Fostering Multidisciplinary Collaboration in Artificial Intelligence and Machine Learning Education: Perspectives from the AI-READI Bootcamp

Taiki W Nishihara, Fritz GP Kalaw, Adelle Engmann, Aya Motoyoshi, Paapa Mensah-Kane, Deepa Gupta, Victoria Patronilo, Linda M Zangwill, Shahin Hallaj, Amirhossein Panahi, Garrison Cottrell, Bradley Voytek, Virginia R de Sa, Sally L Baxter

Submitted to: JMIR Medical Education
on: August 28, 2025

Table of Contents

Fostering Multidisciplinary Collaboration in Artificial Intelligence and Machine Learning Education: Perspectives from the AI-READI Bootcamp

Taiki W Nishihara[1]; Fritz GP Kalaw[1, 2]; Adelle Engmann[3]; Aya Motoyoshi[4]; Paapa Mensah-Kane[5]; Deepa Gupta[6]; Victoria Patronilo[1]; Linda M Zangwill[1]; Shahin Hallaj[1, 2]; Amirhossein Panahi[7]; Garrison Cottrell[8]; Bradley Voytek[6, 7, 9, 10]; Virginia R de Sa[6, 7]; Sally L Baxter[1, 2]

[1]Division of Ophthalmology Informatics and Data Science Viterbi Family Department of Ophthalmology and Shiley Eye Institute, Hamilton Glaucoma Center University of California, San Diego La Jolla US
[2]Department of Medicine, Division of Biomedical Informatics University of California, San Diego La Jolla US
[3]Stanford Deep Data Research Center Department of Genetics Stanford University Palo Alto US
[4]Department of Ophthalmology University of Washington Seattle US
[5] School of Pharmacy South University Savannah US
[6]Department of Cognitive Science University of California, San Diego La Jolla US
[7]Hal?c?o?lu Data Science Institute University of California, San Diego La Jolla US
[8]Department of Computer Science and Engineering University of California, San Diego La Jolla US
[9]Neurosciences Graduate Program University of California, San Diego La Jolla US
[10] Kavli Institute for Brain and Mind University of California, San Diego La Jolla US

Corresponding Author:
Sally L Baxter
Division of Ophthalmology Informatics and Data Science
Viterbi Family Department of Ophthalmology and Shiley Eye Institute, Hamilton Glaucoma Center
University of California, San Diego
9415 Campus Point Drive
La Jolla
US

Abstract

Background: The integration of artificial intelligence (AI) and machine learning (ML) into biomedical research requires a workforce fluent in both computational methods and clinical applications. Structured, interdisciplinary training opportunities remain limited, creating a gap between data scientists and clinicians. The National Institutes of Health's Bridge2AI initiative launched the Artificial Intelligence–Ready and Exploratory Atlas for Diabetes Insights (AI-READI) Data Generation Project to address this gap. AI-READI is creating a multimodal, FAIR (Findable, Accessible, Interoperable, and Reusable) dataset—including ophthalmic imaging, physiologic measurements, wearable sensor data, and survey responses—from approximately 4,000 participants with or at risk for type 2 diabetes. In parallel, AI-READI established a yearlong mentored research program that begins with a two-week immersive summer bootcamp to provide foundational AI/ML skills grounded in domain-relevant biomedical data.

Objective: To describe the design, iterative refinement, and outcomes of the AI-READI Bootcamp, and to share lessons for creating future multidisciplinary AI/ML training programs in biomedical research.

Methods: Held annually at UC San Diego, the bootcamp combines 80 hours of lectures, coding sessions, and small-group mentorship. Year 1 introduced Python programming, classical ML techniques (e.g., logistic regression, convolutional neural networks), and data science methods such as principal component analysis and clustering, using public datasets. In Year 2, the curriculum was refined based on structured participant feedback—reducing cohort size to increase individualized mentorship, integrating the AI-READI dataset (including retinal images and structured clinical variables), and adding modules on large language models and FAIR data principles. Participant characteristics and satisfaction were assessed through standardized pre- and post-bootcamp surveys, and qualitative feedback was analyzed thematically by independent coders.

Results: Seventeen participants attended Year 1 and seven attended Year 2, with an instructor-to-student ratio of approximately 1:2 in the latter. Across both years, post-bootcamp evaluations indicated high satisfaction, with Year 2 participants reporting improved experiences due to smaller cohorts, earlier integration of the AI-READI dataset, and greater emphasis on applied learning. In Year 2, mean scores for instructor effectiveness, staff support, and overall enjoyment were perfect (5.00/5.00). Qualitative feedback emphasized the value of working with domain-relevant, multimodal datasets; the benefits of peer collaboration; and the applicability of skills to structured research projects during the subsequent internship year.

Conclusions: The AI-READI Bootcamp illustrates how feedback-driven, multidisciplinary training embedded within a longitudinal mentored research program can bridge technical and clinical expertise in biomedical AI. Core elements—diverse trainee cohorts, applied learning with biomedical datasets, and sustained mentorship—offer a replicable model for preparing health professionals for the evolving AI/ML landscape. Future iterations will incorporate additional pre-bootcamp onboarding modules, objective skill assessments, and long-term tracking of research engagement and productivity.

(JMIR Preprints 28/08/2025:83154)
DOI: https://doi.org/10.2196/preprints.83154

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**
Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http
No. Please do not make my accepted manuscript PDF available to anyone. I understand that if I later pay to participate in <a href="https:/

Original Manuscript

Fostering Multidisciplinary Collaboration in Artificial Intelligence and Machine Learning Education: Perspectives from the AI-READI Bootcamp

Taiki W. Nishihara[1], Fritz G.P. Kalaw[1,2], Adelle Engmann[3], Aya Motoyoshi[4], Paapa Mensah-Kane[5], Deepa Gupta[6], Victoria Patronilo[1], Linda M. Zangwill[1], Shahin Hallaj[1,2], Amirhossein Panahi[7], Garrison Cottrell[8], Bradley Voytek[6,7,9,10], Virginia R. de Sa[6,7], Sally L. Baxter[1,2]

Affiliations:
1. Division of Ophthalmology Informatics and Data Science, Hamilton Glaucoma Center, Viterbi Family Department of Ophthalmology and Shiley Eye Institute, University of California San Diego, La Jolla, CA, USA
2. Division of Biomedical Informatics, Department of Medicine, University of California San Diego, La Jolla, CA, USA
3. Stanford Deep Data Research Center, Department of Genetics at Stanford Medicine, Palo Alto, CA, USA
4. Department of Ophthalmology, University of Washington, Seattle, WA, USA
5. School of Pharmacy, South University, Savannah, GA, USA
6. Department of Cognitive Science, University of California San Diego, La Jolla, CA, USA
7. Halıcıoğlu Data Science Institute, University of California San Diego, La Jolla, CA, USA
8. Department of Computer Science and Engineering, University of California San Diego, La Jolla, CA, USA
9. Neurosciences Graduate Program, University of California San Diego, La Jolla, CA, USA
10. Kavli Institute for Brain and Mind, University of California San Diego, La Jolla, CA, USA

Correspondence:
Sally L. Baxter, MD, MSc
Associate Professor of Ophthalmology and Medicine (Division of Biomedical Informatics)
University of California San Diego
9415 Campus Point Drive
La Jolla, CA 92093
s1baxter@health.ucsd.edu
(858) 534-8413

ABSTRACT

Background:
The integration of artificial intelligence (AI) and machine learning (ML) into biomedical research requires a workforce fluent in both computational methods and clinical applications. Structured, interdisciplinary training opportunities remain limited, creating a gap between data scientists and clinicians. The National Institutes of Health's Bridge2AI initiative launched the Artificial Intelligence–Ready and Exploratory Atlas for Diabetes Insights (AI-READI) Data Generation Project to address this gap. AI-READI is creating a multimodal, FAIR (Findable, Accessible, Interoperable, and Reusable) dataset—including ophthalmic imaging, physiologic measurements, wearable sensor data, and survey responses—from approximately 4,000 participants with or at risk for type 2 diabetes. In parallel, AI-READI established a yearlong mentored research program that begins with a two-week immersive summer bootcamp to provide foundational AI/ML skills grounded in domain-relevant biomedical data.

Objective:
To describe the design, iterative refinement, and outcomes of the AI-READI Bootcamp, and to share lessons for creating future multidisciplinary AI/ML training programs in biomedical research.

Methods:
Held annually at UC San Diego, the bootcamp combines 80 hours of lectures, coding sessions, and small-group mentorship. Year 1 introduced Python programming, classical ML techniques (e.g., logistic regression, convolutional neural networks), and data science methods such as principal component analysis and clustering, using public datasets. In Year 2, the curriculum was refined based on structured participant feedback—reducing cohort size to increase individualized mentorship, integrating the AI-READI dataset (including retinal images and structured clinical variables), and adding modules on large language models and FAIR data principles. Participant characteristics and satisfaction were assessed through standardized pre- and post-bootcamp surveys, and qualitative feedback was analyzed thematically by independent coders.

Results:
Seventeen participants attended Year 1 and seven attended Year 2, with an instructor-to-student ratio of approximately 1:2 in the latter. Across both years, post-bootcamp evaluations indicated high satisfaction, with Year 2 participants reporting improved experiences due to smaller cohorts, earlier integration of the AI-READI dataset, and greater emphasis on applied learning. In Year 2, mean scores for instructor effectiveness, staff support, and overall enjoyment were perfect (5.00/5.00). Qualitative feedback emphasized the value of working with domain-relevant, multimodal datasets; the benefits of peer collaboration; and the applicability of skills to structured research projects during the subsequent internship year.

Conclusions:
The AI-READI Bootcamp illustrates how feedback-driven, multidisciplinary training embedded within a longitudinal mentored research program can bridge technical and clinical expertise in biomedical AI. Core elements—diverse trainee

cohorts, applied learning with biomedical datasets, and sustained mentorship—offer a replicable model for preparing health professionals for the evolving AI/ML landscape. Future iterations will incorporate additional pre-bootcamp onboarding modules, objective skill assessments, and long-term tracking of research engagement and productivity.

Keywords: artificial intelligence, machine learning, biomedical research, interdisciplinary training, data science, curriculum development, translational research, medical education

INTRODUCTION

Artificial intelligence (AI) has demonstrated transformative potential in healthcare—deep learning algorithms can now screen for diabetic retinopathy

from fundus photographs[1] and predict patient-specific glycemic fluctuations[2] with performance comparable to expert clinicians. Yet a persistent gap exists between model developers and clinical end users.
Clinicians often lack formal training in machine learning (ML) and data science. Reflecting this broader gap, only about 28% of ML model development studies included clinicians, and their input was frequently limited[3]. Similarly, in the United Kingdom, just 13.8% of trainee doctors felt they were adequately prepared for the introduction of AI into clinical practice[4]. Engineers and computer scientists, in turn, are not routinely trained in the clinical, regulatory, or ethical complexities of healthcare delivery. This disconnect limits interdisciplinary collaboration, undermines the translational impact of AI tools, and risks producing models that are less effective in real-world clinical practice[5-7].

In response to these challenges, a growing number of national and institutional efforts have emerged to cultivate a more integrated biomedical AI workforce. The National Institutes of Health (NIH) launched the Bridge2AI initiative in 2022 to support the development of FAIR (Findable, Accessible, Interoperable, and Reusable) multimodal datasets alongside coordinated workforce development[8]. Among its flagship Data Generation Projects (DGPs), the Artificial Intelligence–Ready and Exploratory Atlas for Diabetes Insights (AI-READI) is curating a comprehensive dataset—spanning ophthalmic imaging, physiologic measurements, wearable sensor data, and survey responses—from approximately 4,000 individuals with or at risk for type 2 diabetes[9,10].

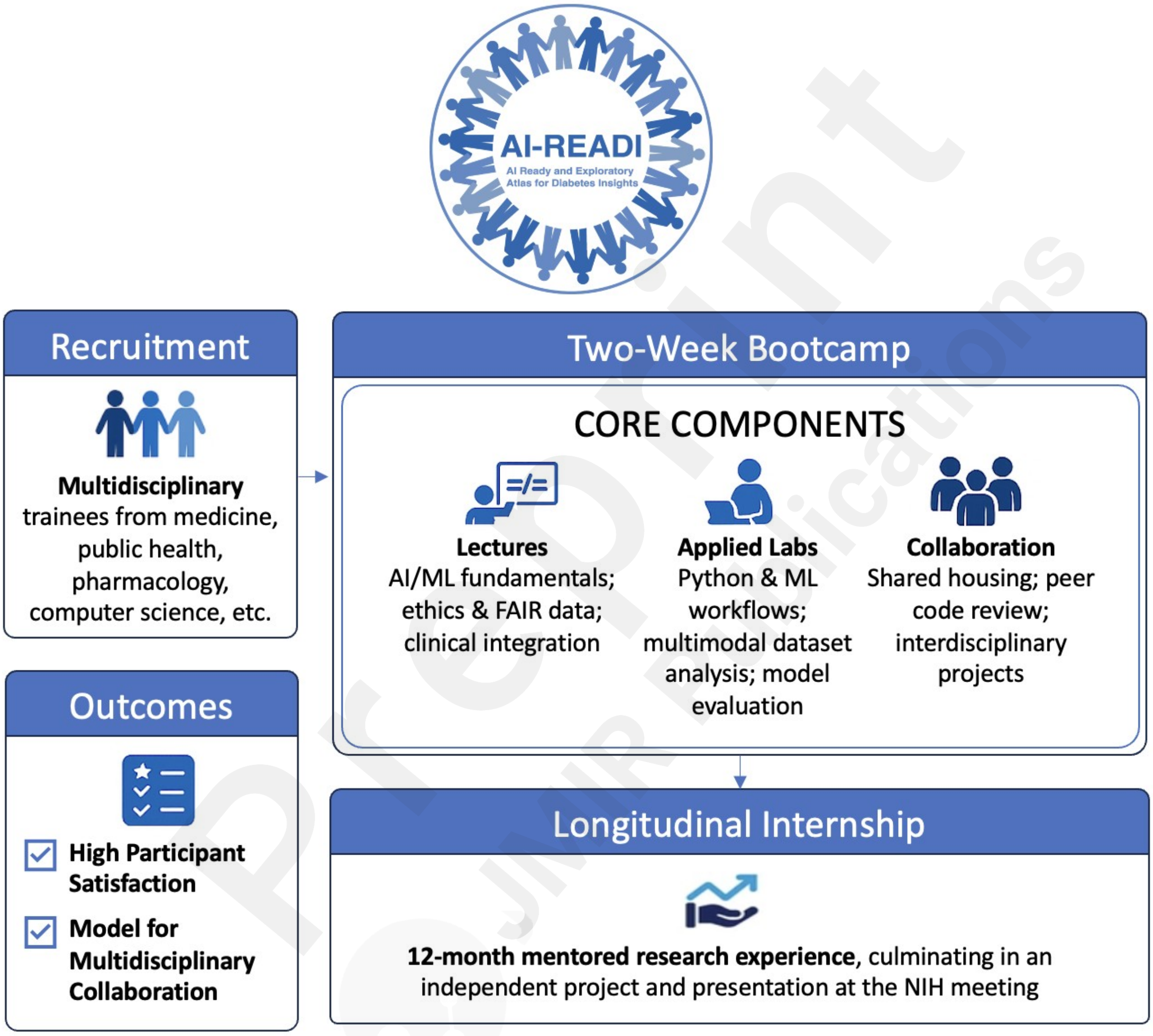
While numerous AI training programs exist—ranging from Massive Open Online Courses (MOOCs) to short-term institutional electives—many rely on generic or narrowly scoped datasets, offer limited interdisciplinary interaction, or lack sustained mentorship[11–13]. In contrast, the AI-READI Bootcamp was developed to prepare learners to engage with structured, domain-relevant biomedical data in ways that mirror the complexity of real-world research. The bootcamp serves as a launchpad to a yearlong immersive research internship, enabling sustained, mentored project work immediately following foundational instruction (Figure 1).

The bootcamp was designed for a multidisciplinary cohort, bringing together trainees from medicine, neuroscience, public health, computer science, engineering, among others. Led by faculty with extensive experience in NIH and National Science Foundation funded training initiatives and data science education through UC San Diego's Halıcıoğlu Data Science Institute, the curriculum integrates seminars in machine learning, statistics, and responsible AI with notebook-based coding labs. These hands-on sessions are anchored in the first public release of the AI-READI dataset and focus on applied learning around data structure, bias, and clinical relevance.

Each cohort (Year 1 in 2023; Year 2 in 2024) was independently developed—the Year 2 curriculum was iteratively refined based on feedback from the inaugural cohort. This feedback-driven design approach supports learner engagement and reflects broader trends in AI education emphasizing modular content, scaffolded mentorship, and interdisciplinary collaboration[12–14].

In this manuscript, we describe the design and iteration of the AI-READI Bootcamp; report on participant characteristics, satisfaction outcomes, and feedback; and share lessons learned to inform institutions seeking to build inclusive, practice-driven AI training programs in healthcare.

Figure 1. Structure, Key Curricular Components, and Integration of the AI-READI Bootcamp into the Longitudinal Internship Program



METHODS

AI-READI Intern Recruitment and Bootcamp Participant Selection

Participants for the year-long AI-READI internship program were recruited from a wide range of academic and professional backgrounds, including computer science, engineering, medicine, public health, nursing, pharmacy, and other allied health fields. The selection process prioritized quantitative aptitude, scientific curiosity, and interdisciplinary interest, rather than prior coding experience. Applicants were asked to indicate whether they had completed college-level coursework in calculus, linear algebra, or statistics. While the review committee preferred some background in college-level mathematics, this was not a strict eligibility requirement. Outreach strategies included a detailed informational brochure posted on the AI-READI website and disseminated via faculty webpages, journals, mailing lists, and social media. Alumni, faculty mentors, and current trainees also contributed to recruitment through word-of-mouth and community engagement.

Applicants completed an online application that included educational history, research experience, a 750-word personal statement, and one faculty recommendation. A review panel scored each application using a 1–5 scale across four domains: academic achievement, technical skills, research experience, and recommendation strength. Top-ranked applicants were offered AI-READI–funded internship positions (6 in Year 1; 5 in Year 2). Additional high-scoring candidates were invited to participate in the AI-READI Bootcamp as non-funded participants (11 in Year 1; 2 in Year 2).

Bootcamp Structure and Educational Objectives

The AI-READI Bootcamp was designed as a two-week, immersive, in-person educational experience hosted annually at the UC San Diego. It served as both a foundational training program and the launchpad for a yearlong mentored research internship. The bootcamp emphasized collaborative, application-oriented learning tailored to participants with diverse disciplinary backgrounds and varying degrees of technical preparedness.

Educational objectives included:

- Establishing proficiency in core programming workflows using Python, Jupyter notebooks, and GitHub.
- Introducing foundational principles of machine learning, including supervised and unsupervised techniques.
- Providing applied experience through structured coding labs using multimodal, domain-relevant biomedical datasets.
- Promoting reproducible and ethical research practices.
- Fostering interdisciplinary collaboration, critical thinking, and cohort cohesion.

The curriculum was designed to engage multiple domains of Bloom's taxonomy[15], blending didactic instruction to build knowledge (cognitive), applied coding to develop technical skills (psychomotor), and ethics discussions to foster responsible AI use (affective).

Participants engaged in 80 hours of lectures, coding tutorials, and small-group mentorship sessions. Dormitory housing was provided to facilitate peer learning, collaborative debugging, and informal knowledge exchange. Instruction was delivered by a multidisciplinary faculty team with expertise in computer science, data science, medicine, public health, and ethics. Curriculum content was iteratively refined between cohorts based on post-bootcamp feedback (see Results).

Participant Characteristics and Baseline Data Collection

Prior to the bootcamp, all participants completed a standardized intake form capturing demographic and educational data. Collected variables included age, gender, highest degree attained, primary discipline, prior experience with programming languages (e.g., Python, R, SQL), and self-reported exposure to AI and machine learning. These data informed real-time instructional decisions and helped the teaching team tailor lab groupings, pacing, and mentorship to each cohort's skill profile.

Post-Bootcamp Survey and Feedback Analysis
At the conclusion of the bootcamp, participants were invited to complete an evaluation survey designed to assess both instructional quality and overall experience. The survey included:

- Quantitative items: Seven core statements rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), addressing the usefulness of lectures, quality of facilities, instructor effectiveness, alignment with expectations, support from staff, organizational quality, and overall enjoyment.
- Qualitative items: Open-ended prompts invited feedback on the most and least valuable components of the bootcamp, suggestions for improvement, and logistical considerations (e.g., scheduling, pacing, housing).

Survey responses were collected anonymously. Quantitative data were analyzed using descriptive statistics. Qualitative responses were reviewed independently by two coders using thematic analysis. Emerging themes were compared, and discrepancies in coding were resolved through discussion. Resulting insights were used to iteratively refine curriculum content, pacing, and instructional methods between years.

RESULTS

Participant Characteristics
A total of 17 trainees participated in Year 1 of the AI-READI Bootcamp and 7 in Year 2. As shown in Table 1, participants represented a diverse range of academic and disciplinary backgrounds, including ophthalmology, public health, pharmacology, neuroscience, engineering, and computer science. Educational attainment and programming experience varied widely, reflecting the bootcamp's deliberate design to attract learners with strong quantitative potential regardless of formal coding background.

Table 1. Participant Characteristics of Bootcamp Cohorts

Characteristic	Year 1 (N=17)	Year 2 (N=7)
Age, mean (years)	33	32
Race, n (%)		
Asian	8 (47.1%)	3 (42.9%)
African American	3 (17.6%)	2 (28.6%)
White	4 (23.5%)	1 (14.3%)

Other	2 (11.8%)	0 (0%)
Sex, n (%)		
Male	9 (52.9%)	2 (28.6%)
Female	8 (47.1%)	5 (71.4%)
Highest degree, n (%)		
PhD/MD	15 (88.2%)	4 (57.1%)
MA/MS/MPH	2 (11.8%)	1 (14.3%)
BA/BS	0 (0%)	2 (28.6%)
Funding, n (%)		
AI-READI–funded	6 (35.3%)	5 (71.4%)
Non-AI-READI–funded	11 (64.7%)	2 (28.6%)
Disciplinary background, n (%)		
Ophthalmology	12 (70.6%)	1 (14.3%)
Public Health	1 (5.9%)	1 (14.3%)
Pharmacology	1 (5.9%)	1 (14.3%)
Neuroscience	1 (5.9%)	0 (0%)
Engineering	1 (5.9%)	0 (0%)
Biochemistry	1 (5.9)	0 (0%)
Behavioral Science	0 (0%)	1 (14.3%)
Computer Engineering	0 (0%)	1 (14.3%)
Medicine	0 (0%)	1 (14.3%)
Molecular Biology	0 (0%)	1 (14.3%)
Familiarity with programming language, n (%)		
Python	3 (27.3%)	4 (57.1%)
R	5 (45.5%)	4 (57.1%)
SQL	1 (9.1%)	2 (28.6%)
JAVA	0 (0%)	1 (14.3%)
MATLAB	2 (18.2%)	1 (14.3%)
Julia	0 (0%)	1 (14.3%)
C	0 (0%)	1 (14.3%)
C++	3 (27.3%)	1 (14.3%)

Survey Feedback and Satisfaction Outcomes

Post-bootcamp surveys were completed by 13 of 17 Year 1 participants (76%) and 4 of 7 Year 2 participants (57%). Mean quantitative scores were strong across both years, with improvements observed in Year 2 (Table 2). Year 2 respondents gave perfect average scores (5.00) in three key categories: instructor effectiveness, staff support, and overall enjoyment. Other items—including lecture usefulness, organizational quality, educational alignment, and facility adequacy—received scores ranging from 4.50 to 4.75, with no metric falling below a 4.0 average.

Table 2. Post-Bootcamp Evaluation: Comparison of Year 1 and Year 2

Item	Year 1 (n=13)	Year 2 (n=4)

	Avg.	Min	Max	Avg.	Min	Max
The lectures were helpful to my learning and development	4.46	2.00	5.00	4.75	4.00	5.00
The bootcamp facility was in an accessible location and adequate	4.46	2.00	5.00	4.75	4.00	5.00
The instructors helped me understand the subject matter	4.31	1.00	5.00	5.00	5.00	5.00
The bootcamp met my educational needs and expectations	4.31	1.00	5.00	4.75	4.00	5.00
I had adequate support from the program staff and faculty	4.46	1.00	5.00	5.00	5.00	5.00
The bootcamp was well organized	4.23	1.00	5.00	4.50	4.00	5.00
I enjoyed the bootcamp overall	4.46	2.00	5.00	5.00	5.00	5.00

Qualitative feedback from Year 1 identified several key areas for improvement. Trainees appreciated the conceptual depth of lectures but expressed a desire for more applied content aligned with their anticipated research tasks. Some noted that the larger cohort size made coding labs difficult to manage, and many requested smaller groups to facilitate individualized troubleshooting. The hands-on labs and mentorship—both from faculty and peers—were consistently described as the most valuable aspects of the program. Trainees also highlighted the social benefits of shared housing and peer interaction in fostering collaboration and a sense of community.

The redesigned Year 2 curriculum addressed many of these concerns. Qualitative responses emphasized the value of earlier integration of the AI-READI dataset, greater alignment between instructional content and research projects, and the strength of peer collaboration. Participants noted that receiving more materials and agendas in advance would have further improved their preparation, particularly for more technical content. Several interns described the bootcamp as an effective foundation for their upcoming research, boosting both confidence and competence.

Together, these findings support the bootcamp's iterative design and affirm that refinements in Year 2 enhanced learner experience while preserving core strengths in applied instruction, mentorship, and interdisciplinary collaboration.

Curriculum Iteration Across Cohorts

The instructional team implemented a series of structural and pedagogical updates between Year 1 and Year 2 based on survey findings and debriefing sessions. Most notably, the Year 2 cohort size was reduced to increase instructional support, achieving a faculty-to-student ratio of approximately 1:2. Version control (Git/GitHub) and environment setup were moved earlier in the curriculum to establish reproducibility practices from the outset. Structured, domain-relevant data from the AI-READI project was incorporated longitudinally throughout the bootcamp, allowing trainees to work directly with multimodal variables—including color fundus photographs and clinical metadata—mirroring the complexity of biomedical research workflows.

New content was also introduced to reflect evolving learner needs and faculty expertise. Mini-seminars on FAIR data principles, AI-READI schema design, and agile project management were added to help trainees navigate the practical considerations of working with large-scale biomedical datasets. A dedicated half-day session on large language models (LLMs) introduced transformer architectures and prompted discussion about the potential and limitations of generative AI in healthcare. The Year 2 capstone project involved fine-tuning RETFound, a retina-specific foundation model for institutional classification of retinal images, sparking critical conversations around domain generalizability and site-specific bias. A summary of key updates is provided in Table 3.

Table 3. Iterative Curriculum Development: Year 1 to Year 2

Dimension	Year 1 Focus	Year 2 Iteration & Rationale
Programming Foundations	Introduced Python and Jupyter via guided exercises	Emphasized Pandas and real-world data operations to support more independent analysis
Tools & Environment	Introduced GitHub and IDEs for version control	Moved these to earlier sessions to promote reproducibility from the start
Machine Learning (ML) Concepts	Covered regression, SoftMax, convolutional neural networks (CNNs), and backpropagation	Added large language models (LLMs) and expanded gradient descent labs for deeper understanding
Data Science Techniques	Principal component analysis (PCA) on	Expanded with exploratory data analysis (EDA), digital

	face images, K-means, spectral clustering	signal processing (DSP), and feature extraction using biomedical data
Applied Learning	Face clustering lab, glucose lab	Shifted to retinal image analysis to integrate clinical relevance earlier
Ethics & Fairness	Discussed racial bias in pain expression	Broadened to data pitfalls and fairness across AI pipelines
Clinical Integration	Minimal use of clinical data	Directly used clinical variables and retinal images from the AI-READI database for hands-on ML
Student Engagement	Lunch talks and informal discussion	Continued lunch talks, more structured mini-seminars

Detailed Curriculum Content

In Year 1, instruction began with two days of foundational training in Python and Jupyter Notebooks, followed by classical machine learning topics including logistic regression, SoftMax regression, and convolutional neural networks (CNNs). Applied labs included a backpropagation-based “Eigenface” exercise and unsupervised clustering methods—principal component analysis (PCA), K-means, and spectral clustering—applied to facial image datasets. Later sessions introduced Git/GitHub, digital signal processing (DSP), and a glucose modeling lab. The ethics component included a journal club on racial bias in AI and a didactic session on common pitfalls in data science. Informal lunch talks provided a forum for trainees to share their research interests and academic journeys. The complete Year 1 curriculum is presented in Table 4.

In Year 2, curriculum design was explicitly shaped by Year 1 feedback. The program began with 2.5 days of instruction in Python, GitHub, and exploratory data analysis (EDA), followed by machine learning exercises using AI-READI’s handheld fundus images and structured clinical variables. Image processing and DSP modules were expanded to reflect the importance of multimodal feature engineering in biomedical AI. A new half-day module introduced large language models, including transformer architecture fundamentals and interactive case studies. The capstone project, which centered on RETFound fine-tuning, helped participants synthesize technical skills while grappling with issues of domain adaptation and equity in AI deployment. Daily lunch seminars addressed responsible data practices, collaborative research workflows, and data schema interpretation. The full Year 2 curriculum is available in Table 5.

Table 4. Year 1 AI-READI Bootcamp Lecture Breakdown

Day	Session Topics	Format
1	Bootcamp orientation; Introduction to Python, Jupyter notebooks	Lecture + Hands-on Labs
2	Python, IDEs, Jupyter workflows	Lecture + Coding

		Practice
3	Introduction to machine learning, Perceptrons, gradient descent; logistic and SoftMax regression	Lecture + Lab
4	Backpropagation, deep learning fundamentals; representation learning	Lecture + Lab + Discussion
5	Convolutional neural networks	Lecture + Lab
6	GitHub version control; Introduction to pandas	Lecture + Coding Labs
7	Linear algebra review; regression models; regression lab	Lecture + Regression Lab
8	Principal Component Analysis (PCA), face lab, K-means, spectral clustering	Lecture + Lab
9	Clustering lab; discussion on racial bias in data; pitfalls in data science	Lecture + Lab + Ethics Discussion
10	Digital signal processing (DSP); glucose lab; closing reflections	Lecture + Lab + Closing

Table 5. Year 2 AI-READI Bootcamp Lecture Breakdown

Day	Session Topics	Format
1	Introduction to Python, Jupyter, IDEs; GitHub version control	Lecture + Hands-on Labs
2	Python Pandas, joining datasets, exploratory data analysis (EDA)	Lecture + Coding Exercises
3	Correlations, health sheet overview, data visualization	Lecture + Lab
4	Digital Signal Processing (DSP), feature extraction, basic image processing	Lecture + Lab
5	Linear algebra, regression models (linear, nonlinear, ridge, lasso)	Lecture + Regression Lab
6	Principal Component Analysis (PCA), image alignment, introduction to clustering	Lecture + PCA Lab
7	Clustering (K-means), pitfalls in data science	Lecture + Lab + Discussion
8	Machine learning intro, Perceptrons, logistic/SoftMax regression	Lecture + Gradient Descent Lab
9	Backpropagation, deep learning, representation learning, ML best practices	Lecture + Eigenface Lab
10	Convolutional neural networks, introduction to large language models (LLMs)	Lecture + Coding Demos

DISCUSSION

Principal Results and Learner Outcomes

The AI-READI Bootcamp successfully delivered foundational AI/ML education to a multidisciplinary cohort of biomedical trainees, consistently achieving high satisfaction and confidence ratings across two consecutive years. In Year 2, survey scores improved across all domains compared to Year 1. Specifically, mean post-bootcamp ratings rose from a range of 4.23–4.46 (Year 1, n=13) to 4.50–5.00 (Year 2, n=4), with three categories—“instructors’ teaching,” “staff support,” and “overall enjoyment”—receiving perfect 5.00 averages. These results align with Kirkpatrick’s training evaluation model (Levels 1 and 2 outcomes), reflecting strong learner satisfaction and perceived knowledge gains[16]. Qualitative feedback indicated the bootcamp served as an effective foundation for upcoming research, increasing participants’ confidence and competence (Level 3 outcome).

Bridging Disciplinary Divides in AI/ML Education

As artificial intelligence reshapes biomedical research and clinical practice, there is a growing awareness of a skills gap between data scientists and clinicians[17–19]. Engineers may lack clinical context, while physicians often have limited exposure to algorithmic thinking or data analytics. This gap can limit translational innovation and undermine interdisciplinary collaboration.

The AI-READI Bootcamp was intentionally structured to address this divide. Trainees came from diverse disciplines—including medicine, neuroscience, engineering, public health, and pharmacology—and participated in integrated mentorship from faculty across diverse domains. This model reflects best practices highlighted by existing AI curriculum review[6,12,13] and aligns with collaborative learning approaches commonly used in health professions education—such as interprofessional education and team-based learning—which foster interdisciplinary teamwork and shared problem-solving[20].

Building Engagement Through Iterative Refinement

Curricular refinements between years—most notably the integration of AI-READI datasets, reallocation of lecture time to small-group coding sessions, and a reduced cohort size—were driven by structured participant feedback. While Year 1 feedback emphasized the need for smaller lab groups and more hands-on mentorship, Year 2 participants praised the earlier integration of multimodal biomedical data and the value of peer collaboration.

A central design principle of the bootcamp was anchoring abstract machine learning concepts in domain-specific datasets. Using the AI-READI flagship dataset—including fundus photographs and structured clinical variables—trainees explored topics such as site-level variability and domain shift. This applied approach fostered deeper understanding of the complexities of data-driven healthcare AI and strengthened engagement by connecting technical exercises to relevant biomedical contexts.

These strategies align with educational scholarship promoting experiential learning and authentic data environments[21] and reflect evidence that short-format programs can be highly effective when they provide feedback loops, applied learning, and targeted mentorship.

Situating the Bootcamp in the National AI Training Ecosystem

The AI-READI Bootcamp contributes to a growing ecosystem of NIH-supported efforts aimed at expanding the biomedical AI/ML workforce. As part of the Bridge2AI program, AI-READI joins other Data Generation Projects (DGPs) such as VOICE, which has hosted AI summer schools and hackathons focused on precision public health, and Collaborative Hospital Repository Uniting Standards (CHoRUS), which offers CME-accredited single day clinical AI workshops covering dataset curation, pair programming, and mentored labs[10].

Beyond Bridge2AI, the AIM-AHEAD Consortium has established part-time fellowships, faculty development programs, and mentored research opportunities designed to expand AI capacity across graduate students, healthcare professionals, and non-academic communities[22]. These offerings are typically designed to be completed alongside other roles and emphasize flexibility and accessibility.

In addition to these national efforts, several academic institutions have developed innovative models for AI education[13]. At Stanford, students work in interdisciplinary teams to apply machine learning to clinical problems. The Duke Institute for Health Innovation matches medical trainees with data scientists to co-develop AI tools. The University of Florida has established academic–industry partnerships to create AI-driven diagnostic technologies, while the Carle Illinois College of Medicine offers courses co-taught by clinicians and engineers that integrate AI into the medical curriculum. These efforts reflect the increasing institutional commitment to incorporating AI into health professions education. However, many of these institutional programs are structured as electives, departmental initiatives, or short-term engagements.

Extending Learning Through Longitudinal Mentorship

In contrast, the AI-READI Bootcamp is embedded in a yearlong, full-time mentored research internship. Immediately following the bootcamp, trainees join interdisciplinary teams working on projects in ophthalmic imaging, wearable sensors, health disparities, and other domains. This scaffolded, project-based model supports skill retention, deeper engagement, and peer learning through collaborative debugging, shared housing, and group presentations—practices shown to enhance confidence and performance in technical training[23]. Unlike many existing AI training programs, which are often short-term, lecture-based, and primarily evaluated through learner satisfaction, AI-READI offers close mentorship, applied learning, and sustained research involvement.

Together, these national and institutional efforts reflect a growing consensus that AI/ML education must be interdisciplinary and grounded in applied data contexts. The AI-READI Bootcamp complements and extends this evolving landscape by offering a scalable, high-impact approach to cultivating a diverse and capable biomedical AI workforce.

Lessons Learned and Recommendations

Our experience designing and refining the AI-READI Bootcamp suggests several important lessons for future initiatives. Modular, scaffolded content enables learners with varying backgrounds to progress in parallel. The use of curated, domain-relevant datasets grounds abstract concepts in applied contexts, fostering deeper engagement. Participants valued the theoretical framing but reported that they learned most effectively through practical, hands-on components, suggesting future bootcamps should emphasize applied coding while keeping lectures concise and focused.

Equally important are the program's structural features. Maintaining a low faculty-to-student ratio supports real-time troubleshooting and individualized feedback. Embedding bootcamps into longitudinal research structures promotes meaningful skill transfer and project ownership. Structured and informal peer support—through shared housing, collaborative debugging, and group presentations—strengthens technical skills, enhances problem-solving, and builds lasting professional networks. These practices align with curriculum frameworks emphasizing structure, assessment, real-world alignment, and longitudinal mentorship[6,11–13].

Limitations and Future Directions

This study is limited by its single-site implementation and small sample size (Year 1: n=17; Year 2: n=7), which may affect generalizability. The Year 2 post-bootcamp ratings, while high, are based on only four respondents. Self-reported metrics also introduce potential bias, and the absence of objective skills assessments limits our ability to measure knowledge retention and performance gains directly.

To address these gaps, future iterations will incorporate pre- and post-bootcamp assessments aligned with Kirkpatrick Level 2 outcomes and explore longitudinal tracking of trainee outputs such as publications, presentations, and subsequent AI-related research involvement. In the future, we also plan to place additional emphasis on pre-bootcamp onboarding module (Table 6) with diagnostic tools, curated readings, and practice exercises to enhance baseline preparedness and maximize in-person learning time.

By systematically refining the curriculum, expanding delivery formats, and strengthening evaluation, the AI-READI Bootcamp can continue to serve as a scalable, high-impact model for preparing a diverse, interdisciplinary workforce to advance biomedical AI/ML research. To support transparency and adoption, we have provided full access to all bootcamp materials, readings, and onboarding instructions via the AI-READI Bootcamp GitHub repository (Table 6).

Table 6. Pre-Bootcamp Onboarding Module and Recommended Readings

Category	Resource	Details / Access
Core Online Text	*Dive into Deep Learning* (D2L)	https://d2l.ai/

Bootcamp GitHub Repository	AI-READI Bootcamp GitHub	https://github.com/voytek/AI-READI-Bootcamp
Readings	Berisha et al., *Digital medicine and the curse of dimensionality*, npj Digital Medicine 2021	Available on Bootcamp GitHub Readings page
	Bishop, *Pattern Recognition and Machine Learning* (2006)	Chapter 1; intro to Ch. 9 & section 9.1; intro to Ch. 12 & section 12.1; Appendix C
	Ezer & Whitaker, *Data science for the scientific life cycle*, eLife 2019	Available on Bootcamp GitHub Readings page
	Obermeyer et al., *Dissecting racial bias in an algorithm used to manage the health of populations*, Science 2019	Available on Bootcamp GitHub Readings page
	Rumelhart, Hinton, Williams, Ch. 8 in *Parallel Distributed Processing: Explorations in the Microstructure of Cognition: Foundations*, 1987	Available on Bootcamp GitHub Readings page
	Strang, Ch. 6 in *Introduction to Linear Algebra*, 2016	Also see YouTube lectures
	Wilkinson et al., *The FAIR Guiding Principles*	Available on Bootcamp GitHub Readings page

	for scientific data management and stewardship, Scientific Data 2016	
	Zou & Schiebinger, *Design AI so that it's fair*, Nature 2018	Available on Bootcamp GitHub Readings page
Helpful Links	Introduction to Python	Available on Bootcamp GitHub Readings page
	Git terminology	Available on Bootcamp GitHub Readings page
	Setting up Git	Available on Bootcamp GitHub Readings page

ACKNOWLEDGEMENTS

We thank the faculty instructors, teaching assistants, and administrative staff at UC San Diego for their invaluable contributions to the planning and delivery of the AI-READI Bootcamp. We also thank the AI-READI interns for their active participation and constructive feedback, which directly informed improvements to the Year 2 curriculum.

This work was supported by the National Institutes of Health (NIH) through the Bridge2AI program under award number [OT2OD032644]. The views expressed in this manuscript are those of the authors and do not necessarily represent the official views of the NIH.

CONFLICTS OF INTEREST

No conflicts of interest to report.

DATA AVAILABILITY

The post-bootcamp evaluation data (quantitative survey responses and deidentified qualitative feedback) are available from the corresponding author upon reasonable request. These data are not publicly posted to preserve participant confidentiality.

AUTHOR CONTRIBUTIONS

Conceptualization: SLB (lead), TWN, FGPK, AE, AM, PMK, DG, VP, LMZ

Data curation: TWN, AE, AM, PMK, DG, VP
Formal analysis: TWN, AE, AM, PMK, DG, VP
Methodology: TWN, AE, AM, PMK, DG, VP, SH, AP, SLB, LMZ, GC, BV, VRdS
Supervision: SLB
Writing – original draft: TWN (lead), FGPK, AE, AM, PMK, DG
Writing – review & editing: TWN (lead), FGPK, AE, AM, PMK, DG, VP, SH, AP, SLB, LMZ, GC, BV, VRdS

ABBREVIATIONS

Abbreviation	Definition
AI	Artificial Intelligence
ML	Machine Learning
AI-READI	Artificial Intelligence–Ready and Exploratory Atlas for Diabetes Insights
CNN	Convolutional Neural Network
PCA	Principal Component Analysis
EDA	Exploratory Data Analysis
DSP	Digital Signal Processing
LLM	Large Language Model
FAIR	Findable, Accessible, Interoperable, and Reusable
MOOC	Massive Open Online Course

REFERENCES

1. Gulshan V, Peng L, Coram M, et al. Development and Validation of a Deep

Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. *JAMA*. 2016;316(22):2402. doi:10.1001/jama.2016.17216

2. Faruqui SHA, Du Y, Meka R, et al. Development of a Deep Learning Model for Dynamic Forecasting of Blood Glucose Level for Type 2 Diabetes Mellitus: Secondary Analysis of a Randomized Controlled Trial. *JMIR MHealth UHealth*. 2019;7(11):e14452. doi:10.2196/14452

3. Schwartz JM, Moy AJ, Rossetti SC, Elhadad N, Cato KD. Clinician involvement in research on machine learning-based predictive clinical decision support for the hospital setting: A scoping review. *J Am Med Inform Assoc JAMIA*. 2021;28(3):653-663. doi:10.1093/jamia/ocaa296

4. Scheetz J, Rothschild P, McGuinness M, et al. A survey of clinicians on the use of artificial intelligence in ophthalmology, dermatology, radiology and radiation oncology. *Sci Rep*. 2021;11(1):5193. doi:10.1038/s41598-021-84698-5

5. Chen S, Yu J, Chamouni S, Wang Y, Li Y. Integrating machine learning and artificial intelligence in life-course epidemiology: pathways to innovative public health solutions. *BMC Med*. 2024;22(1):354. doi:10.1186/s12916-024-03566-x

6. Valikodath NG, Cole E, Ting DSW, et al. Impact of Artificial Intelligence on Medical Education in Ophthalmology. *Transl Vis Sci Technol*. 2021;10(7):14. doi:10.1167/tvst.10.7.14

7. Armoundas AA, Narayan SM, Arnett DK, et al. Use of Artificial Intelligence in Improving Outcomes in Heart Disease: A Scientific Statement From the American Heart Association. *Circulation*. 2024;149(14). doi:10.1161/CIR.0000000000001201

8. AI-READI Consortium, Writing Committee, Baxter SL, et al. AI-READI: rethinking AI data collection, preparation and sharing in diabetes research and beyond. *Nat Metab*. 2024;6(12):2210-2212. doi:10.1038/s42255-024-01165-x

9. AI-READI Consortium. Flagship Dataset of Type 2 Diabetes from the AI-READI Project. Published online 2024:2.01 TB, 165,051 files. doi:10.60775/FAIRHUB.2

10. Bridge to Artificial Intelligence (Bridge2AI) | NIH Common Fund. Accessed August 8, 2025. https://commonfund.nih.gov/bridge2ai

11. Charow R, Jeyakumar T, Younus S, et al. Artificial Intelligence Education Programs for Health Care Professionals: Scoping Review. *JMIR Med Educ*. 2021;7(4):e31043. doi:10.2196/31043

12. Tolentino R, Baradaran A, Gore G, Pluye P, Abbasgholizadeh-Rahimi S. Curriculum Frameworks and Educational Programs in AI for Medical Students, Residents, and Practicing Physicians: Scoping Review. *JMIR Med Educ*.

2024;10:e54793. doi:10.2196/54793

13. Mir MM, Mir GM, Raina NT, et al. Application of Artificial Intelligence in Medical Education: Current Scenario and Future Perspectives. *J Adv Med Educ Prof*. 2023;11(3). doi:10.30476/jamp.2023.98655.1803

14. Global Forum on Innovation in Health Professional Education, Board on Global Health, Health and Medicine Division, National Academies of Sciences, Engineering, and Medicine. *Artificial Intelligence in Health Professions Education: Proceedings of a Workshop*. (Cuff PA, Forstag EH, eds.). National Academies Press; 2023:27174. doi:10.17226/27174

15. Orgill BD, Nolin J. Learning Taxonomies in Medical Simulation. In: *StatPearls*. StatPearls Publishing; 2025. Accessed August 8, 2025. http://www.ncbi.nlm.nih.gov/books/NBK559109/

16. Heydari MR, Taghva F, Amini M, Delavari S. Using Kirkpatrick's model to measure the effect of a new teaching and learning methods workshop for health care staff. *BMC Res Notes*. 2019;12(1):388. doi:10.1186/s13104-019-4421-y

17. Chen JH, Asch SM. Machine Learning and Prediction in Medicine — Beyond the Peak of Inflated Expectations. *N Engl J Med*. 2017;376(26):2507-2509. doi:10.1056/NEJMp1702071

18. Wartman SA, Combs CD. Medical Education Must Move From the Information Age to the Age of Artificial Intelligence. *Acad Med*. 2018;93(8):1107-1109. doi:10.1097/ACM.0000000000002044

19. Mesko B. The role of artificial intelligence in precision medicine. *Expert Rev Precis Med Drug Dev*. 2017;2(5):239-241. doi:10.1080/23808993.2017.1380516

20. Haidet P, Kubitz K, McCormack WT. Analysis of the Team-Based Learning Literature: TBL Comes of Age. *J Excell Coll Teach*. 2014;25(3-4):303-333.

21. Kjelvik MK, Schultheis EH. Getting Messy with Authentic Data: Exploring the Potential of Using Data from Scientific Research to Support Student Data Literacy. Gardner S, ed. *CBE—Life Sci Educ*. 2019;18(2):es2. doi:10.1187/cbe.18-02-0023

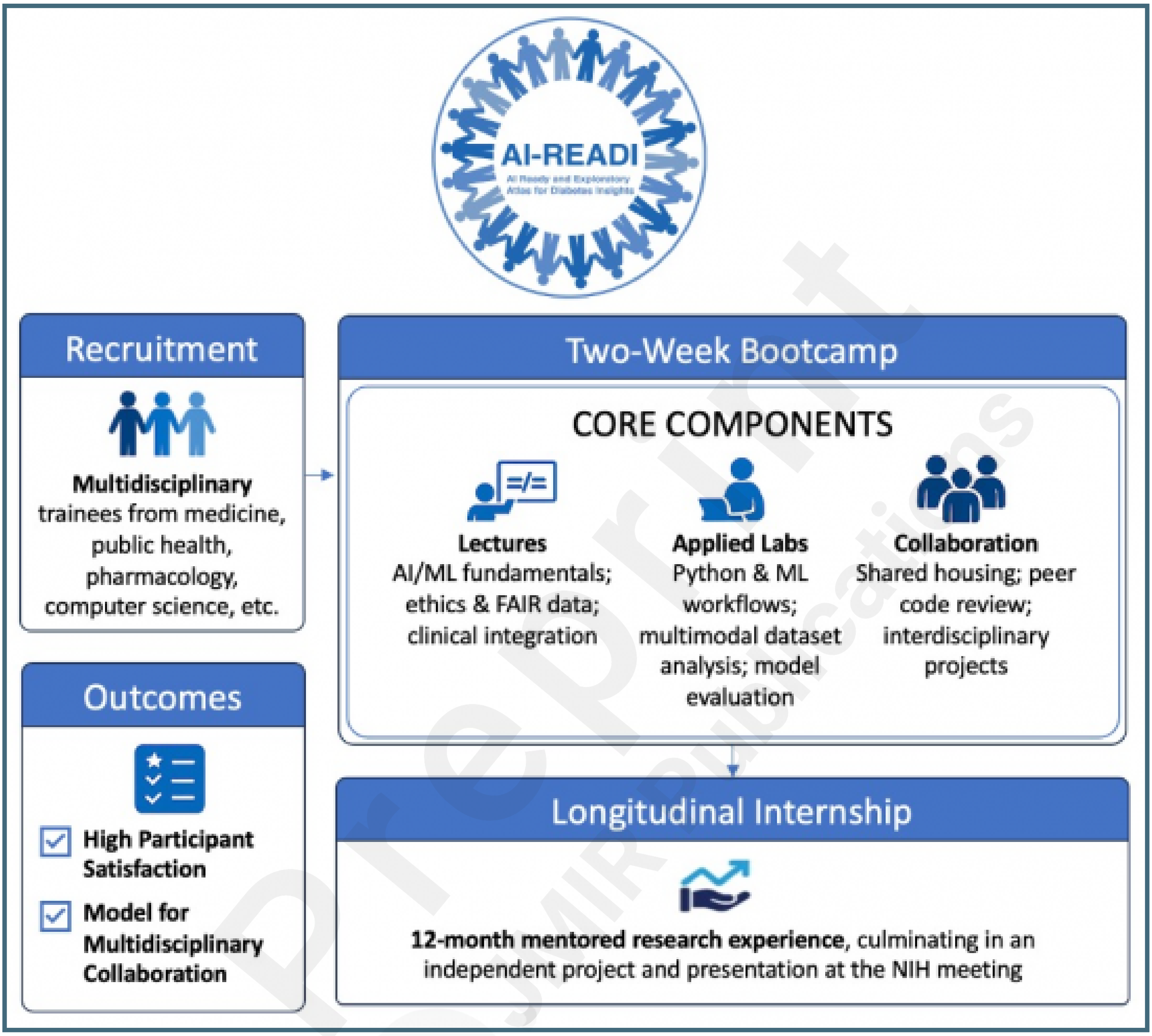
22. AIM-AHEAD Programs. https://www.aim-ahead.net/programs/

23. Bonnie LHA, Cremers GR, Nasori M, Kramer AWM, Van Dijk N. Longitudinal training models for entrusting students with independent patient care?: A systematic review. *Med Educ*. 2022;56(2):159-169. doi:10.1111/medu.14607

Supplementary Files

Figures

Untitled.


AI-READI
AI Ready and Exploratory Atlas for Diabetes Insights
Recruitment
Multidisciplinary trainees from medicine, public health, pharmacology, computer science, etc.
Two-Week Bootcamp
CORE COMPONENTS
Lectures
AI/ML fundamentals; ethics & FAIR data; clinical integration
Applied Labs
Python & ML workflows; multimodal dataset analysis; model evaluation
Collaboration
Shared housing; peer code review; interdisciplinary projects
Outcomes
High Participant Satisfaction
Model for Multidisciplinary Collaboration
Longitudinal Internship
12-month mentored research experience, culminating in an independent project and presentation at the NIH meeting