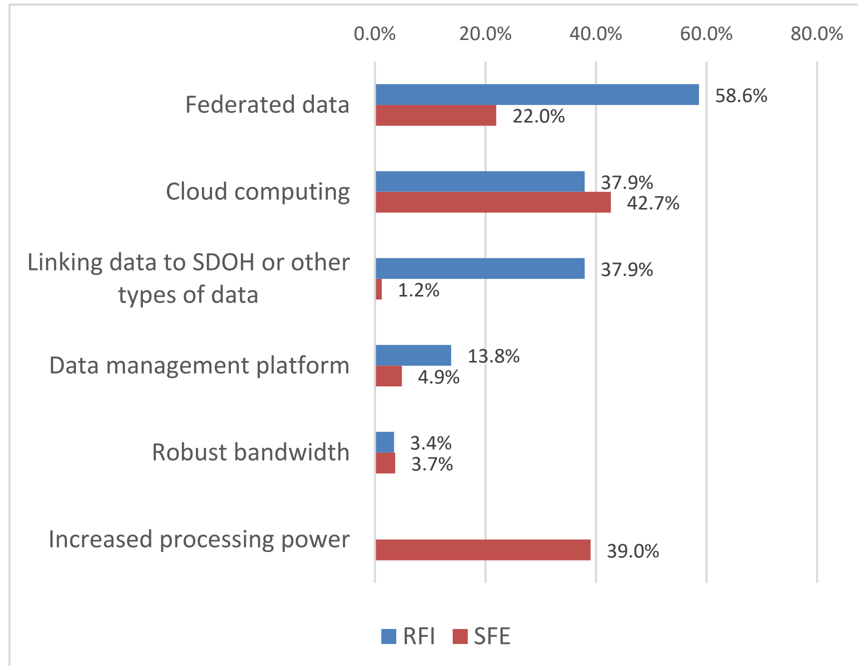
Exhibit 9 presents the current infrastructure available (Code Category F) noted by RFI respondents, and **Exhibit 10** presents the infrastructure needed (Code Category H), as reported by RFI and SEF respondents. More than half of the RFI respondents indicated that computational tools, AI or ML capabilities, and cloud access were currently available, and only 10 percent of them indicated there was no or minimum infrastructure. Among those reporting infrastructure needs, federated data, cloud computing, and linking SDOH data were reported among RFI respondents, while federated data, cloud computing, and increased processing power were indicated by SEF respondents.

Exhibit 9: Current infrastructure available (Code Category F) among those discussing the topic in the RFI (N=20)*



*Multiple forms of infrastructure could be captured per individual RFI respondent

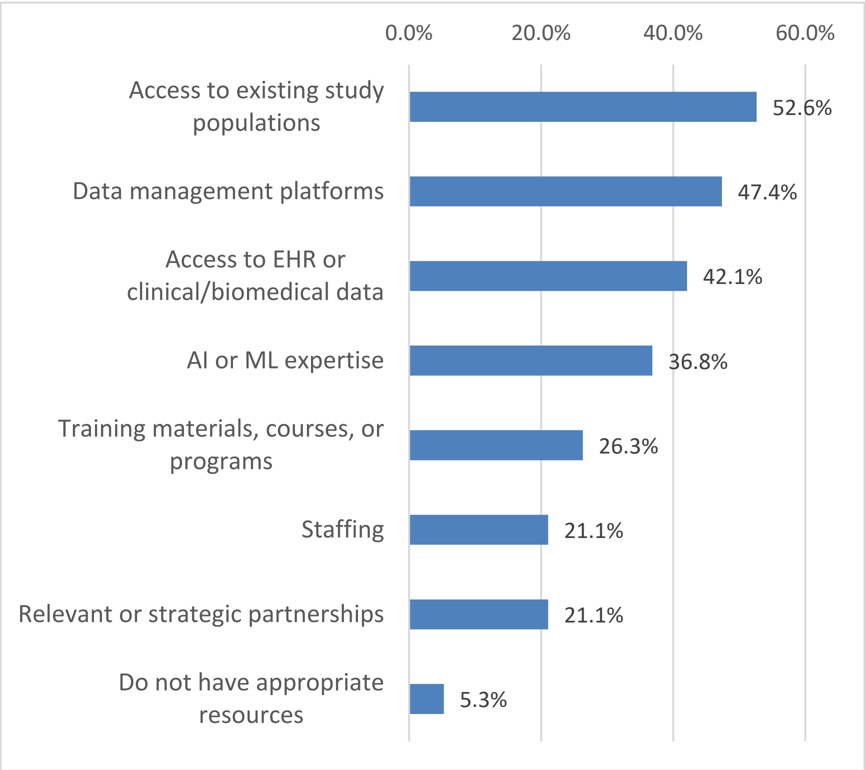
Exhibit 10: Reported infrastructure needed (Code Category H) among those discussing the topic in the RFI (N=27) and SEF (N=82)*



*Multiple forms of infrastructure could be captured per individual RFI or SEF

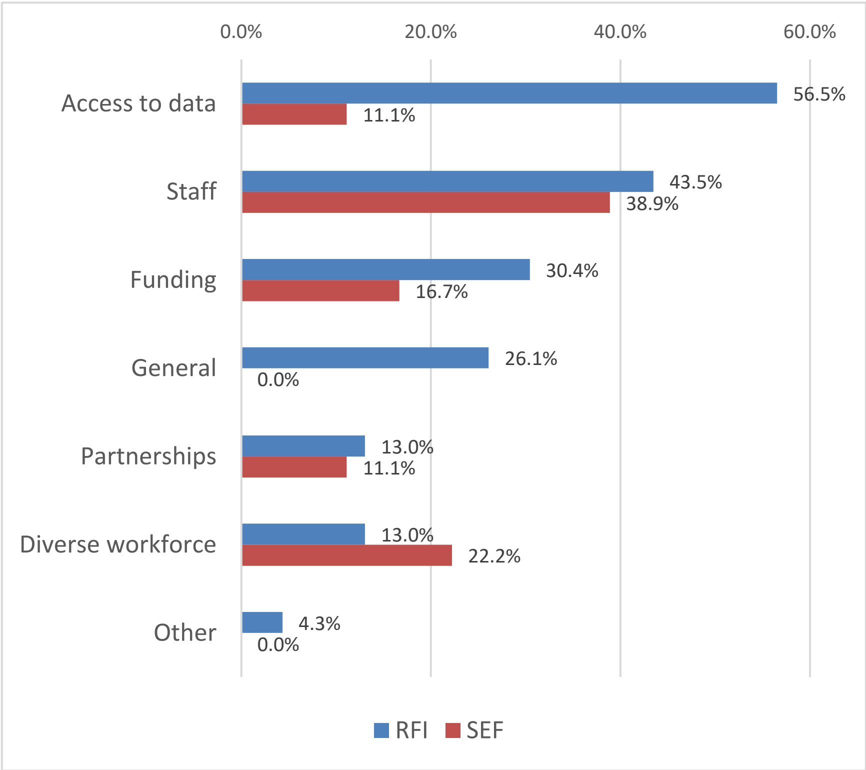
Exhibit 11 presents the current resources available (Code Category G) noted by RFI respondents, and **Exhibit 12** presents the resources needed (Code Category I), as reported by RFI and SEF respondents. More than half of the RFI respondents indicated that access to existing study populations were currently available, and nearly half indicated that data management platforms were available. Only 5 percent of RFI respondents indicated that they did not have appropriate resources available. Among the types of resources needed, staff was noted to be a needed resource by nearly 40% of respondents to both the RFI an SEF. RFI respondents were more inclined to indicate access to data being a need compared to SEF respondents.

Exhibit 11: Current resources available (Code Category G) among those discussing the topic in the RFI (N=18)*



*Multiple resources could be captured per individual RFI respondent.

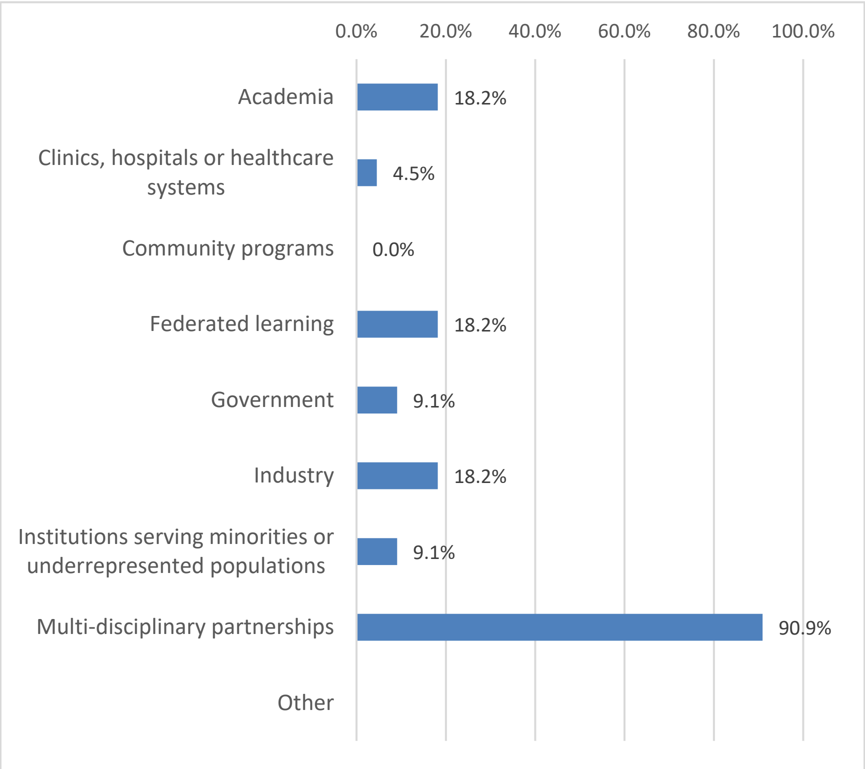
Exhibit 12: Reported resources needed (Code Category I) among those discussing the topic in the RFI (N=26) and SEF (N=18)*



*Multiple resources could be captured per individual RFI or SEF respondent

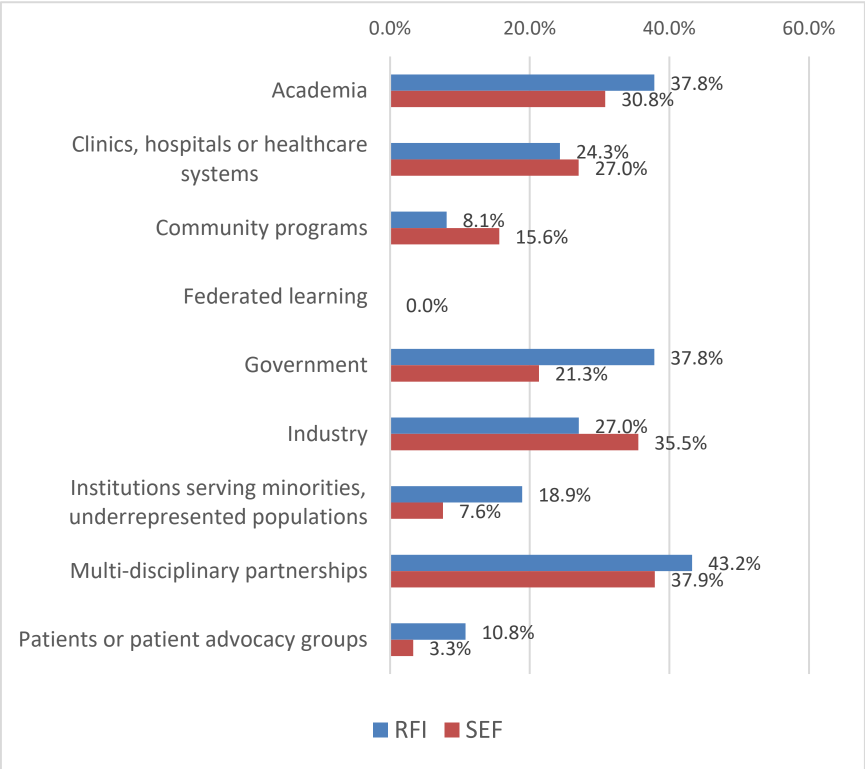
Exhibit 13 presents the current partnerships available (Code Category K) noted by RFI respondents, and **Exhibit 14** presents the partnerships needed (Code Category L) as reported by RFI and SEF respondents. Multi-disciplinary partnerships were the most reported form of partnerships indicated, while none of the RFI respondents indicated that community program partnerships were currently available. While multi-disciplinary partnerships were the most noted to be available, they were also indicated as being the most needed types of partnerships by both RFI and SEF respondents. Federated learning was not reported as a needed partnership from both RFI and SEF respondents.

Exhibit 13: Current partnerships available (Code Category K) among those discussing the topic in the RFI (N=22)*



*Multiple resources could be captured per individual RFI respondent.

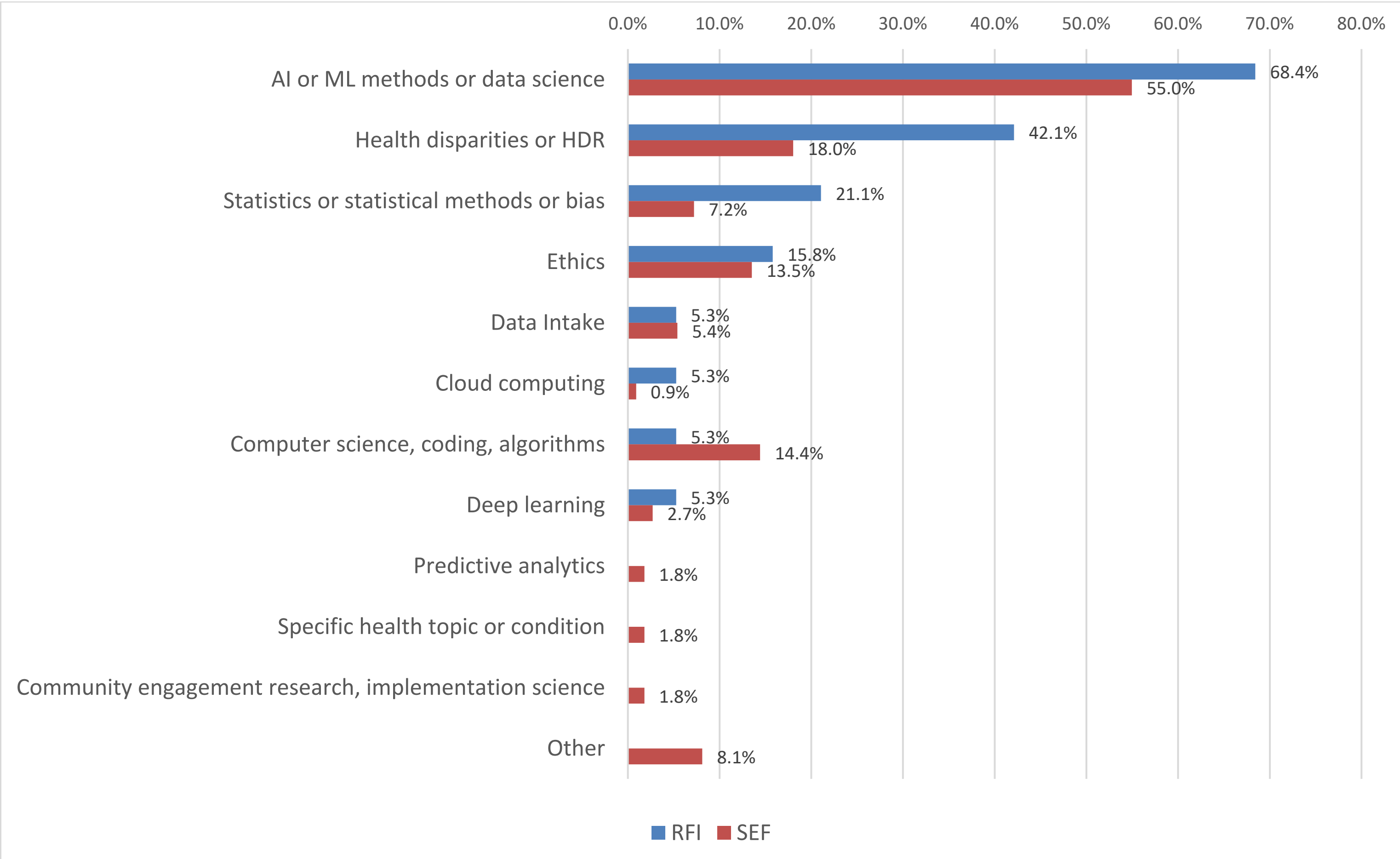
Exhibit 14: Reported partnerships needed (Code Category L) among individuals discussing the topic in the RFI (N=37) and SEF (N=211)



*Multiple resources could be captured per individual RFI or SEF respondent

Exhibit 15 presents the training topics needed (Code Category R) as reported by the RFI and SEF respondents. For both RFI and SEF respondents, AI or ML methods or data science and health disparities were the highest need training topic. Predictive analytics, specific health topics/conditions, and community engagement resources were the least reported training needs among SEF respondents and these topics were not coded among RFI respondents. Few RFI respondents reported training available (Code Category P).

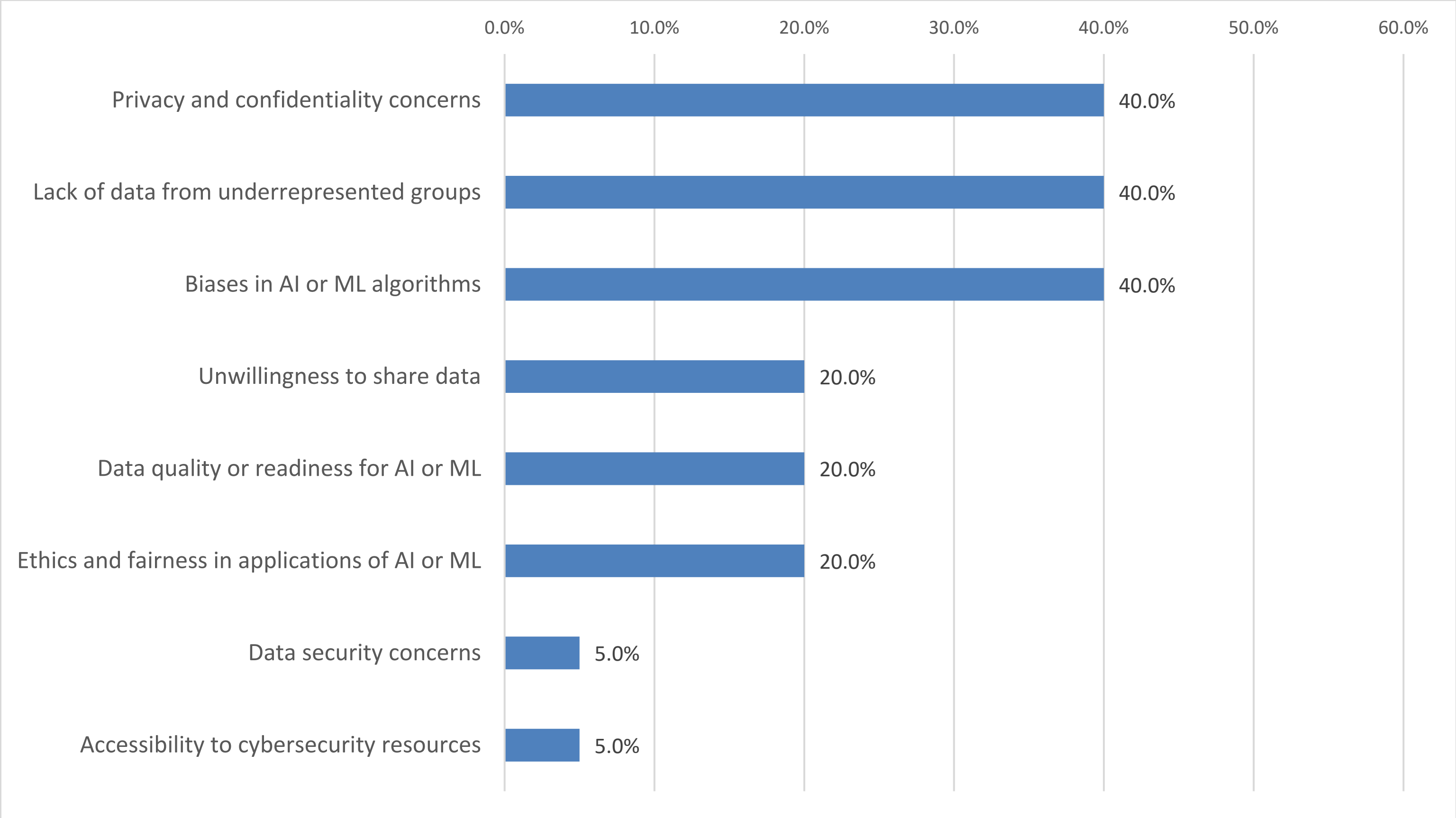
Exhibit 15: Reported training topics needed (Code Category R) among those discussing the topic in the RFI (N=19) and SEF (N=111)*



*Multiple training topics could be captured per individual RFI or SEF respondent

Exhibit 16 presents the challenges and limitations using AI or ML indicated by RFI respondents (Code Category U). The most noted challenges and limitations included privacy confidentiality concerns, lack of data from underrepresented groups, and biases in AI or ML algorithms. Data security concerns and accessibility to cybersecurity resources were the least noted challenges and limitations.

Exhibit 16: Challenges or limitations using AI or ML (Code Category U) among individuals discussing the topic in the RFI (N=20)*



*Multiple challenges could be captured per individual RFI respondent

Appendix A – RFI Questions

1. Use of AI/ML for health disparities and inequities research. Examples of specific comments include, but are not limited to:
    a. Knowledge, experience, and interest in using AI/ML for health disparities and inequities research
    b. High priority research topics of interest (e.g., biomedical research, predictive modeling, community-engagement research, implementation science, clinical studies)
    c. Types of pilot studies that could inform future health disparities research

2. Infrastructure and resources for AI/ML application and research. Examples of specific comments include, but are not limited to:
    a. Current infrastructure available (e.g., local network drive, cloud access)
    b. Resources available (e.g., staffing, data management platforms, access to EHR and other types of biomedical research and clinical data, access to existing study populations)
    c. Infrastructure and/or resources needed (federated data, cloud computing etc.)

3. Partnerships approaches for AI/ML application. Examples of specific comments include, but are not limited to:
    a. Interest in establishing multi-disciplinary partnerships and networks
    b. Current partnerships, networks, or initiatives that could be leveraged
    c. Types of partnerships or networks desired or needed
    d. Strategies to ensure and build trust for substantial and sustaining impact
    e. Willingness, interest, or concerns to sharing data and resources

4. Training for AI/ML approaches and health disparities and inequities. Examples of specific comments include, but are not limited to:
    a. Training and type of training resources currently available or accessible
    b. Level of training needed (e.g., students, early career, late career)
    c. Types of training needed (e.g., data science and AI/ML methods, cloud computing, health disparities research, community engagement research and implementation science)
    d. Novel approaches to facilitate training

5. Opportunities, challenges, and considerations with using AI/ML to study health disparities and inequities. Examples of specific comments include, but are not limited to:
    a. Opportunities for using AI/ML
    b. Challenges or limitations to using AI/ML
    c. Concerns or needs of special or unique populations
    d. Considerations for using AI/ML (e.g., overall purpose, future uses, consent)

Appendix B - Qualitative Analysis Methodology

Overview

All RFI responses, attachments, and Stakeholder Engagement Forum comments were uploaded to a database created in NVivo, a qualitative software package that allows for the management, coding, and analysis of large volumes of qualitative data. A team of five analysts used NVivo to develop and apply a set of codes to all text responses and attachments, and then conduct a thematic analysis to identify themes in the data.

Codebook Development

NIH provided a preliminary set of structured codes to be applied to the RFI responses. Members of the analytic team first read through comments in order to further develop codes that could be applied to the complete range of both the RFI and Stakeholder Engagement Forum responses. The team enhanced the NIH-provided code set by adding codes to existing categories, adding categories where necessary, and developing definitions for each code to ensure that all RFI topics and subtopics were covered. RFI questions (see Appendix A) and Stakeholder Engagement Forum registration questions (see Introduction) were mapped to topic areas, code categories, and data sources is shown in Table B1.

Table B1

RFI Topic	Topic Area	Code Category	Code Category Description	Data Source Applied to
Any		A	Emphasized the Need to Prioritize on Under-resourced Institutions/MSIs	RFI
1a	Research Use	B	AI/ML for HD Research (Knowledge, Experience,	RFI
1b		C	Topics of Research Interest	RFI and Forum
1c		D	Types of Data Interested	RFI
1c		E	Interested Disease Areas	RFI
2a	Infrastructure	F	Current Infrastructure Level	RFI
2b		G	Resources Available	RFI
2c		H	Infrastructure Needed	RFI
2c		I	Resources Needed	RFI and Forum
3a	Partnerships	J	Interest in Establishing Partnerships	RFI
3b		K	Current Partnerships	RFI
3c		L	Types of Partners Needed	RFI and Forum
3d		M	Strategies to Build Trust	RFI
3e		N	Sharing Data and Resources	RFI
4b	Training	O	Training Level Needed	RFI and Forum
4a		P	Training Available	RFI
4c		Q	Training Needed	RFI and Forum
4a, c		R	Training Topics	RFI and Forum
4d		S	Novel Approaches to Training	RFI and Forum
5a	Opportunities and Challenges	T	Opportunities for Using AI/ML	RFI
5b		U	Challenges or Limitations to Using AI/ML	RFI
5c		V	Concerns or Needs for Special Populations	RFI

5d		W	Other Considerations for Using AI/ML	RFI

The team developed a coding protocol to standardize the coding approach, and interrater reliability was assessed by having all team members independently code the same 3 RFI attachments. The team then met to review and reconcile coding differences, and adjusted the Codebook as needed. The final version of the Codebook can be found in Appendix C.

Coding Process

Each coder was assigned two of five main topic areas to code (Research Use, Infrastructure, Partnerships, Training, Opportunities and Challenges), so that each topic area was double coded by two analysts. All five team members reviewed every response in its entirety, and coded information relevant to their two assigned topic areas. Throughout the coding process, team members consulted with each other about the codes, often to clarify the decision rules about when a comment should be tagged with a particular code. Responses or comments that did not align with an existing code were flagged for group discussion. Additional codes were added for new subcategories in cases where the group reached consensus that existing codes were not sufficient to capture a particular concept. After initial coding was completed, pairs of coders met to discuss and reconcile any discrepancies for their assigned topic areas.

Results

Table B2 shows the total number of non-blank responses, by data source.

Table B2

Data Source	Number Coded
RFI comments	76
RFI attachments	25
Stakeholder Engagement Forum registration questions*	359

*There were 600 registrants to the Stakeholder Engagement Forum, of which 359 responded to the registration questions.

Thematic analysis

After all comments and attachments had been coded and reconciliation was complete, the analytic team conducted a thematic analysis to identify themes and patterns by respondent type (RFI or Stakeholder Engagement Forum) and across the entire dataset. Each team member was assigned as a lead for one specific topic area and was responsible for developing the themes and narrative. The team reviewed and discussed the themes as a group to ensure accuracy and consistency in the approach and across topic areas.

Appendix C – Codebook

Thematic Code	Description
A. Emphasized need to prioritize on under-resourced institutions or MSIs	Specifically recommended that NIH prioritize the use of AIM-AHEAD funds for under-resourced institutions or MSIs. Coded once per response.
B. AI or ML for HD Research	Double code once per response with valence where yes = high and no = low
01 - Knowledge Level	Specifically discussed previous training, credentials, or education in the health disparity-related or AI/ML fields.
02 - Experience Level	Specifically discussed previous working, training, or research experience conducting health disparity research or working in the AI/ML field.
03 - Interest	Specifically expressed interest in conducting AI/ML research.
C. Topics of research interest	
01 - Biomedical research	Clinical, biologic, or pharmaceutical research involving humans or animals conducted in a laboratory setting.
02 - Predictive modelling	Statistical methods aimed at predicting/projecting the probability of a condition or situation occurring, prediction of risk of disease or health/healthcare outcomes, using predictive models to target interventions.
03 - Community-engagement research	Involves the inclusion of non-academic, non-clinical, or non-traditional research entities in research or implementation of interventions, including community-based organizations, religious institutions, and advocacy groups.
04 - Implementation science	The systematic study of methods that support the application of research findings and other evidence-based knowledge into policy and practice (e.g., expanding pilot study across multiple new sites).
05 - Clinical studies or practice	Topics related to clinical interventions in patients, either in a research capacity or in a clinical practice or setting, or clinical decision support.
06 - SDOH	Social determinants of health; conditions in the environments where people are born, live, learn, work, play, worship, and age, including economic and social conditions, that influence individual and group differences in health status.
07 - Rural health	Pertaining to health services, health status or outcomes of rural populations; includes topics related to rural health/healthcare disparities.
08 - Health disparity, health equity, minority health research	Topics related to disparities in health or healthcare among racial, ethnic, or gender/sexual minority groups, including use or improvement of data.
09 - Research about the use of AI or ML	Study of the impact of AI/ML technologies, method-related research, research focused on understanding ethics or mitigation of bias in AI/ML.

Thematic Code	Description
10 - Other research topic interest	Includes research topic interests that do not fall under any of the other research topic interest category.
D. Types of data interested	
01 - EHR	Electronic records from clinical entities including hospitals and primary care providers.
02 - SDOH	Non-clinical data understanding the greater community conditions, such as transportation, housing, and food environment.
03 - Imaging data	Related to medical imaging (X-rays, CT, MRI, ultrasound, PET).
04 - Genomic data	Related to genetic information from individuals.
05 - Mobile health data	Information from or generated from mobile applications and platforms, including text messaging and social media.
06 - Patient generated data	Includes surveys, biometric devices, GPS.
07 - Spatial or geospatial data	Related to geographic locations on Earth; includes references to geocoding, Geographic information systems (GIS), location mapping, satellite data.
08 - Other data type interest	Includes in interest in types of data identified that does not fall under any of the other types of data interest categories.
E. Interested disease areas	
01 - Cancer	Related to topics involving various forms of cancer, including research, screening, diagnosis, and treatment (e.g. chemotherapy, radiation, etc.).
02 - Neuropsychiatric diseases, mental or behavioral health	Related to topics involving behaviors and the well-being of mind and spirit including research, screening, diagnosis, and treatment. Examples include stress management, eating habits, bi-polar conditions, and schizophrenia.
03 - Aging or life expectancy	Related to topics that project life expectancy and natural causes due to aging.
04 - Substance abuse	Topics related to drug (e.g., opioids, cocaine, etc.) and alcohol abuse, including research, screening, prevention, diagnosis, and treatment.
05 - Infectious diseases and STDs	Related to issues infectious diseases (diseases from viruses and bacteria) and sexually transmitted diseases (e.g., HIV, hepatitis, etc.), including research, prevention, screening, diagnosis, and treatment.
06 - Dementia, Alzheimer's, or brain health	Related to conditions involving memory loss or mental deterioration of mental capacity, including research, prevention, screening, diagnosis, and treatment.
07 - Diabetes	Related to diabetes and other metabolic syndrome conditions, including the research, prevention, screening, diagnosis, and treatment of the condition.
08 - Heart Disease	Related to conditions of the heart (e.g., stroke, heart attacks, high blood pressure, etc.), including the research, prevention, screening, diagnosis, and treatment of the condition.

Thematic Code	Description
09 - Asthma	Related to conditions including the research, diagnosis and treatment of the condition.
10 - Dermatology	Related to conditions of the skin (e.g., burn treatment, eczema, lesions, etc.), including the research, prevention, screening, diagnosis, and treatment of skin conditions.
11 - Ophthalmology or conditions of the eye	Related to conditions of the eye (e.g., glaucoma, cataracts, general vision), including the research, prevention, screening, diagnosis, and treatment of eye related conditions.
12 - Maternal, Prenatal, Natal, and Pediatrics	Topics related to the neonatal, natal and post-natal care of child and maternal, as well as care of children (0-17).
13 - Ear, Nose, Throat, and Speech	Topics related to conditions of the ear, nose, throat, or speech, including deafness and speech therapy. Involves the research, prevention, screening, diagnosis, and treatment of the condition.
14 - Other disease areas of interest	Includes disease areas of interest that do not fall under any of the other disease area of interest category.
F. Current infrastructure level	
01 - Local network drive	Encompasses general references of onsite computing resources.
02 - Computational tools, AI or ML capabilities	Common tool sets (e.g., TensorFlow) that allow for conducting AI/ML training and studies.
03 - Cloud access	Any cloud-based information systems.
04 - No or minimum infrastructure	Indication of no current infrastructure and/or no response or mention of it.
G. Resources available	
01 - Do not have appropriate experience	commenter indicates not having appropriate experience at organization for AI/ML application or research
02 - Do not have appropriate resources	commenter indicates in a general sense not having appropriate resources at organization for AI/ML application or research
03 – AI or ML expertise	commenter indicates having expertise in AI/ML
04 - Staffing	commenter indicates having staffing available for AI/ML application or research
05 - Data management platforms	Commenter indicates having data management platforms available for AI/ML application or research.
06 - Access to EHR, other biomedical research or clinical data	Commenter indicates having access to clinical, research, or electronic health record data for AI/ML application or research.
07 - Access to existing study populations	Commenter indicates having access to study populations for AI/ML application or research.
08 - Relevant or strategic partnerships or consortiums	Commenter indicates having existing partnerships or being involved in collaborative groups that are relevant for AI/ML application or research.
09 - Training materials, courses, or programs	Commenter indicates having access to training content for AI/ML application or research.

Thematic Code	Description
H. Infrastructure needed	
01 - Federated data	Distributed (vs centralized) data platforms and services.
02 - Cloud computing	Any cloud-based computing resources and services.
03 - Data management platform	Can include different types of databases, interfaces, and data processing platforms (including EHRs).
04 - Linking data to SDOH or other types of data	Access to interfaces, libraries, and data services specific to SDOH.
05 - Robust bandwidth	Aspects related to internet connectivity.
06 - Increased processing power	Any reference to improved computer/server processing power whether distributed (e.g., cloud-based) or local.
I. Resources needed	
01 - Funding	Includes references to funding needed.
02 - Partnerships	Includes references to partnerships needed.
03 - Staff	Includes references to staffing needs.
04 - Diverse workforce	Includes references to the need for a more diverse workforce.
05 – Access to data	Includes references to data access needs.
06 - General	Includes references to general resource needs.
07 - Other resource needed	Includes references to other resources needed that do not fall into any other resource need category.
J. Interest in establishing partnerships	
01 - Leverage current partnerships, networks, or initiatives	Interest or willingness to leverage current partnerships with other organizations for the purpose of AI/ML to reduce health disparities
02 - Importance of community engagement	Includes references that suggest the respondent considered community engagement important for establishing partnerships.
03 - Partnership readiness	Express readiness or lack of readiness to partner* (Code once per response with valence where Yes = Interested and No = Not Ready)
K. Current partnerships	
01 - Current multi-disciplinary partnerships	Includes references to already established multi-disciplinary partnerships and networks to include individuals representing different disciplines or research areas. For example, data scientists working with clinical researchers and community advocates.
02 - Current federated learning	Includes references to already established partnerships involving a decentralized system with local data control: includes any references to current partnerships described as federated learning and collaborative machine learning without any centralized training data.
03 - Current industry	Includes references to already established partnerships involving the private sector or corporations. For example, cloud computing partners.

Thematic Code	Description
04 - Current academia	Includes any references to already established partnerships with universities or higher education institutions.
05 - Current clinics, hospitals or healthcare systems	Includes any references to already established partnerships with clinical and healthcare organizations.
06 - Current community programs	Includes any references to already established partnerships with community-based organizations.
07 - Current patients or patient advocacy groups	Includes any references to already established partnerships with patients or patient advocacy groups.
08 - Current government	Includes any references to already established partnerships with government agencies or institutes.
09 - Current institutions serving minorities or underrepresented populations	Includes any references to already established current partnerships with organizations or institutions with specific mission to serve minorities.
L. Types of partners needed	
01 - Multi-disciplinary partnerships	Includes references to needed or desired or expressed an interest in multi-disciplinary partnerships and networks to include individuals representing different disciplines or research areas. For example, population health, computer science, and biostatistics.
02 - Federated learning	Includes references to the need or desire to establish partnerships involving a decentralized system with local data control; includes any references to the need or desire for partnerships described as federated learning and collaborative machine learning without any centralized training data.
03 - Industry	Includes any references to the need or desire to form partnerships with the private sector or corporations.
04 - Academia	Includes references to the need or desire to establish partnerships with universities or higher education institutions.
05 - Clinics, hospitals or healthcare systems	Includes any references to the need or desire to form partnerships with clinical and healthcare organizations.
06 - Community programs	Includes any references to the need or desire to form partnerships with community-based organizations.
07 - Patients or patient advocacy groups	Includes any references for the need or desire to form partnerships with patients or patient advocacy groups.
08 - Government	Includes any references for the need or desire to form partnerships with government agencies or institutes.
09 - Institutions serving minorities, underrepresented populations	Includes any references to the need or desire to form partnerships with organizations or institutions with specific mission to serve minorities.
M. Strategies to build trust	Suggestions or proposals for methods, techniques, or strategies for trust building among entities involved in AI/ML research, or among minority groups or populations.
N. Sharing data and resources	

Thematic Code	Description
01 - Interest in sharing data	Includes references to sharing data. Double code with valence codes.
02 - Interest in sharing resources	Includes references to sharing resources. Double code with valence codes.
O. Training level needed	
01 - Grade school or high school	Training or education primarily targeted to young students before university level.
02 - Undergraduate	Training primarily targeted to undergraduate students.
03 - Graduate	Training primarily targeted to graduate students.
04 - Medical students	Training primarily targeted to medical students.
05 - Post-doctoral	Training primarily targeted to post-doctoral students.
06 - Clinicians or healthcare	Training primarily targeted to clinicians and/or healthcare staff.
07 - General public	Training or education targeted for the public, health care consumers, or specific populations about AI/ML technologies or use of data for AI/ML.
P. Training available	Includes any references to training availability. Double coded with Q (i.e., training topics)
Q. Training needed	Includes any references to training needs. Double coded with Q. (i.e., training topics).
R. Training topics	Includes references to training topics. Double-coded with P (i.e., training available) and Q (i.e., training needed)
01 - AI or ML methods or data science	Artificial intelligence or machine learning methods and techniques, data science (use of scientific methods, processes, algorithms and systems to extract knowledge and insights from structured and unstructured data, and to apply knowledge and actionable insights from data).
02 - Data Intake	Related to data entry (process by which data from different sources, structure and/or characteristics is entered into another data storage or processing system).
03 - Cloud computing	Delivery of computing services—including servers, storage, databases, networking, software, analytics, and intelligence—over the Internet ("the cloud").
04 - Computer science, coding, algorithms	Relating to study of computers and computational systems, programming, or coding.
05 - Predictive analytics	Use of statistics and modelling techniques to determine future performance based on current and historical data.
06 - Deep learning	A type of machine learning and artificial intelligence (AI) that imitates the way humans gain certain types of knowledge.
07 – Statistics or statistical methods or bias	Related to statistical methods or statistical bias.
08 - Ethics	Relating to moral principles in conduct of research or science.

Thematic Code	Description
09 - Health disparities or HDR	Health disparities/health disparities research.
10 - Specific health topic or condition	Training in a specific clinical area.
11 - Community engagement research, implementation science	Training in methods for including community entities in research or implementation of interventions, or in methods that support the application of research findings and other evidence-based knowledge into policy and practice (e.g., expanding pilot study across multiple new sites).
S. Novel approaches to training	Suggestions or proposals for new or innovative methods, techniques, or approaches to training for AI/ML
T. Opportunities for using AI or ML NOS	Ideas for using AI/ML that go beyond specific research topics captured in code categories C, D, and E. For example, includes potential for use of natural language processing, precision medicine, open source approach.
U. Challenges or limitations to using AI or ML	
01 - Privacy and confidentiality concerns	Includes record linkage concerns.
02 - Unwillingness to share data	Reluctance on behalf of entities involved in AI/ML research to share data with others.
03 - Lack of data from underrepresented groups	Due to limited individual healthcare access, or due to low-resourced institutions, for example.
04 - Biases in AI or ML algorithms	Includes algorithm training concerns, facial recognition bias.
05 - Data quality or readiness for AI or ML	Includes measurement units, missing demographic data, granularity and accuracy of coding, data timeliness.
06 - Data security concerns	Includes hacking, unauthorized access, unauthorized release.
07 - Ethics and fairness in applications of AI or ML	Includes biased coding of race/ethnicity data, unequal access to the benefits of AI/ML technology, exploitation of minority communities, mistrust in technology in minority communities, unauthorized research use.
08 - Accessibility to cybersecurity resources	Issues related to limited or inequitable access to resources to help ensure IT/data security.
V. Other concerns or needs of special populations	Includes risk of limiting healthcare access due to biased algorithms.
W. Other considerations for using AI or ML	Includes any mentions of considerations for using AL or ML that do not fall under any other category.
X. Valence	
01 – Yes, High, Positive	Code used in combination of other codes to indicate affirmation, strength or positive direction.
02 – No, Low, Negative	Code used in combination of other codes to indicate nullification, weakness or negative direction.