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Tomorrow's Doctors, Tomorrow's Cures®

Learn
Serve
Lead

Building AI Partnerships Across Medicine, Industry, and Government

Sept. 24, 2024

Association of American Medical Colleges

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Harvard Data Science Initiative

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Building AI Partnerships Across Medicine, Industry, and Government

Jamie Fairclough, PhD, MPH, MS
Associate Dean for Research, Assessment, & Evaluation
Data Science & Engineering Unit Director
Roseman University of Health Sciences | College of Medicine

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American Medical Colleges

Why Establish AI Partnerships?

1. **Accelerate Innovation** in medical imaging and diagnostics, clinical decision support systems, drug discovery, and personalized care.
2. **Leverage Resources** from diverse sectors to enhance teaching and learning, research, and clinical outcomes.
3. **Improve Patient Care and Population Health Outcomes** by integrating AI into healthcare systems and public health initiatives.

Benefits of AI Collaborations

- **Enhanced Research Capacity:** Access to AI tools and datasets for cutting-edge research.
- **Interdisciplinary Education:** Train future healthcare leaders in AI and data science techniques.
- **AI-Driven Solutions:** Create AI products validated through clinical trials and research.
- **Expansion:** Partner with other academic institutions and government agencies to increase capacity.
- **Public Health Impact:** Enhance disease surveillance, epidemiology, and healthcare access.

Roseman University of Health Sciences -- College of Medicine

- **Mission:** To align students, educators, and the community in designing and delivering an inclusive and collaborative environment for innovative learning, healthcare, and research.
- RUCOM Location: Las Vegas, NV
- Private | Nonprofit | Startup Medical School

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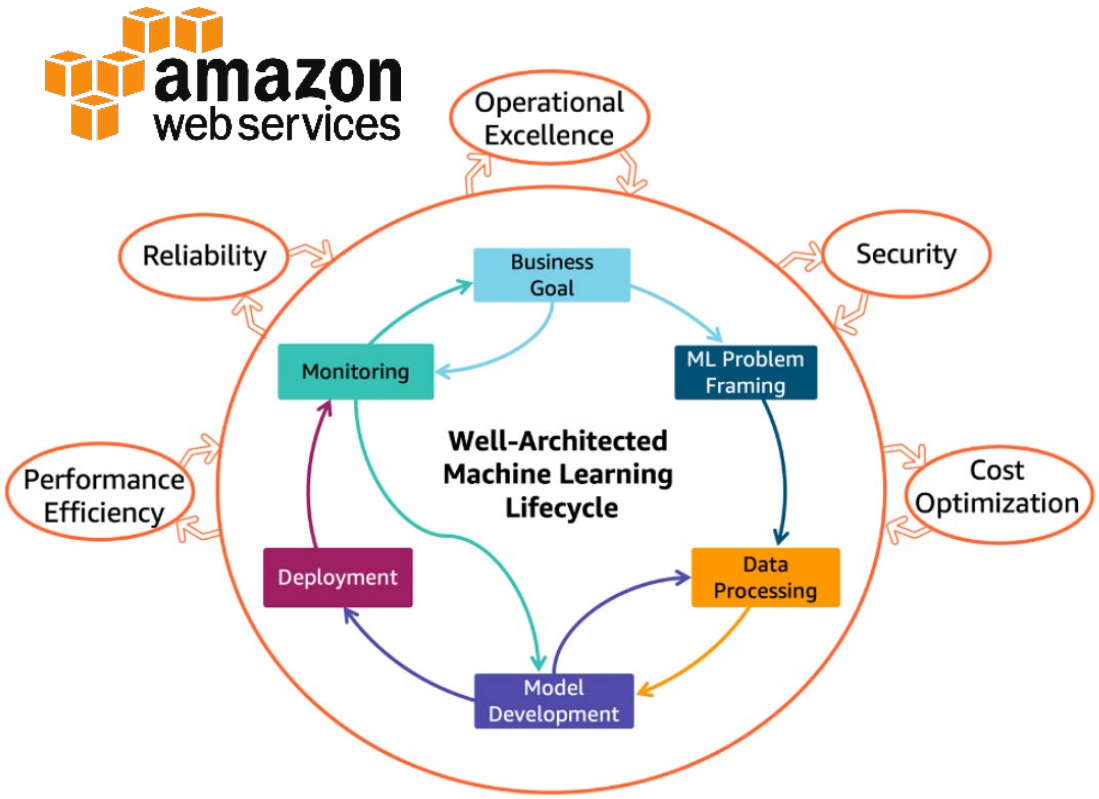
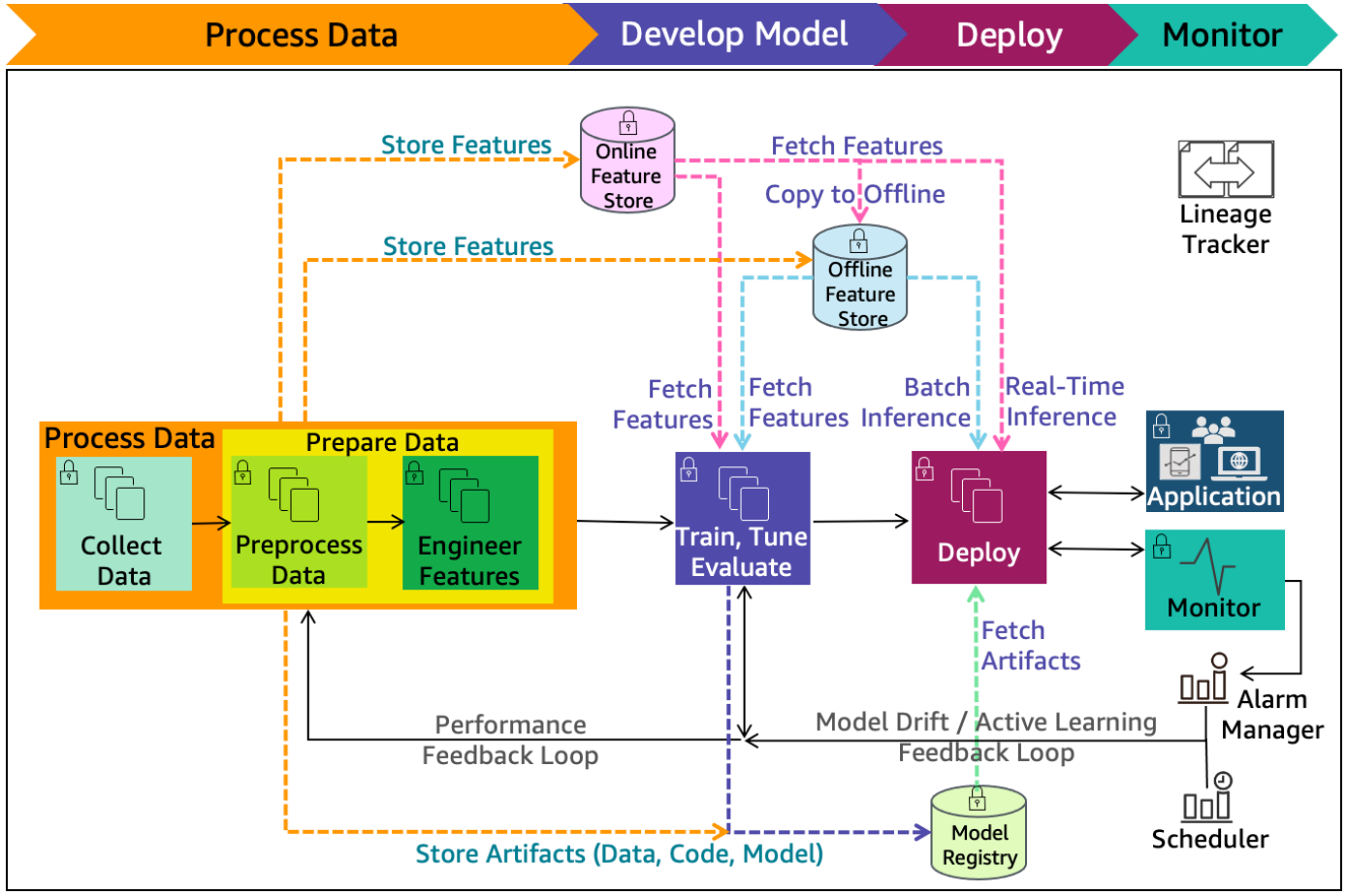
RUCOM Cloud Provider: Amazon Web Services (AWS)





https://docs.aws.amazon.com/wellarchitected/latest/machine-learning-lens/well-architected-machine-learning-lifecycle.html

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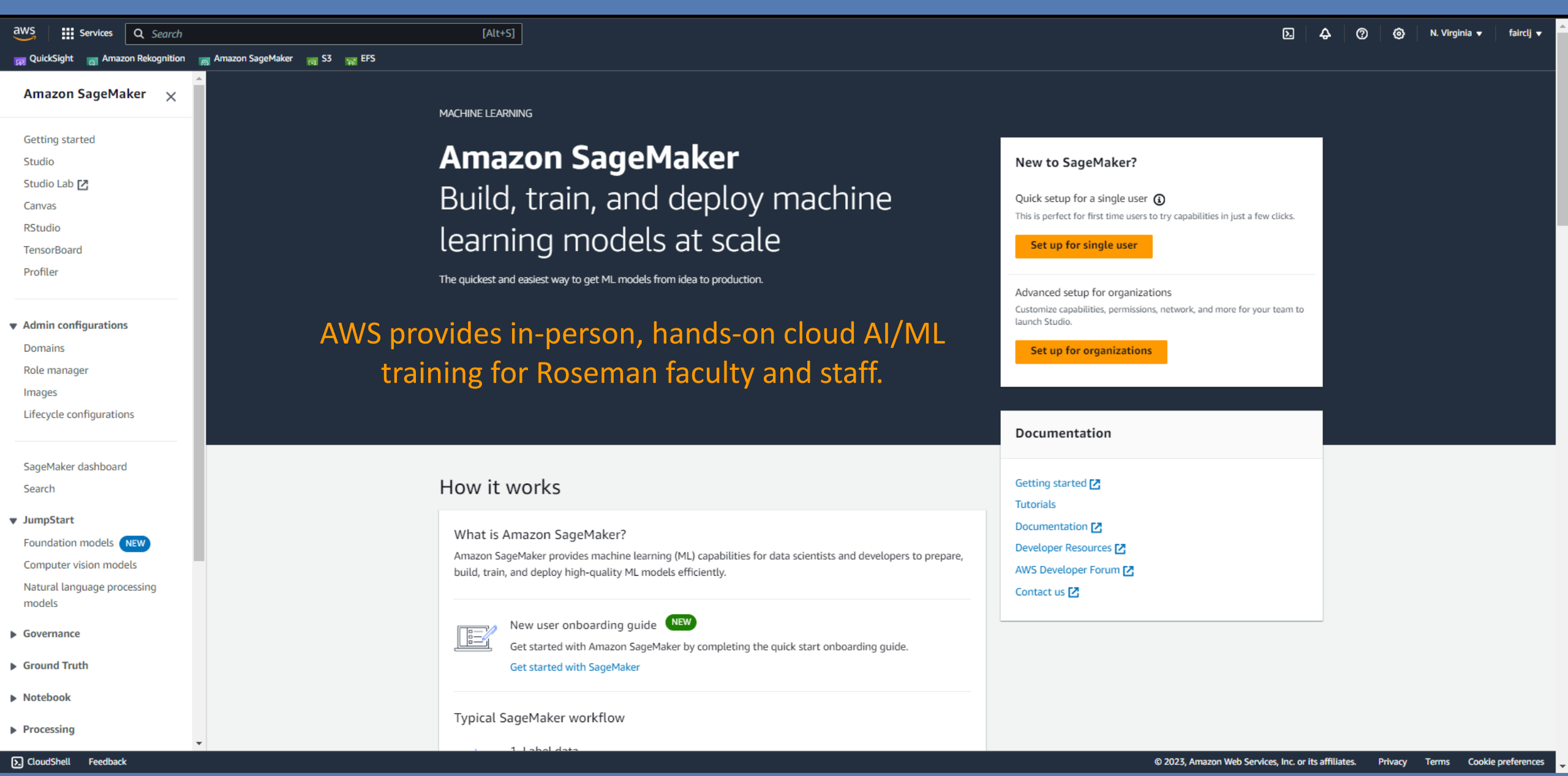

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Ready-to-use models

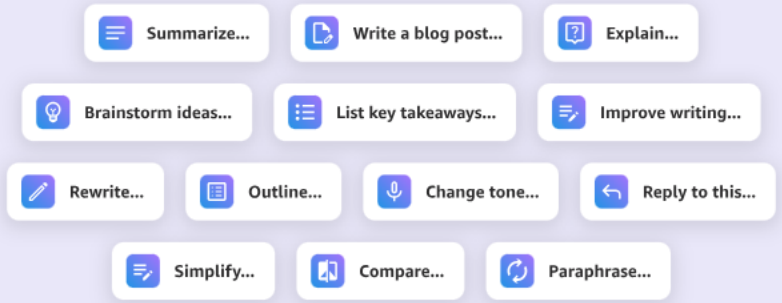
You must have the necessary permissions to make predictions with Ready-to-use models. Go to the SageMaker Console to enable permissions for this account if this hasn't been done already. If you don't have access to the SageMaker Console, contact your administrator. Learn more

New!

Accelerate your productivity using generative AI

Content generation, extraction, summarization, and many more tasks are easier to perform using foundation models from Amazon Bedrock and publicly available models from Amazon SageMaker JumpStart.

Get started now



Search use case

Last used | Grid | List

Can't find the right model? Create a custom model

Generative AI using foundation models

Our content generation models can help you craft engaging narratives, articles, answer questions, and more, tailored to your needs.

Generate, extract and summarize content + Query documents New

Powered by Amazon Bedrock and Amazon SageMaker JumpStart

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Ready-to-use models

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Additional ready-to-use models

Our ready-to-use content extraction models can quickly distill insights from text, image, and document data.

Filter by data type: Text | Image | Document

Object detection in images

Detect objects, concepts, scenes, and actions in your images.

Powered by Amazon Rekognition

Document queries

Extract information from structured documents such as paystubs, bank statements, W-2s, and mortgage application forms by asking questions using natural language.

Powered by Amazon Textract

Sentiment analysis

Detect sentiment in lines of text, which can be positive, negative, neutral, or mixed.

Powered by Amazon Comprehend

Entities extraction

Extract entities, which are real-world objects such as people, places, and commercial items, or units such as dates and quantities, from text.

Powered by Amazon Comprehend

Language detection

Determine the dominant language in text such as English, French or German.

Powered by Amazon Comprehend

Personal information detection

Detect personal information that could be used to identify an individual, such as addresses, bank account numbers, and phone numbers, from text.

Powered by Amazon Comprehend

Text detection in images

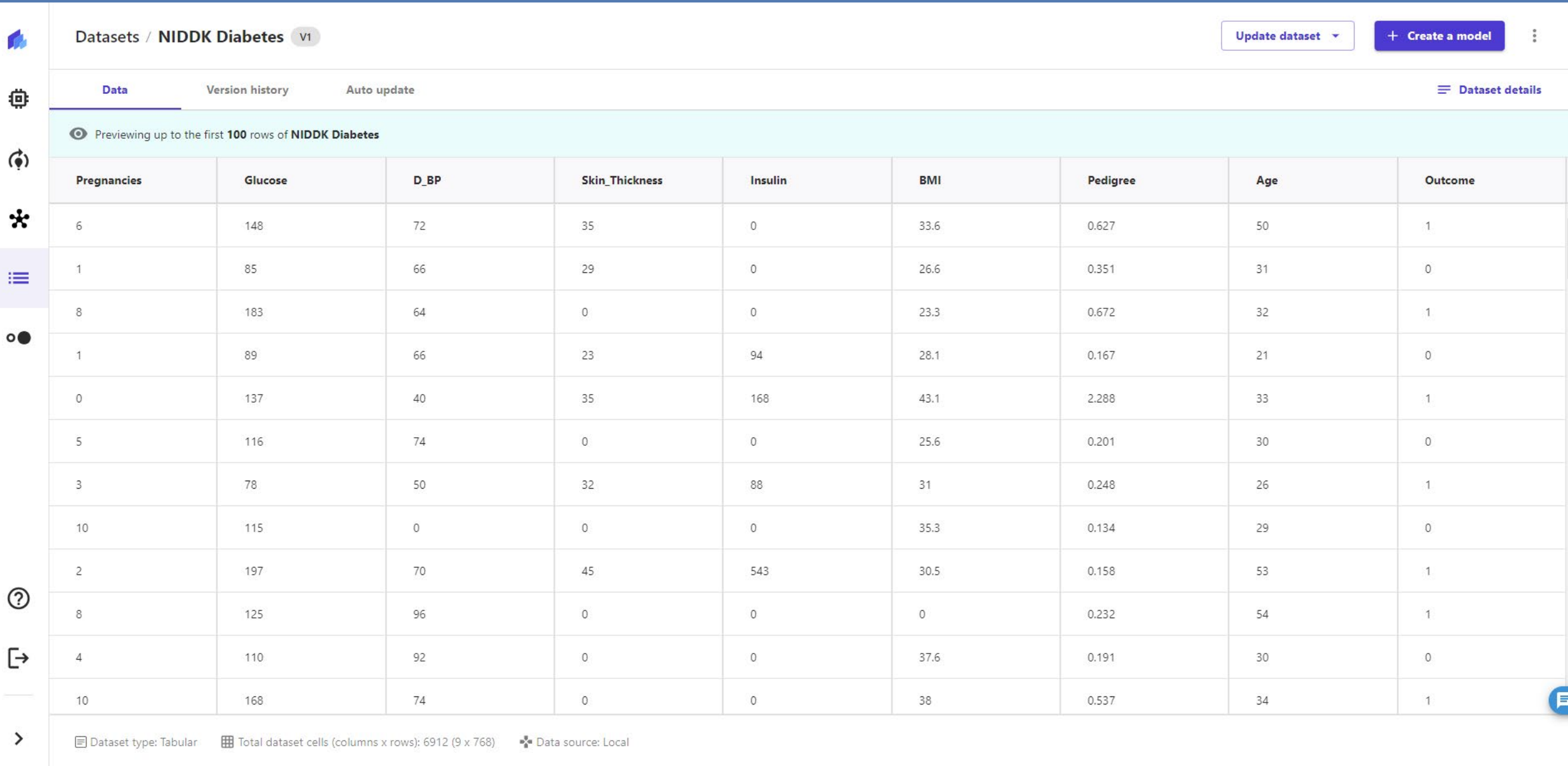
Detect text in your images.

Powered by Amazon Rekognition

Expense analysis

Extract information from invoices and receipts, such as date, number, item prices, total amount, and payment terms.

Powered by Amazon Textract



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Datasets / **NIDDK Diabetes** V1

Update dataset | + Create a model

Data | Version history | Auto update | Dataset details

Previewing up to the first **100** rows of **NIDDK Diabetes**

Pregnancies	Glucose	D_BP	Skin_Thickness	Insulin	BMI	Pedigree	Age	Outcome
6	148	72	35	0	33.6	0.627	50	1
1	85	66	29	0	26.6	0.351	31	0
8	183	64	0	0	23.3	0.672	32	1
1	89	66	23	94	28.1	0.167	21	0
0	137	40	35	168	43.1	2.288	33	1
5	116	74	0	0	25.6	0.201	30	0
3	78	50	32	88	31	0.248	26	1
10	115	0	0	0	35.3	0.134	29	0
2	197	70	45	543	30.5	0.158	53	1
8	125	96	0	0	0	0.232	54	1
4	110	92	0	0	37.6	0.191	30	0
10	168	74	0	0	38	0.537	34	1

Dataset type: Tabular | Total dataset cells (columns x rows): 6912 (9 x 768) | Data source: Local

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My models / NIDDK_Diabetes_Model / **Version 1**

Add version

Select | **Build** | Analyze | Predict | Deploy

No issues have been found in your dataset

Select a column to predict

Choose the target column. The model that you build predicts values for the column that you select.

Target column: Outcome

Value distribution

Model type

SageMaker Canvas automatically recommends the appropriate model type for your analysis.

2 category prediction

Your model classifies Outcome into two categories.

Quick build

Preview model

NIDDK Diabetes

Full dataset: 768 rows

Data visualizer

Column name	Data type	Feature type	Missing	Mismatched	Unique	Mode	Correlation to target	Feature importance
Outcome Target	Numeric	Binary	0.00% (0)	0.00% (0)	2	0	--	--
Glucose	Numeric	-	0.00% (0)	0.00% (0)	136	100	0.467	0.983576
BMI	Numeric	-	0.00% (0)	0.00% (0)	248	32	0.293	0.447098
Age	Numeric	-	0.00% (0)	0.00% (0)	52	22	0.238	0.305223
Pedigree	Numeric	-	0.00% (0)	0.00% (0)	517	0.25	0.174	0.230794
Pregnancies	Numeric	-	0.00% (0)	0.00% (0)	17	1	0.222	0.128893

Total columns: 9 | Total rows: 768 | Total cells: 6,912 | Show dropped columns

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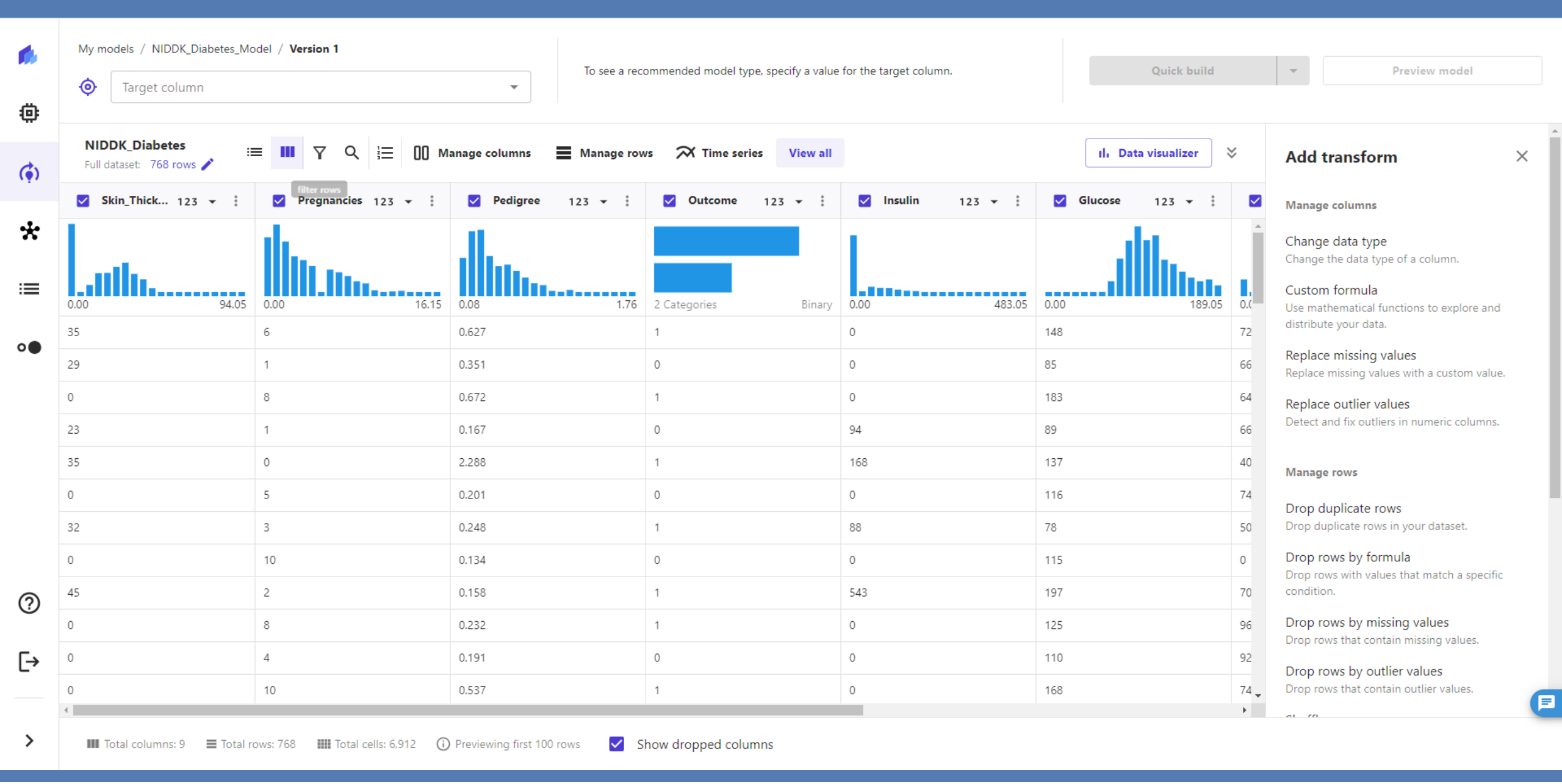
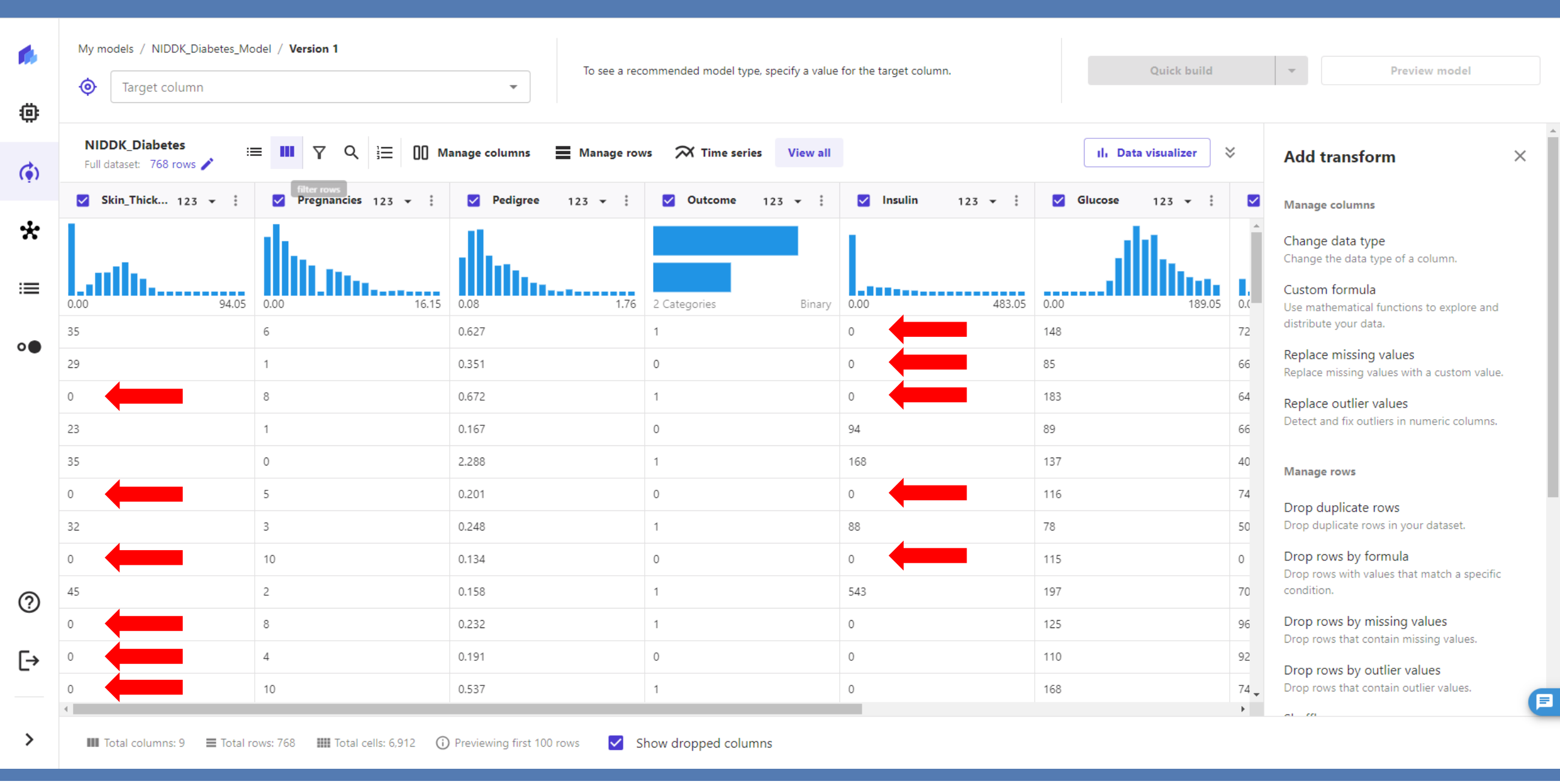




My models / NIDDK_Diabetes_Model / **Version 1**

Add version

Select | Build | **Analyze** | Predict | Deploy

Model status

Accuracy **F1** Optimization metric

87.013% 0.821

The model predicts the correct Outcome 87.013% of the time.

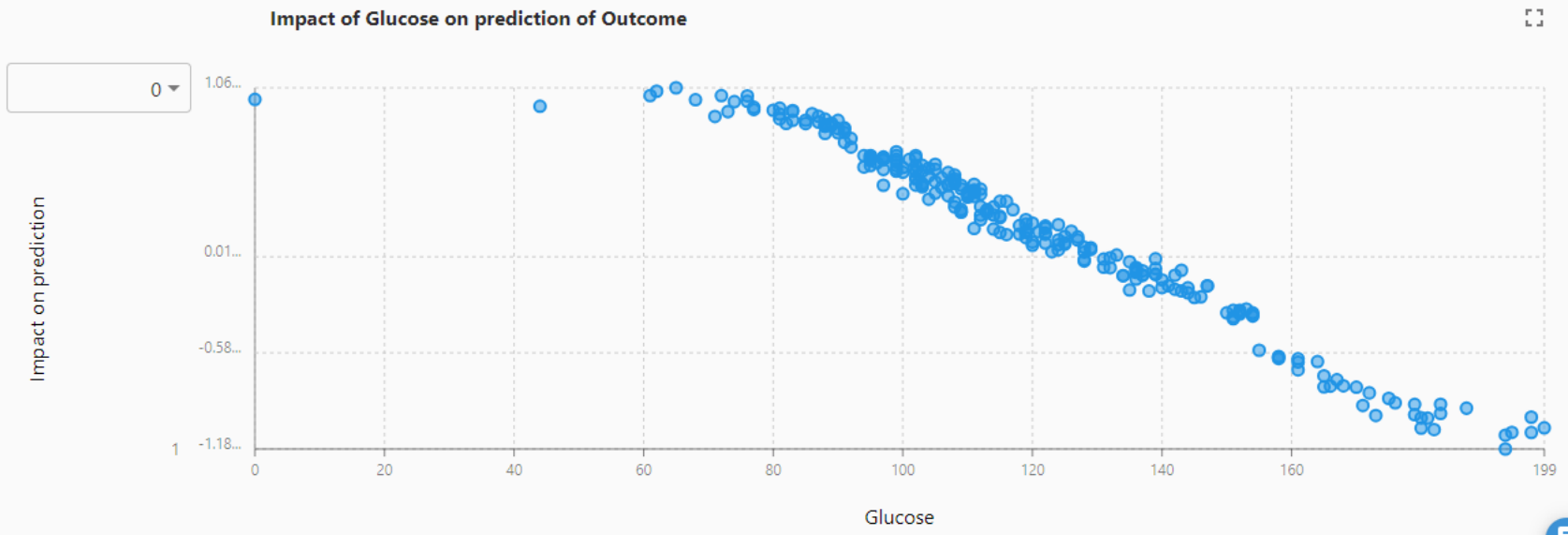
Predict | Deploy

Overview | Scoring

Column impact

Search columns...

1	Glucose	43.248%
2	BMI	19.659%
3	Age	13.421%
4	Pedigree	10.148%
5	Pregnancies	5.667%
6	Insulin	2.892%



NIDDK Diabetes | Total columns: 9 | Total rows: 768 | Total cells: 6,912 | Outcome | 2 category prediction

Predict

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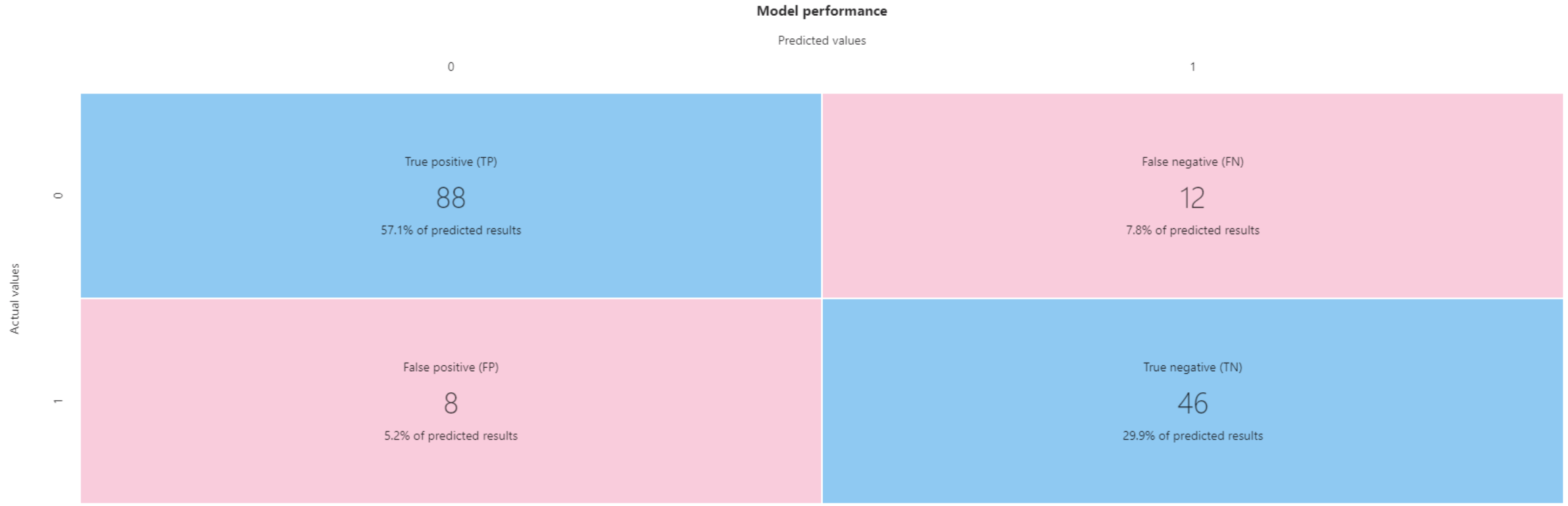
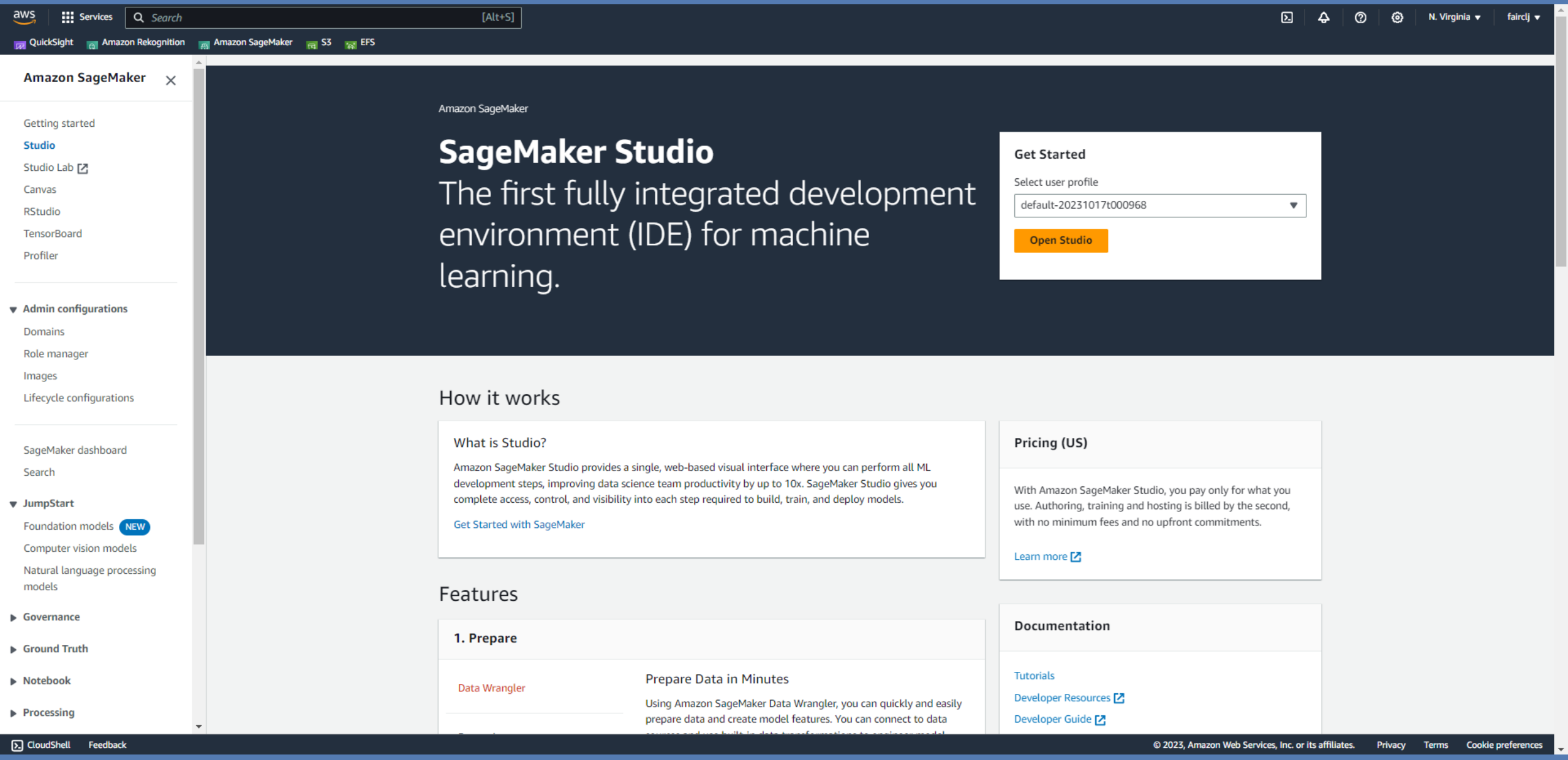
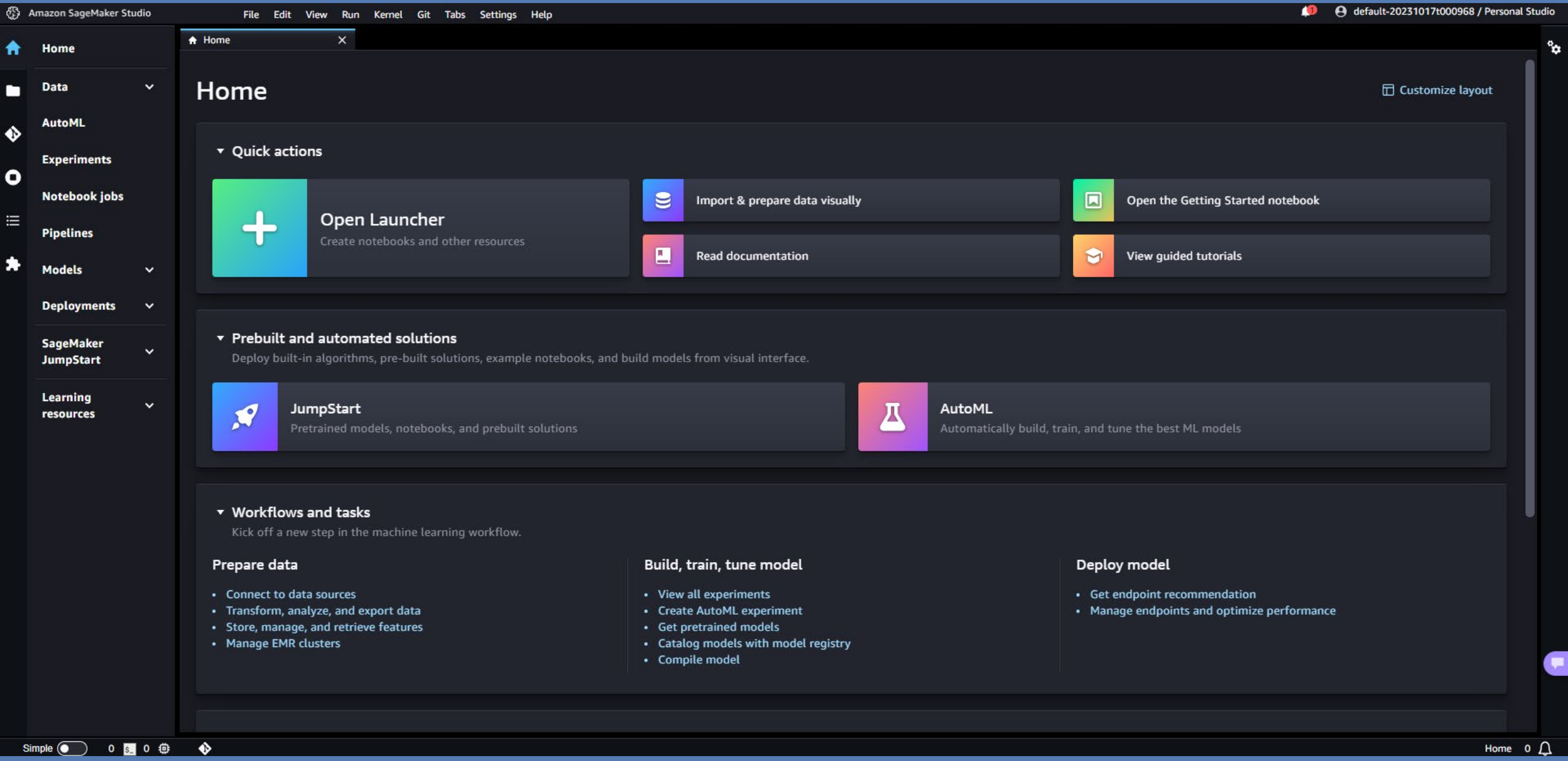
Advanced metrics

Positive Class	F1 (Optimization metric)	Accuracy	Precision	Recall	AUC
0 / 1	89.796%	87.013%	91.667%	88%	0.911



Close | Download





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Home | AutoML | Create experiment

Create an Autopilot experiment

When you create an Autopilot experiment, Amazon SageMaker analyzes your data and creates a notebook with candidate model definitions.
This notebook provides visibility into how models are selected, trained, and tuned.

Experiment and data details > Target and features > Training method and algorithms > Deployment and advanced settings > Review and create

Training method and algorithms

Select the training method for solving your machine learning problems.

- Auto
  Let Autopilot automatically decide the training method based on your dataset size.
- (●) Ensembling
  Autopilot uses an AutoML algorithm that trains a multi-layer stack ensemble model to predict on regression and classification datasets directly from your data.
- Hyperparameter optimization (HPO)
  Autopilot finds the best version of a model by tuning hyperparameters and running training jobs on your data set.

Select the algorithms to improve model prediction accuracies.

7/8 algorithms selected Select all

- [x] **LightGBM**
  A framework that uses tree-based algorithms, gradient boosting, and histogram-based algorithms to optimize speed and memory usage. Trees are grown leaf-wise where leaves with max delta loss are chosen to grow to optimize accuracy.
- [x] **CatBoost**
  A framework that uses tree-based algorithms with gradient boosting. Optimized for handling categorical variables.
- [x] **XGBoost**
  A supervised learning algorithm that attempts to accurately predict a target variable by combining an ensemble of estimates from a set of simpler and weaker models.
- [x] **Random Forest**
  A tree-based algorithm that uses several decision trees on random sub-samples of the data with replacement. The trees are split into optimal nodes at each level. The decisions of each tree are averaged together to prevent overfitting and improve predictions.
- [x] **Extra Trees**
  A tree-based ensemble algorithm that uses several decision trees built on the entire
- [ ] **Linear Models**
  A framework that uses a linear equation to model the relationship between target label

Cancel Previous: Target and features Next: Deployment and advanced settings

Simple 0 0 Create experiment 0

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Training method and algorithms

Select the training method for solving your machine learning problems.

- ○ **Auto** — Let Autopilot automatically decide the training method based on your dataset size.
- ○ **Ensembling** — Autopilot uses an AutoML algorithm that trains a multi-layer stack ensemble model to predict on regression and classification datasets directly from your data.
- ◉ **Hyperparameter optimization (HPO)** — Autopilot finds the best version of a model by tuning hyperparameters and running training jobs on your data set.

Select the algorithms to improve model prediction accuracies.

2/3 algorithms selected ☐ Select all

- ☐ **Linear Models** — A framework that uses a linear equation to model the relationship between two variables target variable and feature variable in observed data.

- ☑ **XGBoost** — A supervised learning algorithm that attempts to accurately predict a target variable by combining an ensemble of estimates from a set of simpler and weaker models.

- ☑ **MLP** — A multilayer perceptron (MLP) and feedforward artificial neural network. This algorithm can handle data that is not linearly separable.

Cancel | Previous: Target and features | Next: Deployment and advanced settings

Simple 0 $_ 0 Create experiment 0

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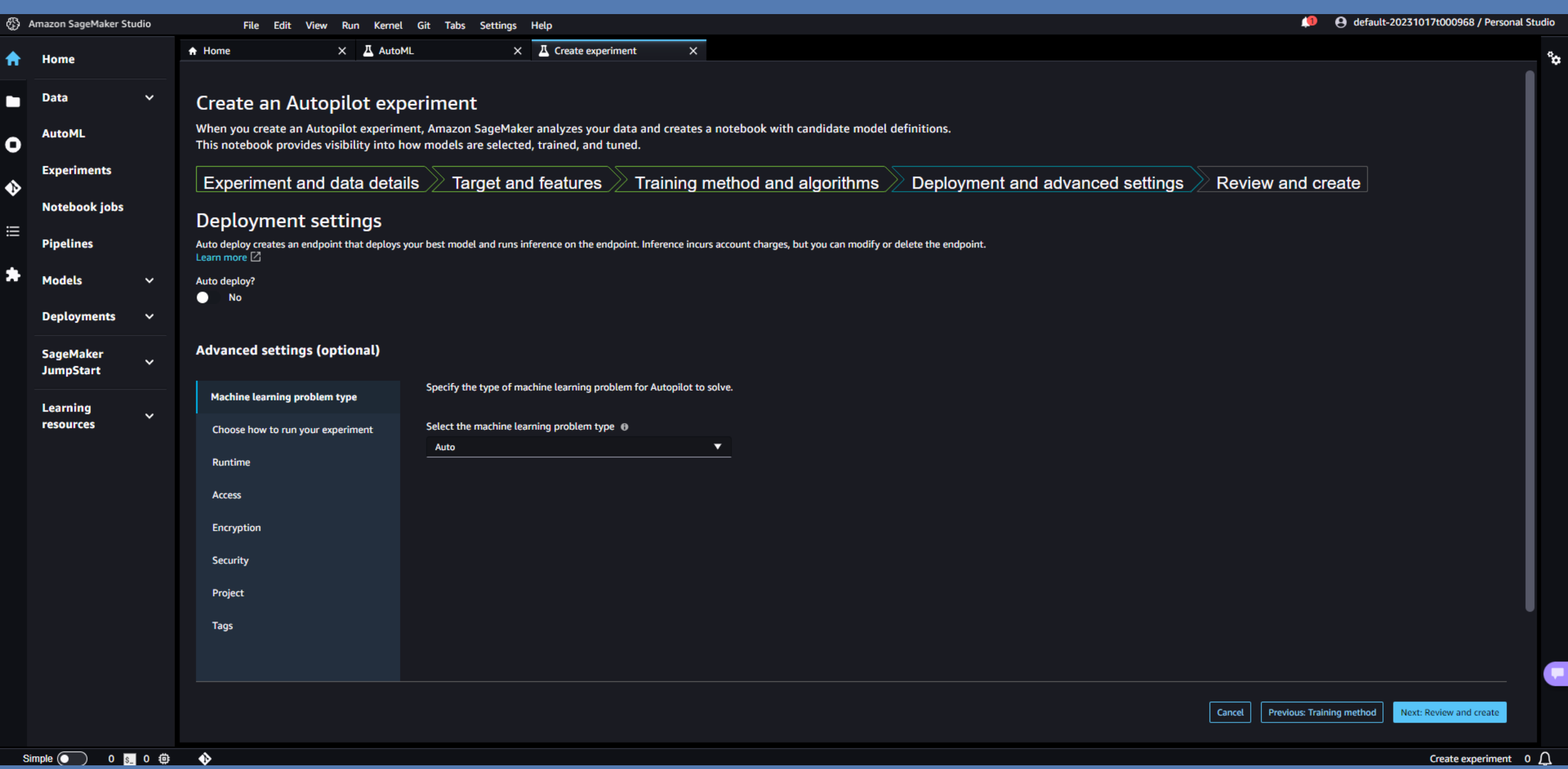

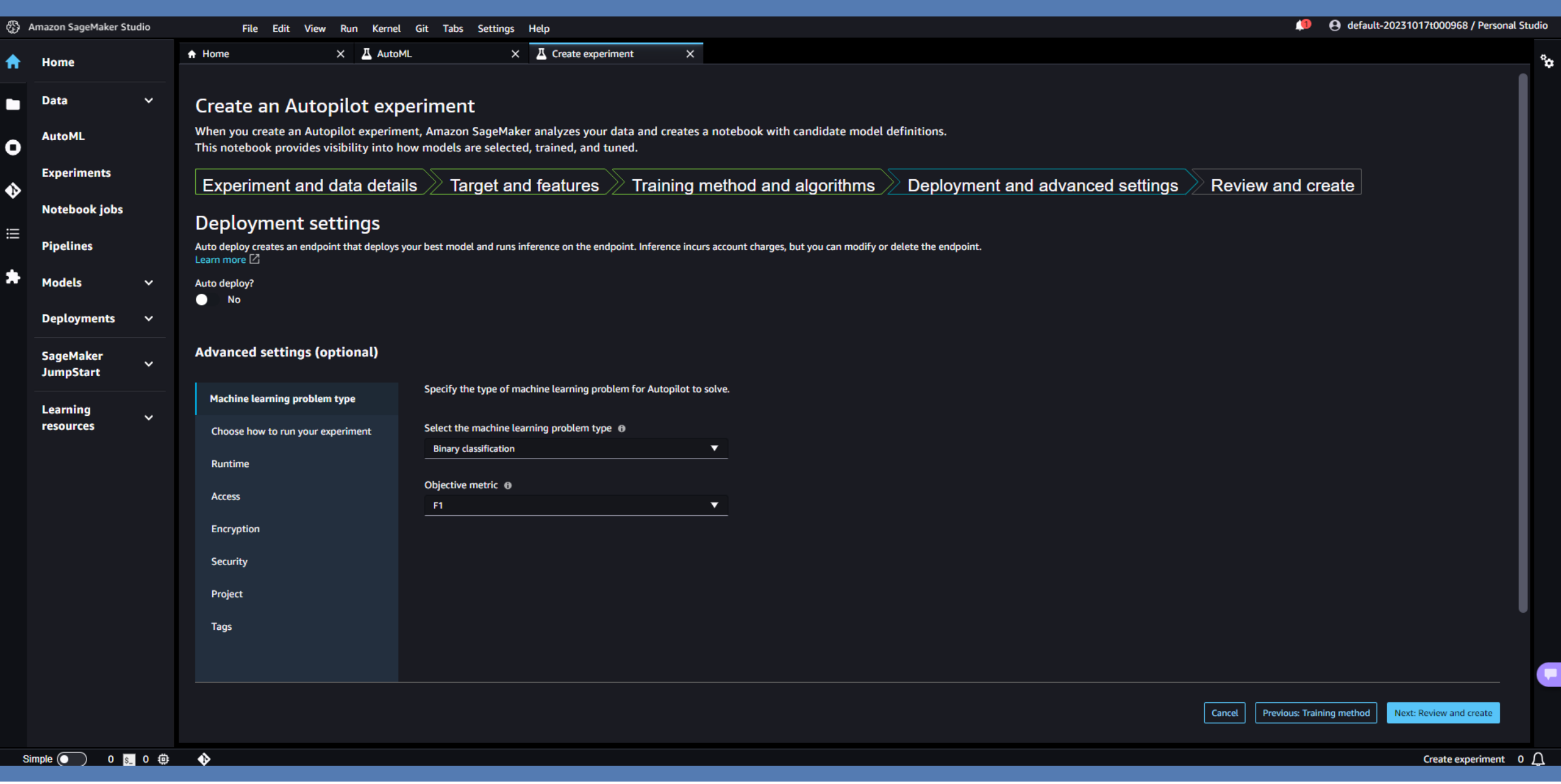

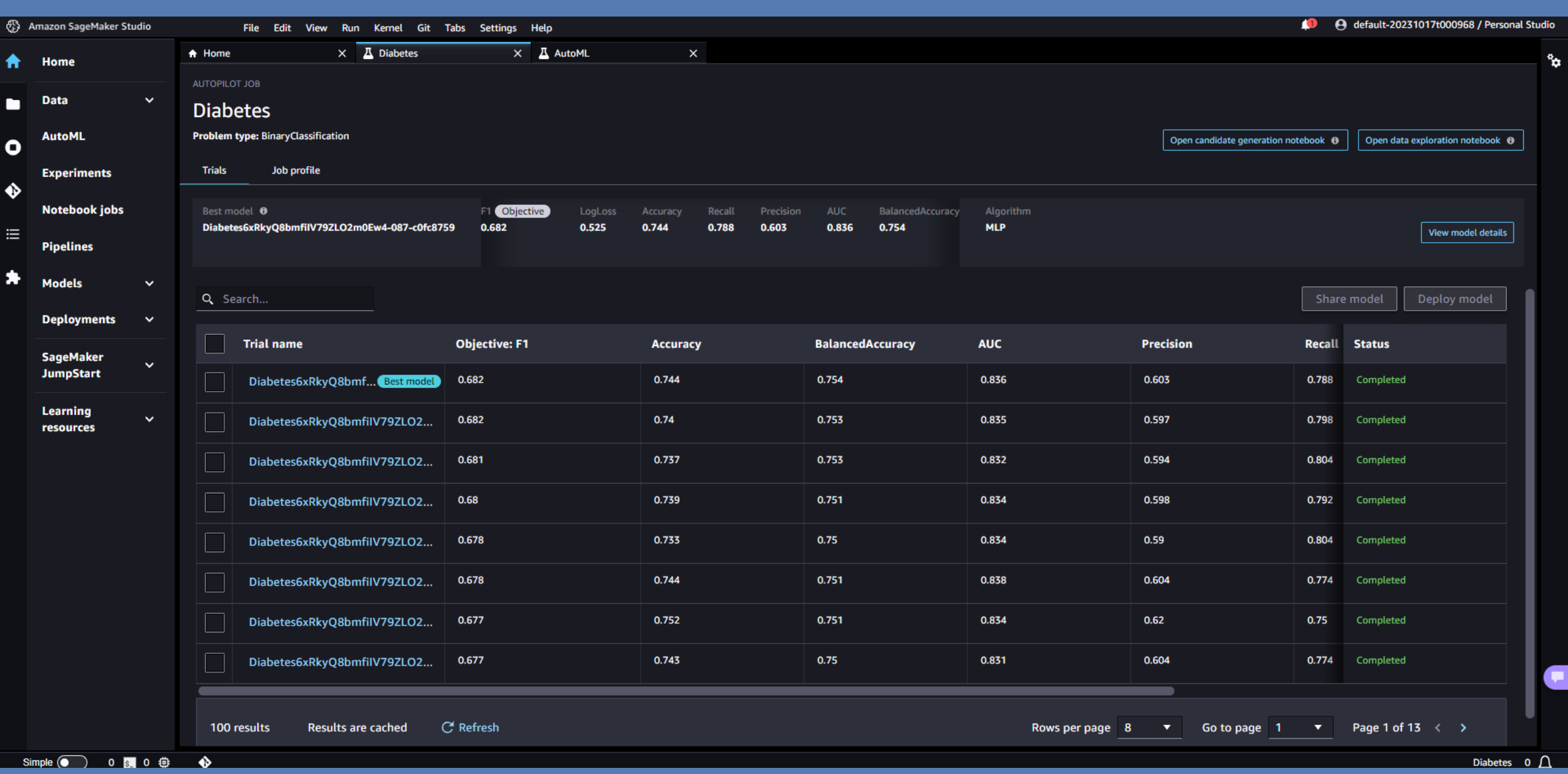

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Autopilot

DIABETES-AWS-AUTO-ML-JOB

COMPLETED

half a minute ago

Share model | Deploy model | Stop training job

Job Name: Diabetes-aws-auto-ml-job

Model: Diabetes6xRkyQ8bmfiIV79ZLO2m0Ew4-087-c0fc8759-aws-trial Best model

Status: Completed

Algorithm: MLP

Explainability | Performance | Artifacts | Network

Model explainability

- **Feature importance**
- **Metrics**
- **Hyper parameters**
- **Resource**

Feature importance

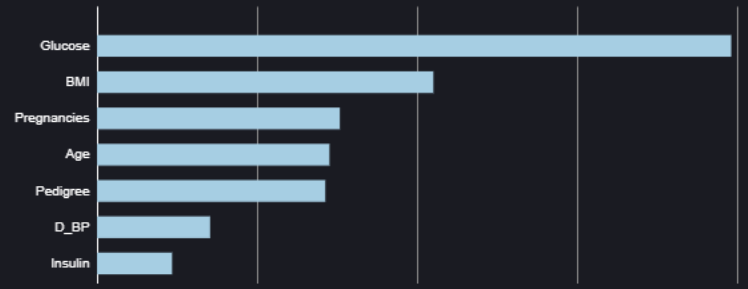
Download Feature Reports

Explaining your model's predictions

Amazon SageMaker Studio helps you understand your machine learning model by portraying the importance of its features in terms of SHAP values. We plot the aggregated SHAP value for each feature across all instances of the dataset.

Your analysis includes multiple predicted columns. Select a predicted column to see feature importance results:

0



Simple 0 0 Model Details 0

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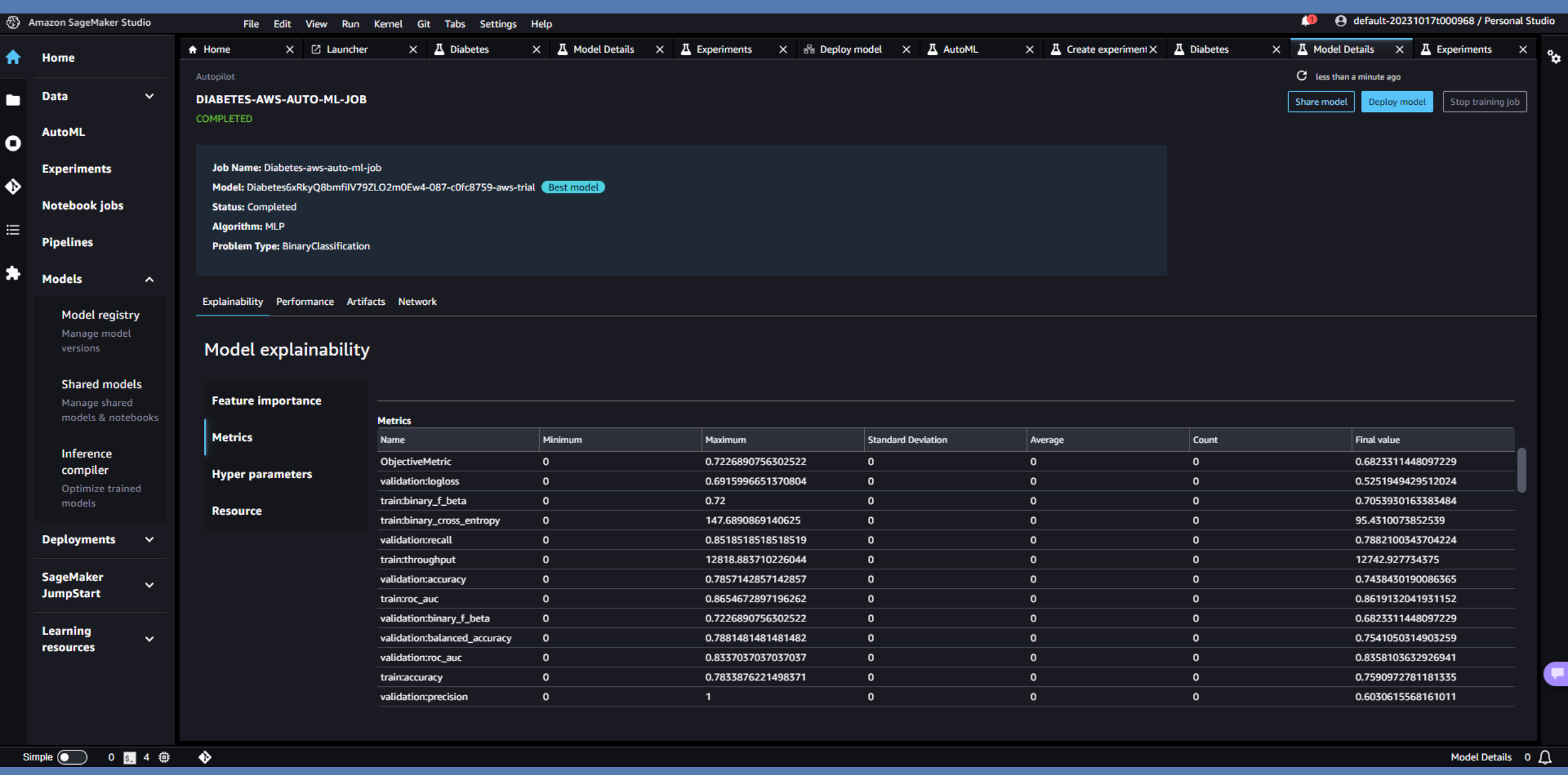

Metrics

Name	Minimum	Maximum	Standard Deviation	Average	Count	Final value
ObjectiveMetric	0	0.7226890756302522	0	0	0	0.6823311448097229
validation:logloss	0	0.6915996651370804	0	0	0	0.5251949429512024
train:binary_f_beta	0	0.72	0	0	0	0.7053930163383484
train:binary_cross_entropy	0	147.6890869140625	0	0	0	95.4310073852539
validation:recall	0	0.8518518518518519	0	0	0	0.7882100343704224
train:throughput	0	12818.883710226044	0	0	0	12742.927734375
validation:accuracy	0	0.7857142857142857	0	0	0	0.7438430190086365
train:roc_auc	0	0.8654672897196262	0	0	0	0.8619132041931152
validation:binary_f_beta	0	0.7226890756302522	0	0	0	0.6823311448097229
validation:balanced_accuracy	0	0.7881481481481482	0	0	0	0.7541050314903259
validation:roc_auc	0	0.8337037037037037	0	0	0	0.8358103632926941
train:accuracy	0	0.7833876221498371	0	0	0	0.7590972781181335
validation:precision	0	1	0	0	0	0.6030615568161011

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Autopilot

DIABETES-AWS-AUTO-ML-JOB

COMPLETED

less than a minute ago

Share model | Deploy model | Stop training job

Job Name: Diabetes-aws-auto-ml-job
Model: Diabetes6xRkyQ8bmfiIV79ZLO2m0Ew4-087-c0fc8759-aws-trial Best model
Status: Completed
Algorithm: MLP

Explainability | Performance | Artifacts | Network

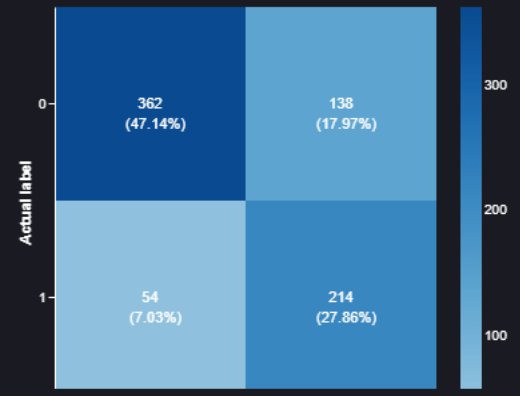
Model performance

Download Performance Reports

- Metrics table
- Confusion Matrix
- Precision Recall Curve
- ROC curve

Note:
The values of the performance metrics in this table may differ from the values reported by Autopilot. The differences tend to appear when training on smaller datasets. The values for the metrics in the table use all the training data once to estimate the performance of a model. Autopilot scores are calculated using k-fold cross-validation resampling method that train a machine learning algorithm on different subsets of the dataset. A score is then calculated for overall performance by averaging the resulting performance metrics for each trial.

Confusion Matrix



Simple | 0 | 0 | Model Details | 0

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Model performance

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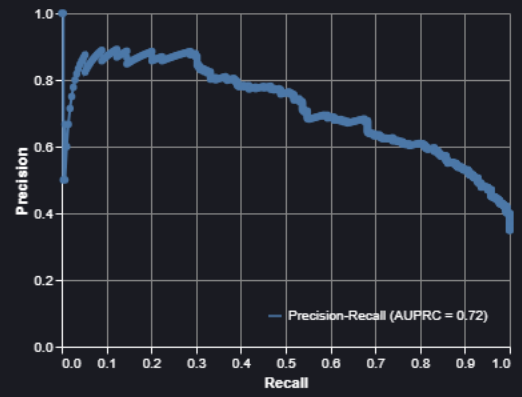
Metrics table

Confusion Matrix

Precision Recall Curve

ROC curve

Precision Recall Curve



Receiver Operating Characteristic (ROC)

Simple | 0 | 0 | Model Details | 0

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DIABETES-AWS-AUTO-ML-JOB

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Model performance

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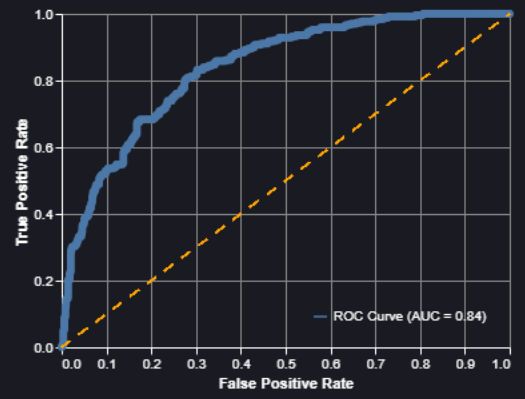
Metrics table

Confusion Matrix

Precision Recall Curve

ROC curve

Receiver Operating Characteristic (ROC)



Simple 0 0

Model Details 0

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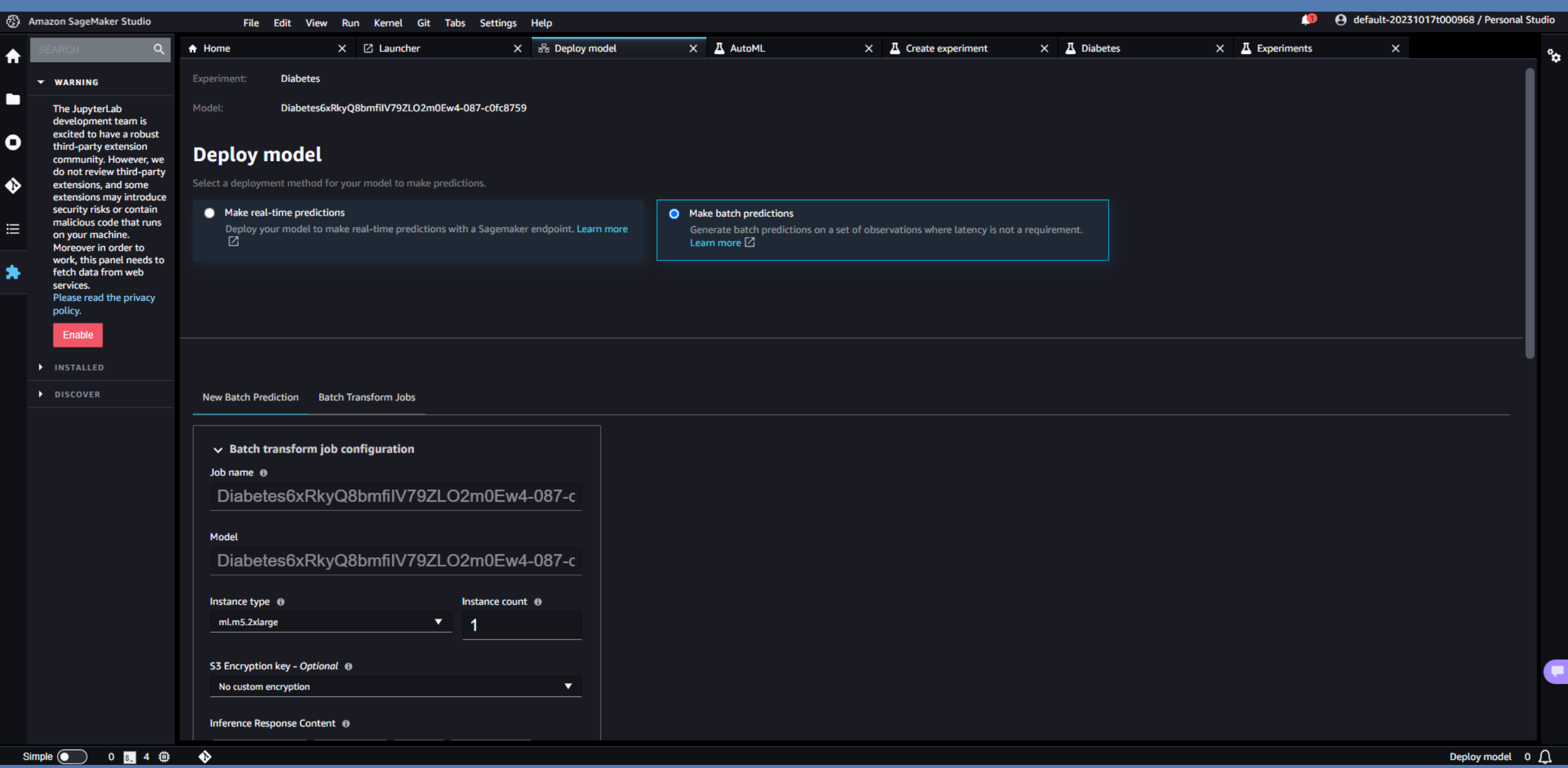

Fall 2023: RUCOM Joined the AWS Academy

- AWS Academy provides free, ready-to-teach cloud computing curriculum, built by the experts at AWS, that fit into existing course structures and include lectures, hands-on labs, knowledge checks, and projects.
- Students/learners can enroll in courses that teach in-demand cloud skills, allowing them to solve business challenges based on actual industry scenarios (including healthcare).
- Educators receive complimentary professional development and mentorship to enhance their own research capacity and industry knowledge.

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AWS Certifications

https://aws.amazon.com/certification/

FOUNDATIONAL

Knowledge-based certification for foundational understanding of AWS Cloud.

No prior experience needed.

PROFESSIONAL

Role-based certifications that validate advanced skills and knowledge required to design secure, optimized, and modernized applications and to automate processes on AWS.

2 years of prior AWS Cloud experience recommended.

ASSOCIATE

Role-based certifications that showcase your knowledge and skills on AWS and build your credibility as an AWS Cloud professional. **Prior cloud and/or strong on-premises IT experience recommended.**

SPECIALTY

Dive deeper and position yourself as a trusted advisor to your stakeholders and/or customers in these strategic areas. **Refer to the exam guides on the exam pages for recommended experience.**

amazon web services

AWS Certified AI Practitioner (AIF-C01) Exam

120 minutes | 85 questions | $75 USD

- Fundamentals of AI and ML
- Fundamentals of Generative AI
- Applications of Foundation Models
- Guidelines for Responsible AI
- Security, Compliance, and Governance for AI Solutions

AWS Certified Machine Learning - Specialty Exam (MLS-C01)

180 minutes | 65 questions | $300 USD

- Data Engineering
- Exploratory Data Analysis
- Modeling
- Machine Learning Implementation and Operations

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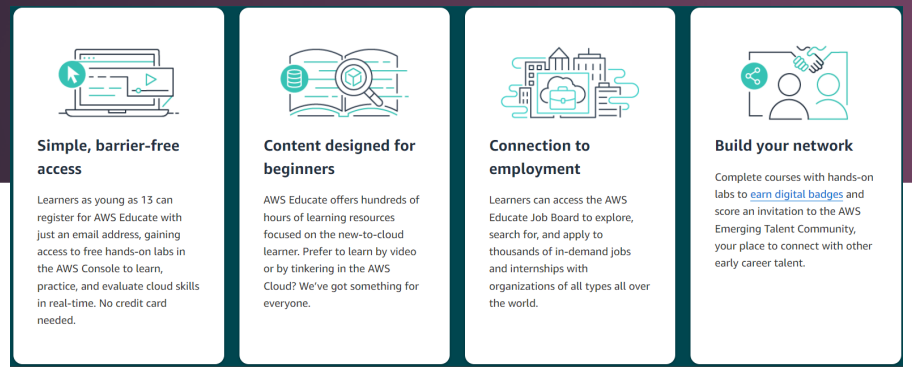

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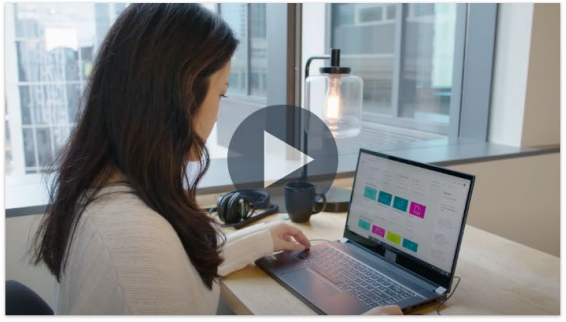
If you're overwhelmed by too many choices when it comes to learning about the cloud, AWS Educate is here to help. Cloud beginners like you are invited to check out our free, self-paced online training resources and labs designed to help you learn, practice, and evaluate your cloud skills without having to create an Amazon account.



https://aws.amazon.com/education/awseducate/

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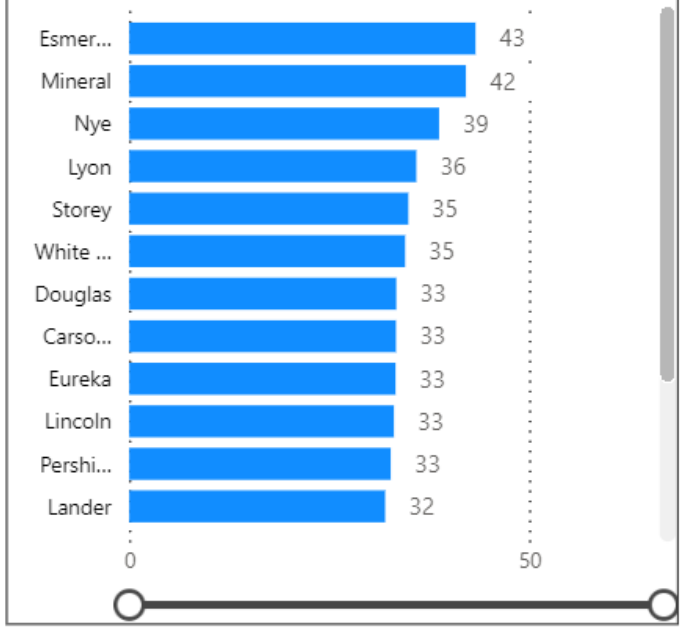
Microsoft Power BI Interactive Report | State of Nevada
Creator: Dr. Jamie Fairclough

AAMC

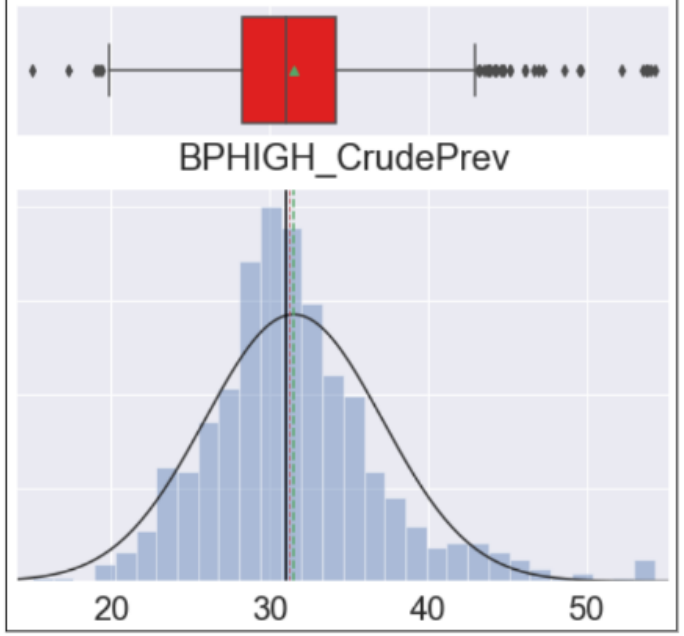
Average BPHIGH CrudePrev

County	CrudePrev	95% CI
Clark	54.30	(49.3, 58.9)
Clark	54.00	(49.5, 58.7)
Clark	53.90	(49.0, 58.5)
Clark	53.70	(49.0, 58.3)
Clark	52.20	(47.4, 57.1)
Clark	49.70	(45.9, 53.3)
Clark	49.60	(45.0, 54.2)
Clark	48.60	(44.3, 53.1)
Clark	47.30	(43.2, 51.3)
Clark	47.00	(43.3, 50.7)
Clark	46.70	(43.1, 50.5)
Mineral	46.10	(40.7, 51.1)
Clark	46.10	(42.2, 50.1)
Clark	46.10	(42.4, 49.9)
Clark	45.20	(41.1, 49.6)
Clark	45.20	(41.7, 48.8)
Clark	44.80	(41.3, 48.2)
Clark	44.65	(40.9, 48.3)

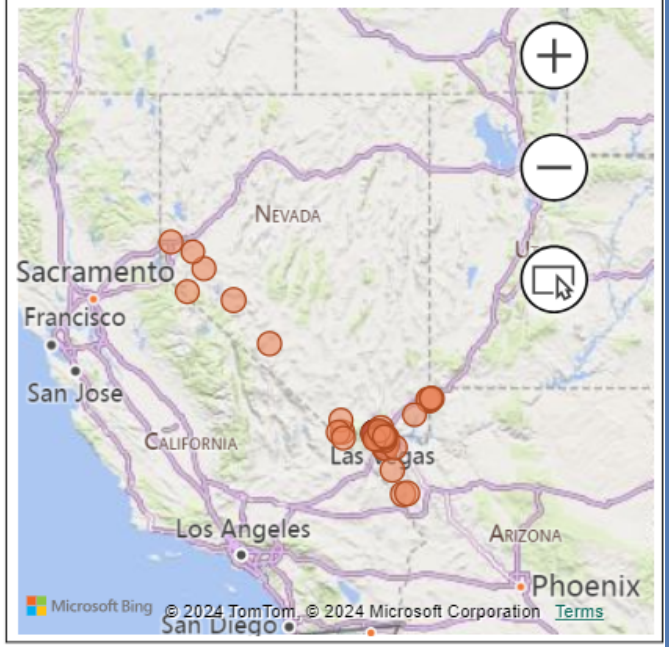
Average BPHIGH_CrudePrev (by County)



Boxplot & Histogram BPHIGH_CrudePrev



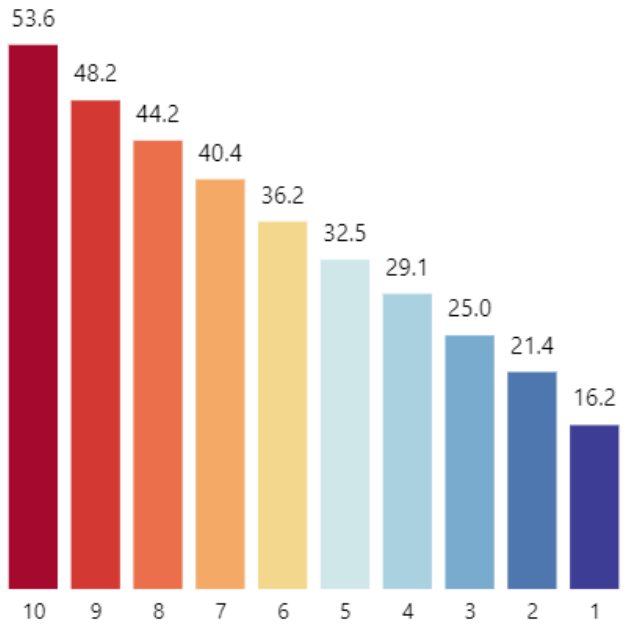
Priority Census Tracts (CrudePrev >= 40)



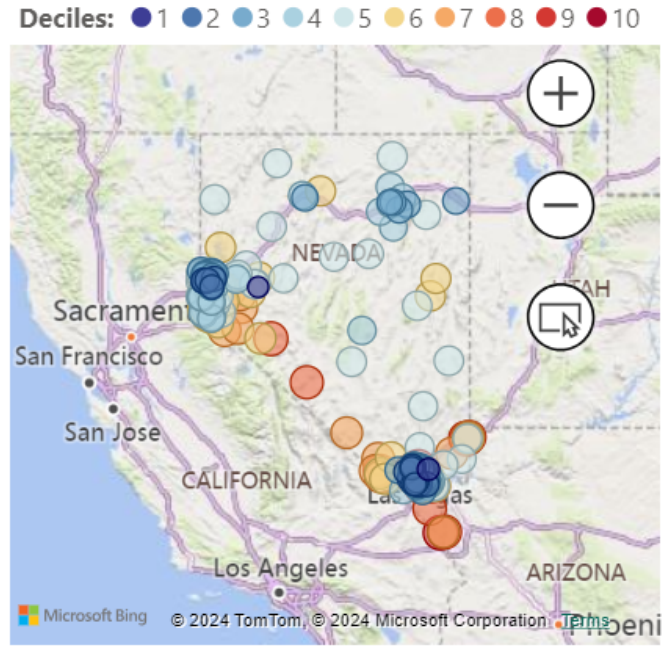
BPHIGH Deciles by County

Decile	County	Outlier	Population
10	Clark	True	2997
10	Clark	True	2797
10	Clark	True	2446
10	Clark	True	1971
10	Clark	True	1951
9	Clark	True	5946
9	Clark	True	3880
9	Clark	True	3852
9	Clark	True	3002
9	Clark	True	2865
9	Clark	True	2206
8	Clark	True	4259
8	Clark	True	3950
8	Clark	True	3585
8	Clark	True	3527
8	Clark	True	3314
8	Clark	True	3226
8	Clark	True	3103

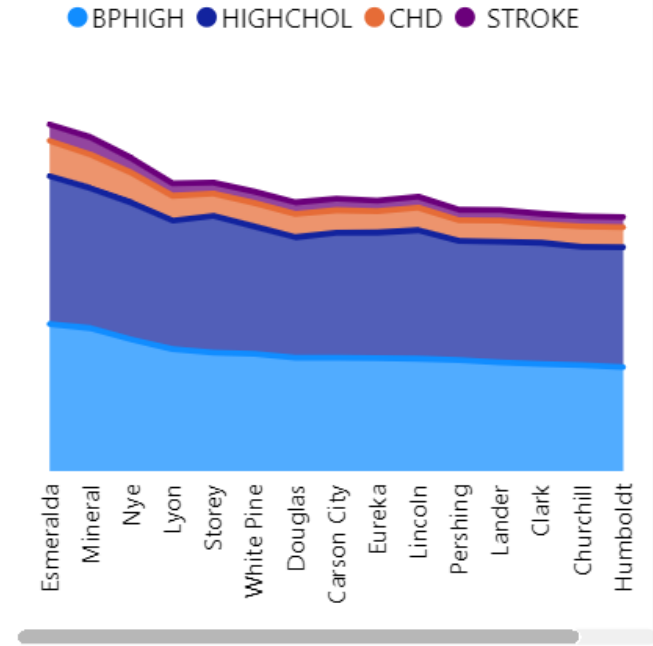
Average BPHIGH_CrudePrev (per Decile)

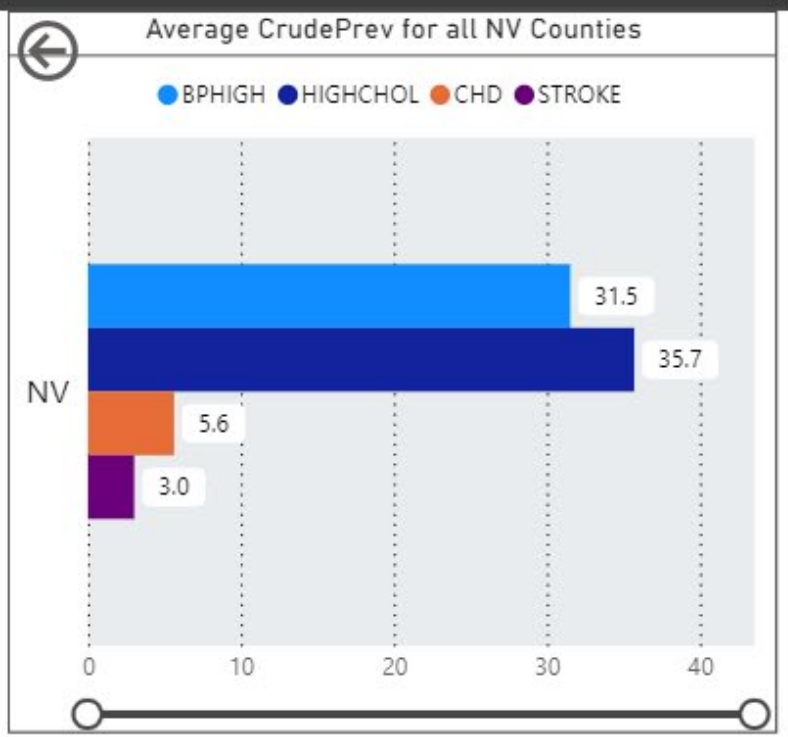


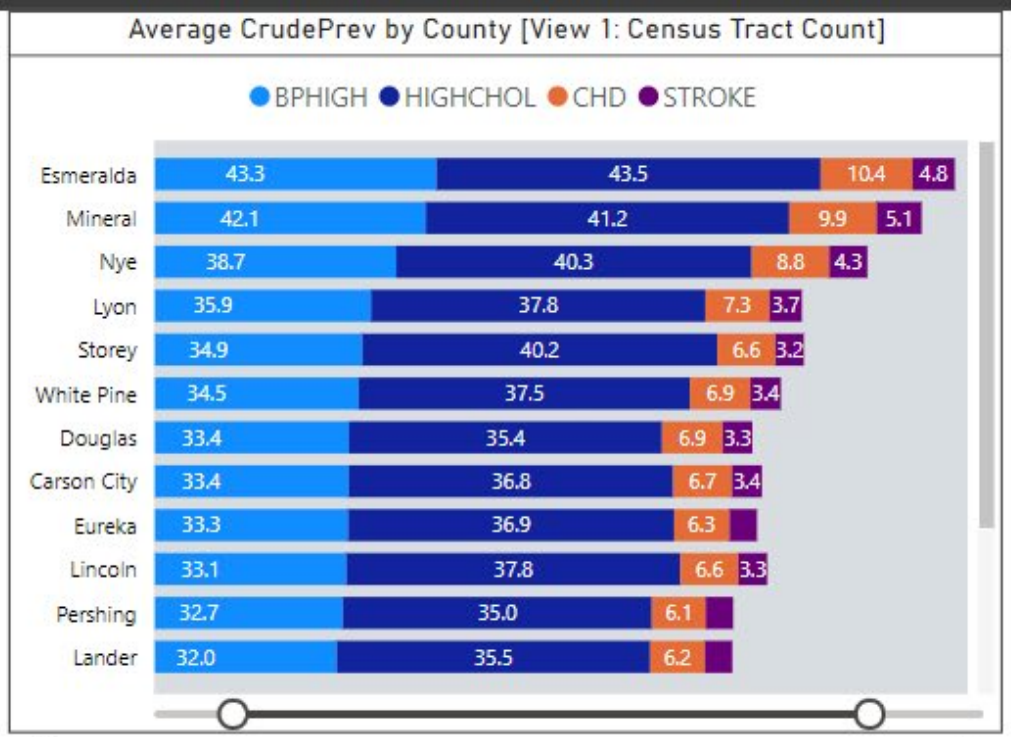
Geolocation for BPHIGH_CrudePrev Deciles

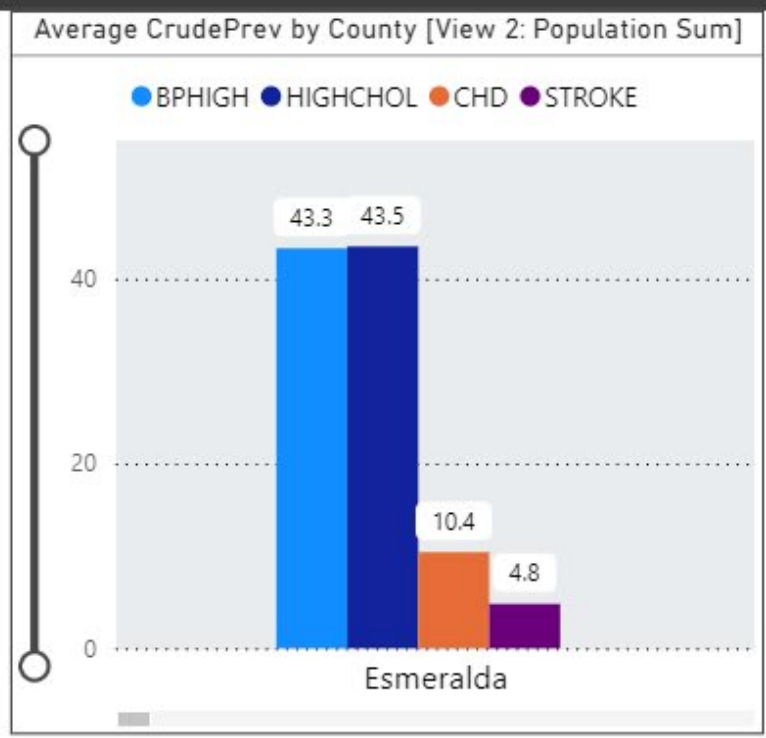


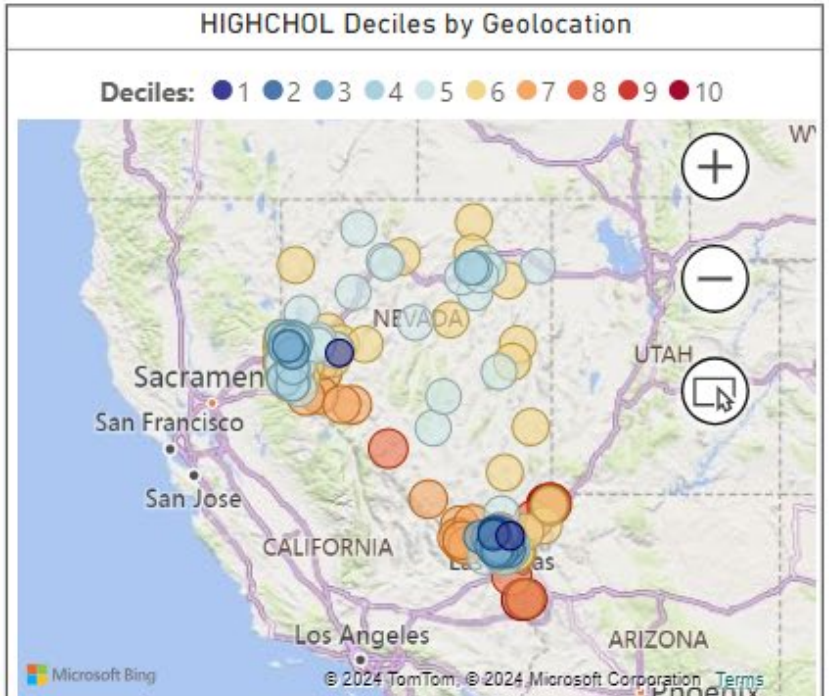
Average CrudePrev Comorbidities (by County)




Average CrudePrev for all NV Counties
BPHIGH HIGHCHOL CHD STROKE
NV
31.5
35.7
5.6
3.0
0
10
20
30
40


Average CrudePrev by County [View 1: Census Tract Count]
BPHIGH HIGHCHOL CHD STROKE
Esmeralda 43.3 43.5 10.4 4.8
Mineral 42.1 41.2 9.9 5.1
Nye 38.7 40.3 8.8 4.3
Lyon 35.9 37.8 7.3 3.7
Storey 34.9 40.2 6.6 3.2
White Pine 34.5 37.5 6.9 3.4
Douglas 33.4 35.4 6.9 3.3
Carson City 33.4 36.8 6.7 3.4
Eureka 33.3 36.9 6.3
Lincoln 33.1 37.8 6.6 3.3
Pershing 32.7 35.0 6.1
Lander 32.0 35.5 6.2


Average CrudePrev by County [View 2: Population Sum]
BPHIGH HIGHCHOL CHD STROKE
43.3
43.5
10.4
4.8
40
20
0
Esmeralda


HIGHCHOL Deciles by Geolocation
Deciles: 1 2 3 4 5 6 7 8 9 10
NEVADA
UTAH
Sacramen
San Francisco
San Jose
CALIFORNIA
Los Angeles
ARIZONA
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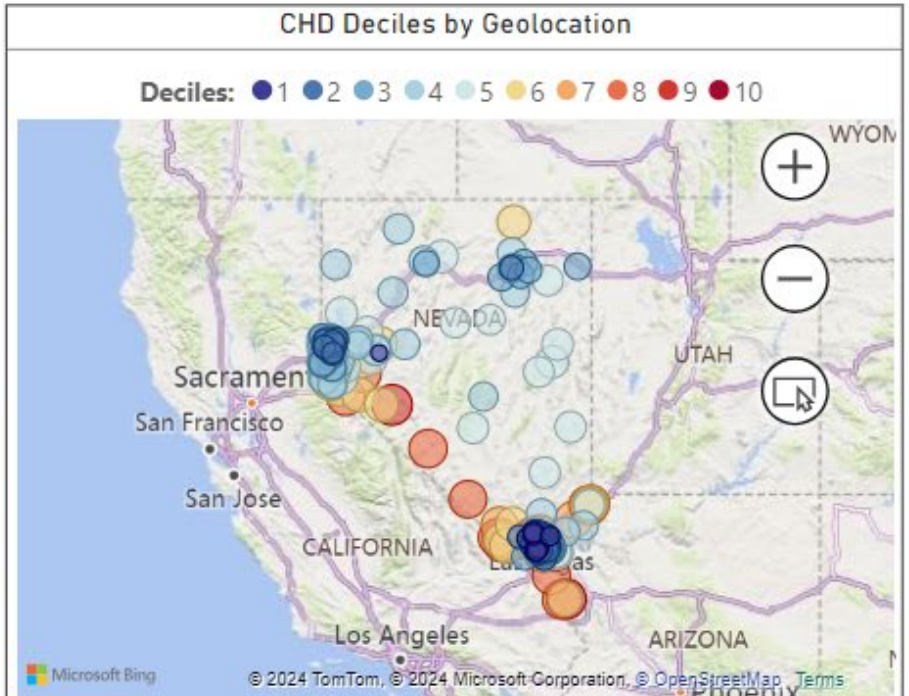
CHD Deciles by Geolocation
Deciles: 1 2 3 4 5 6 7 8 9 10
NEVADA
UTAH
Sacramen
San Francisco
San Jose
CALIFORNIA
Los Angeles
ARIZONA
Microsoft Bing
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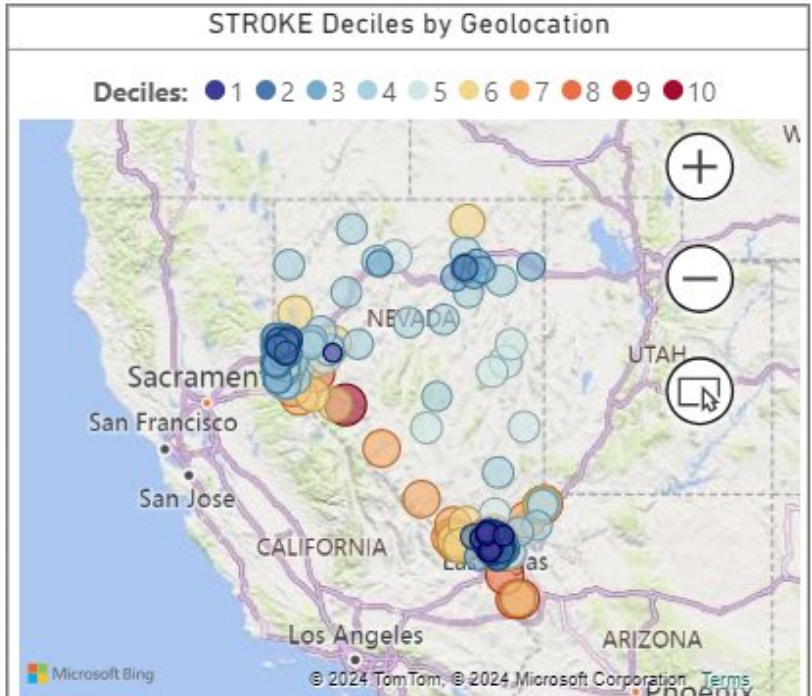
STROKE Deciles by Geolocation
Deciles: 1 2 3 4 5 6 7 8 9 10
NEVADA
UTAH
Sacramen
San Francisco
San Jose
CALIFORNIA
Los Angeles
ARIZONA
Microsoft Bing
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Total Population_SVI

Population Count: 3.03M

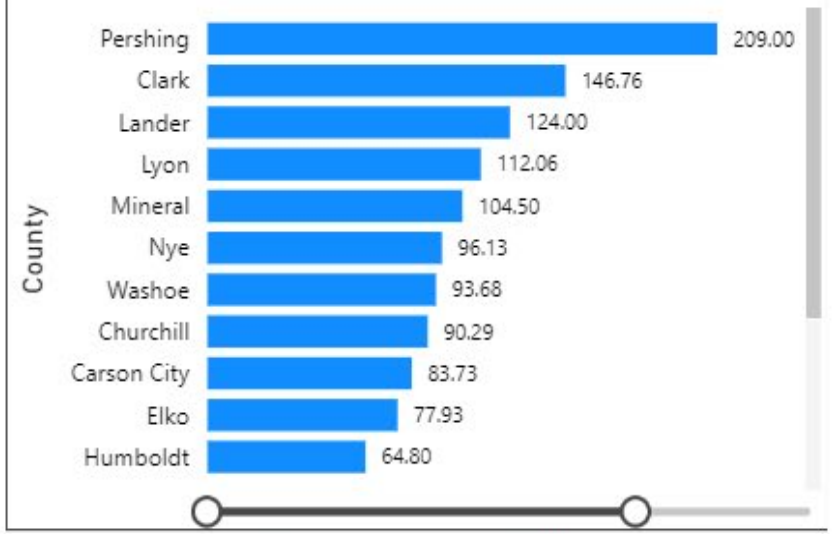
Zero Population_SVI

County	Count	Zip	Population	Area_Sq Miles
Washoe	1	89506	0	5.88
Washoe	1	89506	0	27.16
Nye	1	89023	0	4,180.10
Carson City	1		0	0.00
Douglas	1		0	0.00
Washoe	1		0	0.00
Total	**7**			

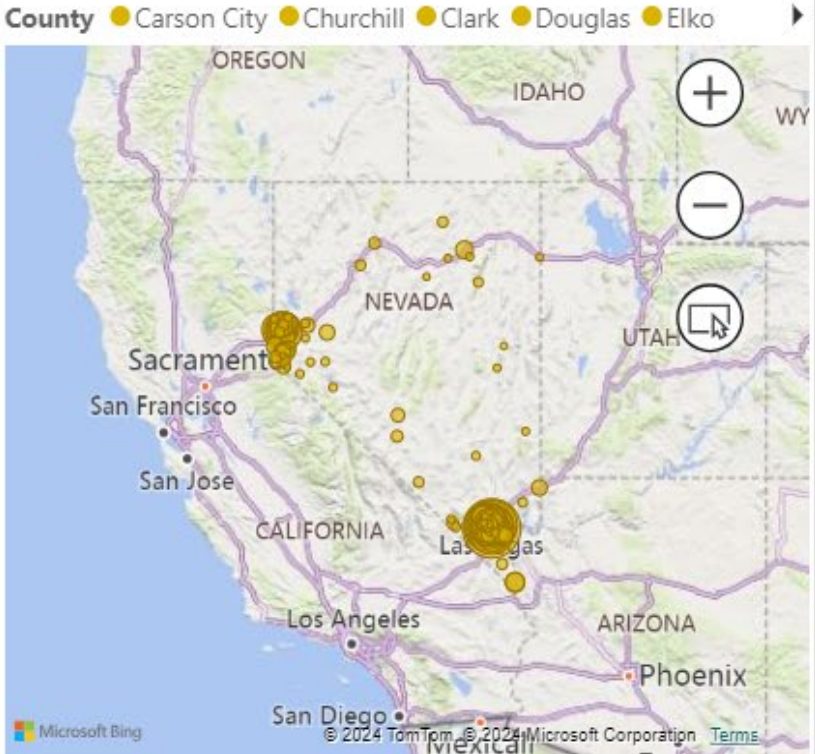
Poverty and Housing Cost-Burdened_SVI

Zip Code	County	Average of 150% Below FPL	Average Housing Cost-Burdened	Avg BPHIGH_Crude Prev
89801	Elko	671.14	248.29	28.16
89815	Elko	700.00	220.00	28.16
89822	Elko	248.00	103.00	28.16
89828	Elko	355.00	128.00	28.16
89833	Elko	583.00	85.00	28.16
89834	Elko	714.00	156.00	28.16
89883	Elko	1121.00	382.00	28.16
	Washoe	0.00	0.00	29.88
Average		**841.61**	**462.98**	**31.52**

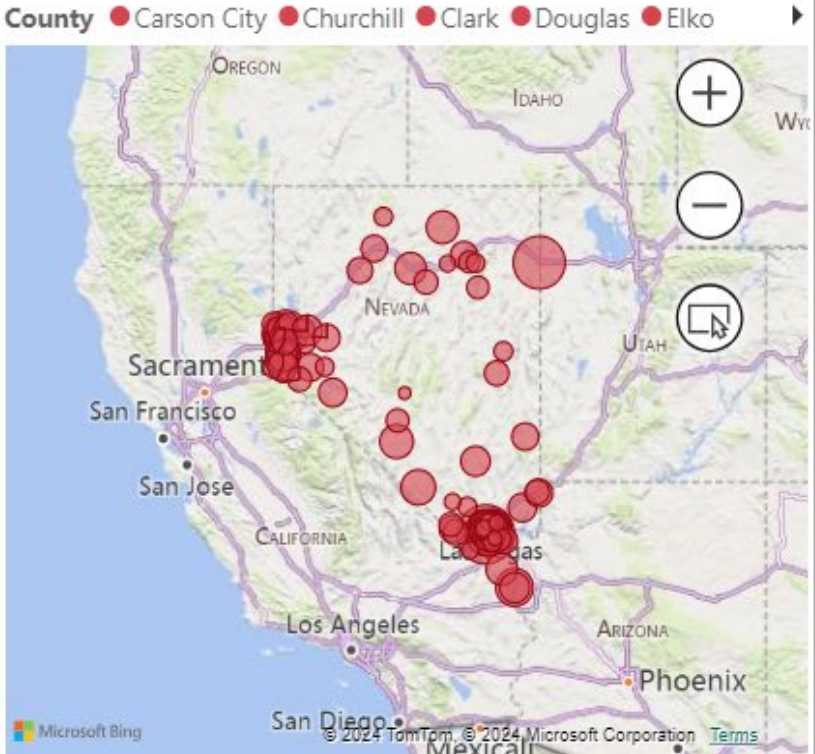
Average Unemployment by County_SVI



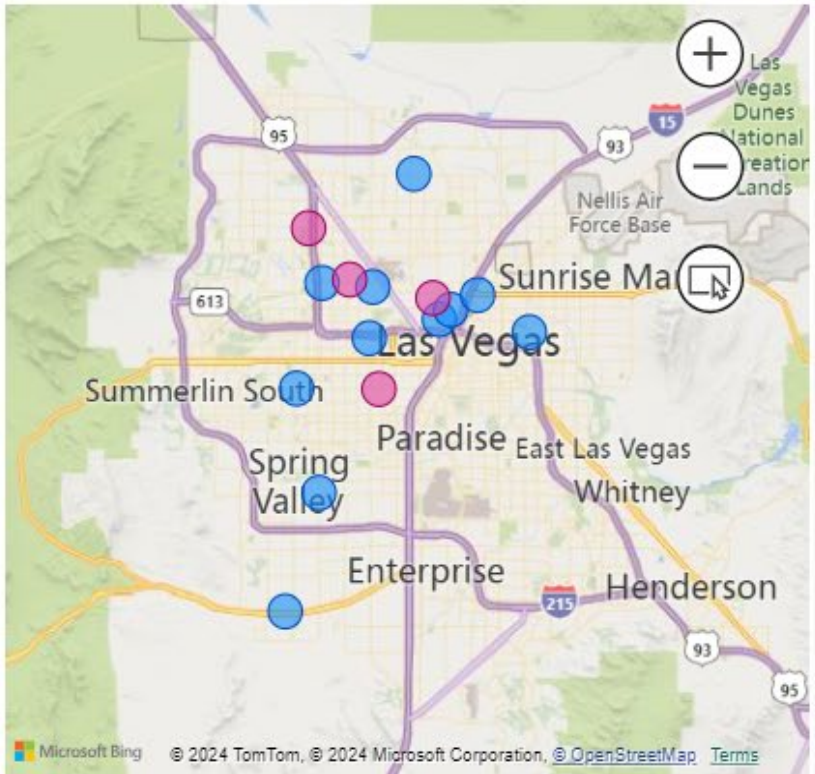
Average of Multi-Unit Structures_SVI



Average of No Vehicle_SVI



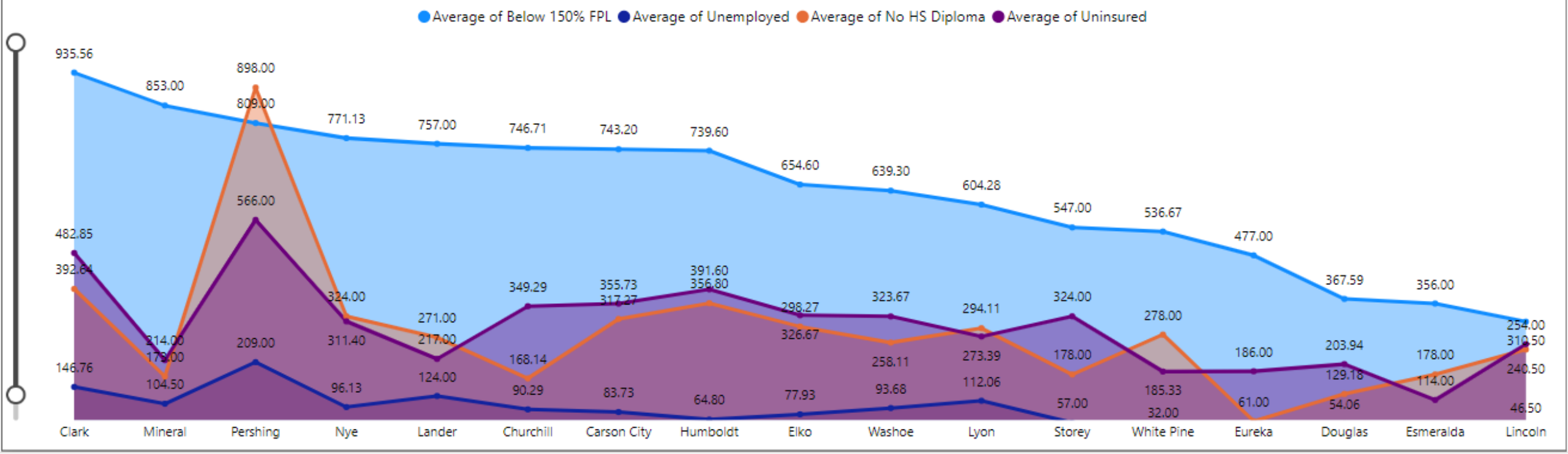
Partner Locations_SVI



Socioeconomic Status and CrudePrev Rates

County	Zip Code	Average of Below 150% FPL	Average of Unemployed	Average of No HS Diploma	Average of Uninsured	Average BPHIGH_CrudePrev	Average of HIGHCHOL_CrudePrev	Average of CHD_CrudePrev	Average of STROKE_CrudePrev	Average of Minority
Esmeralda	89013	356.00	12.00	178.00	114.00	43.30	43.50	10.40	4.80	164.00
Mineral	89415	878.00	99.00	205.00	240.00	42.10	41.15	9.90	5.10	217.00
Mineral	89427	828.00	110.00	141.00	188.00	42.10	41.15	9.90	5.10	212.00
Nye	89003	1017.00	43.00	395.00	461.00	38.74	40.26	8.79	4.31	410.00
Nye	89022	370.00	6.00	183.00	61.00	38.74	40.26	8.79	4.31	268.00
Nye	89023	0.00	0.00	0.00	0.00	38.74	40.26	8.79	4.31	34.00
Nye	89048	755.20	115.20	430.20	327.80	38.74	40.26	8.79	4.31	323.00
Nye	89049	490.00	100.00	109.00	116.00	38.74	40.26	8.79	4.31	278.00
Nye	89060	969.25	102.75	292.75	405.75	38.74	40.26	8.79	4.31	283.00
Nye	89061	1018.50	153.00	425.50	385.50	38.74	40.26	8.79	4.31	347.50
Average		**841.61**	**128.65**	**351.73**	**428.92**	**31.52**	**35.70**	**5.63**	**3.02**	**528.80**

Estimates of Socioeconomic Status (by County)



AI Plans for State Health Department Project

- Use supervised machine learning (ML) to predict cardiovascular health outcomes and identify the most important factors contributing to adverse cardiac events.
- Utilize unsupervised ML for cluster analysis to segment the population based on cardiovascular risk factors and social determinants/drivers of health.
- Leverage Neo4j's graph database to model and analyze complex relationships, uncovering hidden patterns and insights within interconnected population health data.
- Engage in geo-AI research to improve disease surveillance capabilities, particularly in rural/frontier settings.

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May 2024 Meeting: Healthcare AI/Tech Workforce Development (NV)

ORGANIZATION	ATTENDEES
Roseman University of Health Sciences College of Medicine	• Associate Dean & Professor | Data Science & Engineering Unit Director • Biomedical Data Scientist • Data Scientist / Engineer
Amazon Web Services (AWS)	• Sr. Account Manager, Higher Education • Solutions Architect • Academic Medicine & State/Local Government Providers • Public Health Lead | US State & Local Government • Worldwide Public Sector | State & Local Government • Interoperability & Public Health | State & Local Government
Nevada Department of Health and Human Services	• Bureau Chief, Child, Family and Community Wellness • Nutrition Unit Deputy Chief • Population and Health Services Manager • Community Wellness Manager | Chronic Disease Prevention and Health Promotion • Cardiovascular Health Program Coordinator • Chronic Disease Data Coordinator • Biostatistician
Southern Nevada Health District	• Deputy District Health Officer-Operations • Director of Disease Surveillance and Control • Epidemiology Supervisor • Public Health Informatics Supervisor • Senior Epidemiologist
City of Las Vegas	• Workforce Development Officer • Workforce Development Specialist • Management Analyst
American Board of Artificial Intelligence in Healthcare	• Co-Founder & Chief Scientific Officer | VA Radiologist • Board Member | Vice Provost
Johns Hopkins Engineering	• Associate Director | Corporate Engagement for Professional Education

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Considerations for Resource-Constrained Institutions

- Identify community stakeholders interested in AI to build a network for future collaborations or partnerships.
- Leverage scalable compute resources provided by cloud providers (e.g., AWS, Google Cloud, Microsoft) to build and deploy AI/ML models.
- Outsource advanced model development, refinement, and deployment activities to industry partners or data science teams at other academic institutions.
- Partner with industry or other institutions to train faculty, staff, and students/learners on building, managing, and deploying AI projects in cloud environments.

Considerations for Resource-Intensive Institutions

- Offer guidance and best practices on runtime configurations for cloud AI projects underway at smaller/resource-limited institutions.
- For compute-intensive projects, use cloud providers to tap into more powerful resources (e.g., TPUs, Quantum Machine Learning [QML]).
  - Explore how QML is being used in medical research and how it may benefit medical education (e.g., quantum algorithms training on smaller datasets).
- Partner with industry partners (e.g., systems engineers) to advise on how to design intelligent systems for medical/health professions education.
- Work with internal/external data science and engineering teams to strengthen data security/compliance practices and automate seamless integration of structured and unstructured data across disparate systems.

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Learn
Serve
Lead

Building AI Partnerships Across Medicine, Industry, and Government

Jamie Fairclough, PhD, MPH, MS
Roseman University of Health Sciences | College of Medicine

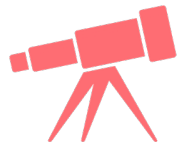
Email: jfairclough@roseman.edu

Association of
American Medical Colleges

MedEdMentor

AAMC AI Webinar

Geoffrey Stetson - Gregory Ow



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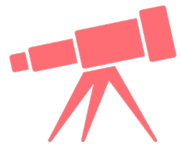
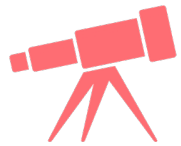
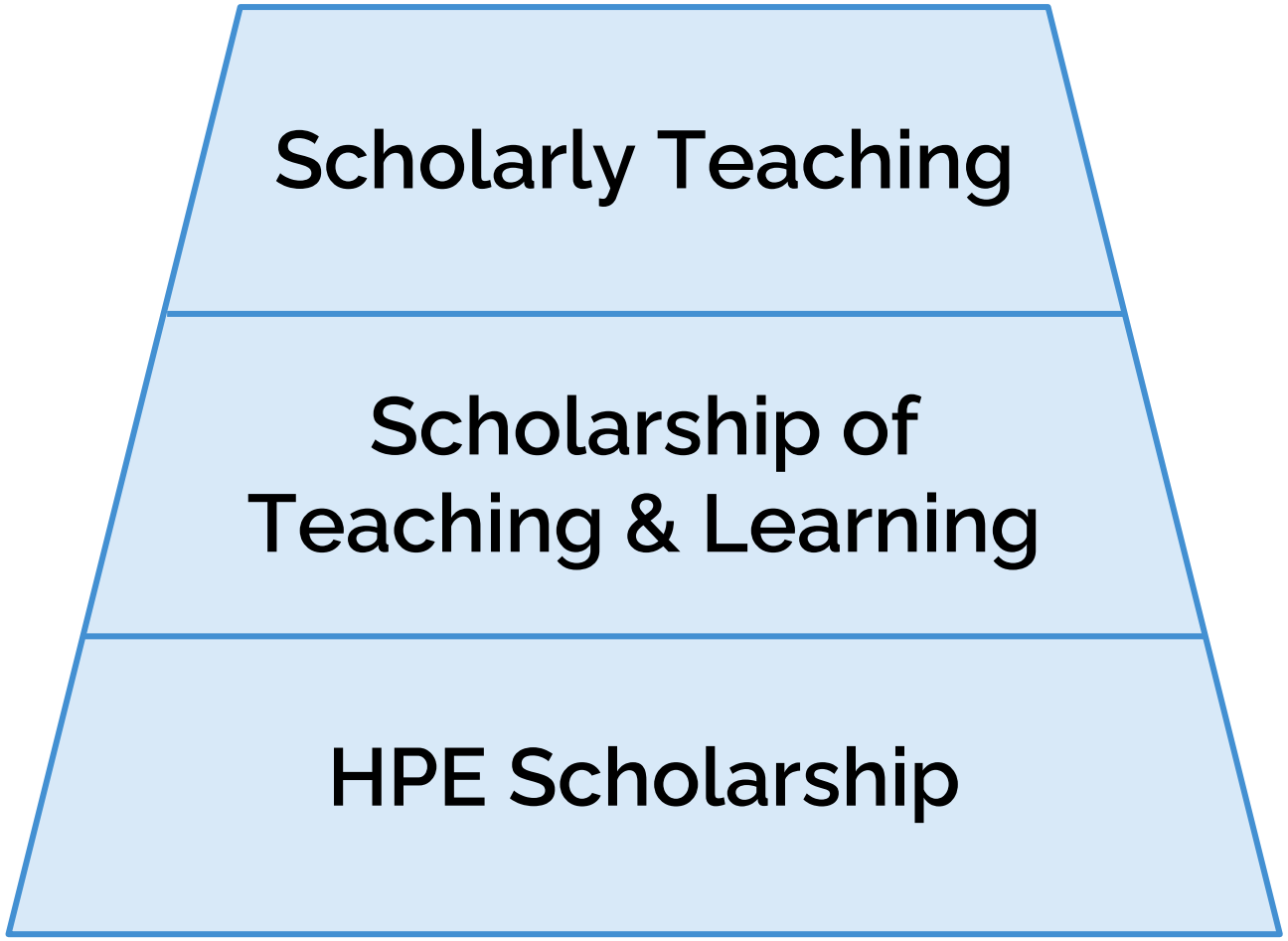
- MedEdMentor is a limited liability company
- Geoff and Greg are co-owners
- Our lifetime revenue is $0
- Josiah Macy Jr. Foundation Grant



Background



We need scholarship at all levels

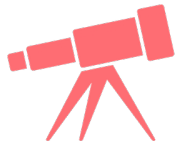


Cleland, J. A., Jamieson, S., Kusurkar, R. A., Ramani, S., Wilkinson, T. J., & Schalkwyk, S. van. (2021). Redefining scholarship for health professions education: AMEE Guide No. 142. Medical Teacher, 1–15.

Personal scholarship struggles

"Early career researchers and those new to theory express challenges employing theory, as well as difficulties with theory-related terminology"

Rees, C., Alwazzan, L., & Gordon, L. (2023). Chapter 2: Theory in Health Professions Education Research. In C. E. Rees, L. V. Monrouxe, B. C. O'Brien, L. J. Gordon, & C. Palermo (Eds.), Foundations of Health Professions Education Research: Principles, Perspectives and Practices.

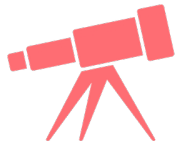


Scholarship is a common struggle

Scholarly Teaching

"Many academic faculty members are educators, yet few are familiar with key education theories that inform their practice"

Gottlieb, M., Boysen-Osborn, M., Chan, T. M., Krzyzaniak, S. M., Pineda, N., Spector, J., & Sherbino, J. (2017). Academic Primer Series: Eight Key Papers about Education Theory. Western Journal of Emergency Medicine, 18(2).
Gibbs, T., Durning, S., & Vleuten, C. V. D. (2011). Theories in medical education: Towards creating a union between educational practice and research traditions. Medical Teacher, 33(3), 183–187.
Samuel, A., Konopasky, A., Schuwirth, L. W. T., King, S. M., & Durning, S. J. (2020). Five Principles for Using Educational Theory: Strategies for Advancing Health Professions Education Research. Academic Medicine, 95(4), 518–522.



Scholarship is a common struggle

Scholarly Teaching

"Many academic faculty members are educators, yet few are familiar with key education theories that inform their practice"

Scholarship of Teaching & Learning

"Changes [in the field]…have been made in the absence of supportive theory, or at least by a poor understanding of educational theory"

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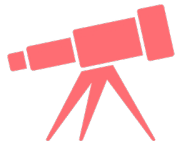

Scholarship is a common struggle

Scholarly Teaching

"Many academic faculty members are educators, yet few are familiar with key education theories that inform their practice"

Scholarship of Teaching & Learning

"Changes [in the field]…have been made in the absence of supportive theory, or at least by a poor understanding of educational theory"

HPE Scholarship

"HPE researchers…particularly those who do not have a background in education or social sciences, may lack a strong grasp of theory"

Gottlieb, M., Boysen-Osborn, M., Chan, T. M., Krzyzaniak, S. M., Pineda, N., Spector, J., & Sherbino, J. (2017). Academic Primer Series: Eight Key Papers about Education Theory. Western Journal of Emergency Medicine, 18(2).
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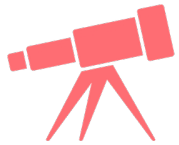
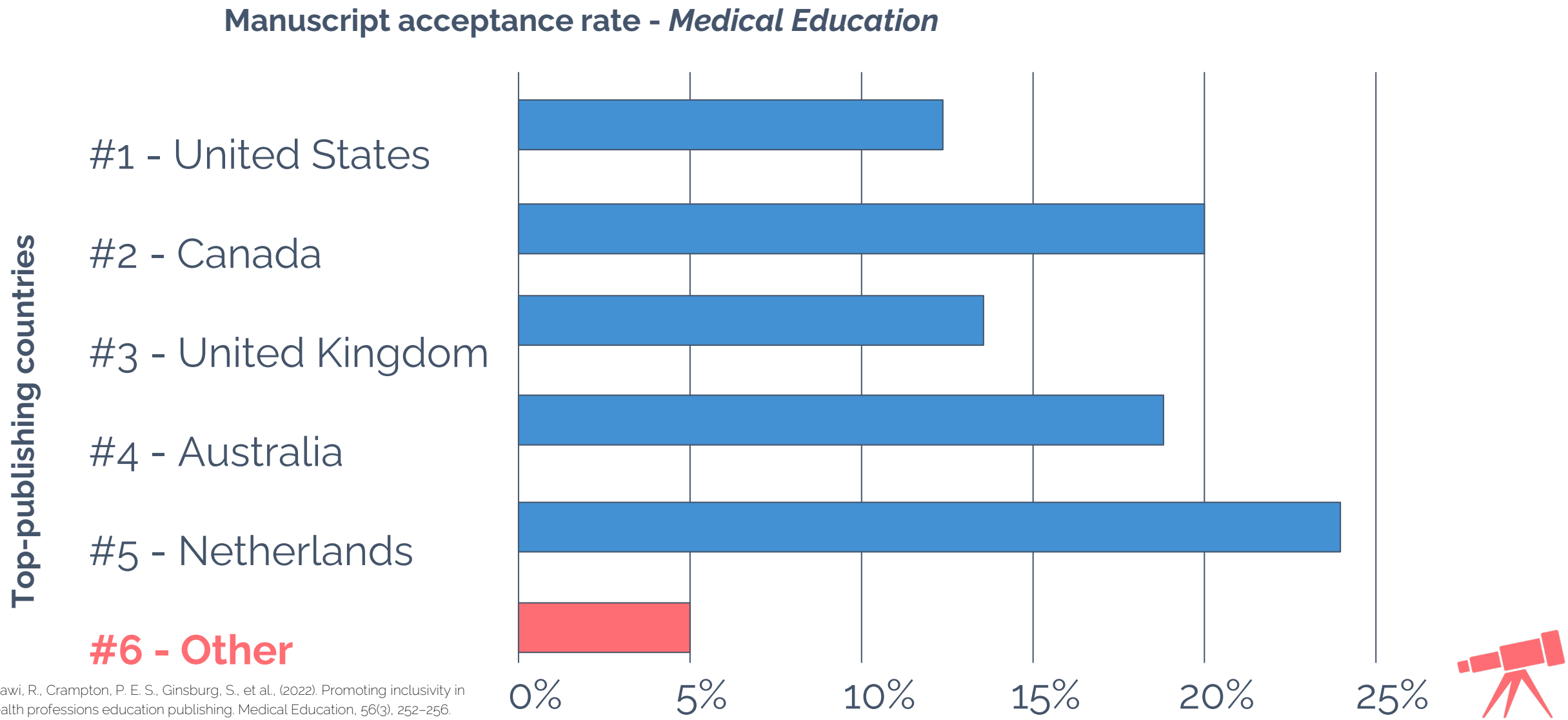
Samuel, A., Konopasky, A., Schuwirth, L. W. T., King, S. M., & Durning, S. J. (2020). Five Principles for Using Educational Theory: Strategies for Advancing Health Professions Education Research. Academic Medicine, 95(4), 518–522.



HPE scholarship lacks diversity



Ajjawi, R., Crampton, P. E. S., Ginsburg, S., et al., (2022). Promoting inclusivity in health professions education publishing. Medical Education, 56(3), 252–256.

Unequal distribution of resources, expertise, and mentorship is a primary driver of the continued struggles of aspiring HPE scholars and the lack of diverse voices in HPE literature

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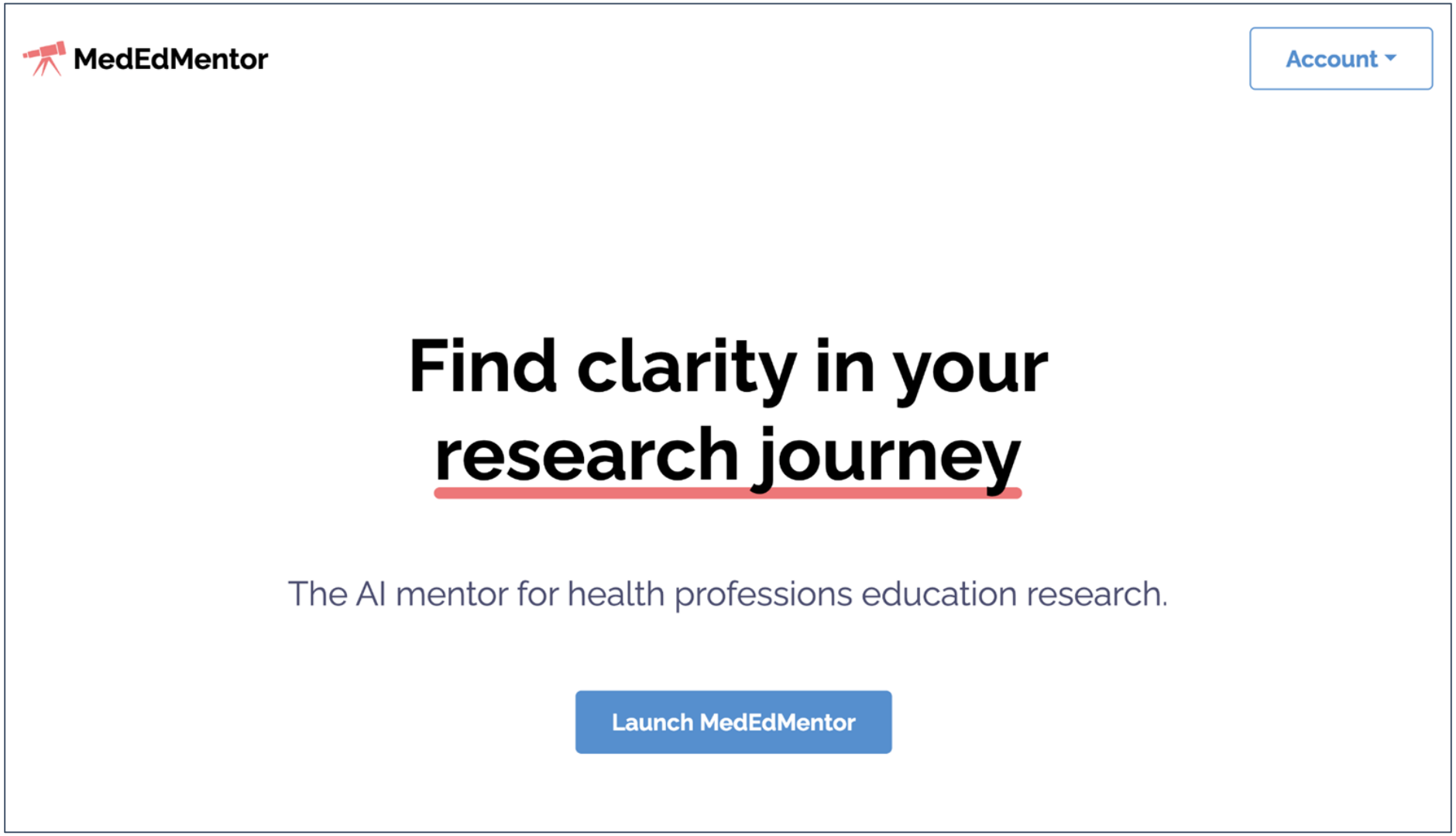
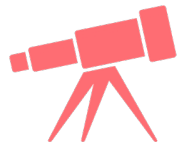


MedEdMentor

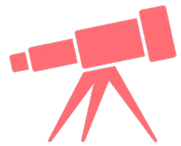
- The digital mentor for HPE scholarship
- Our goal is to make HPE scholarship universally accessible
- Over 1750 users from 95+ countries use MedEdMentor

Design based on the roles of a human mentor

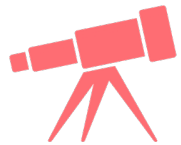
Human Mentor	MedEdMentor	
Orientation to field	**Lessons**	Guides for HPE scholarship
Finding education theories	**Theory Database**	200+ summaries of education theories
Recommending literature	**Literature Search**	HPE-specific literature search
Suggesting theories	**Theory Suggester**	Guidance on what theories to consider



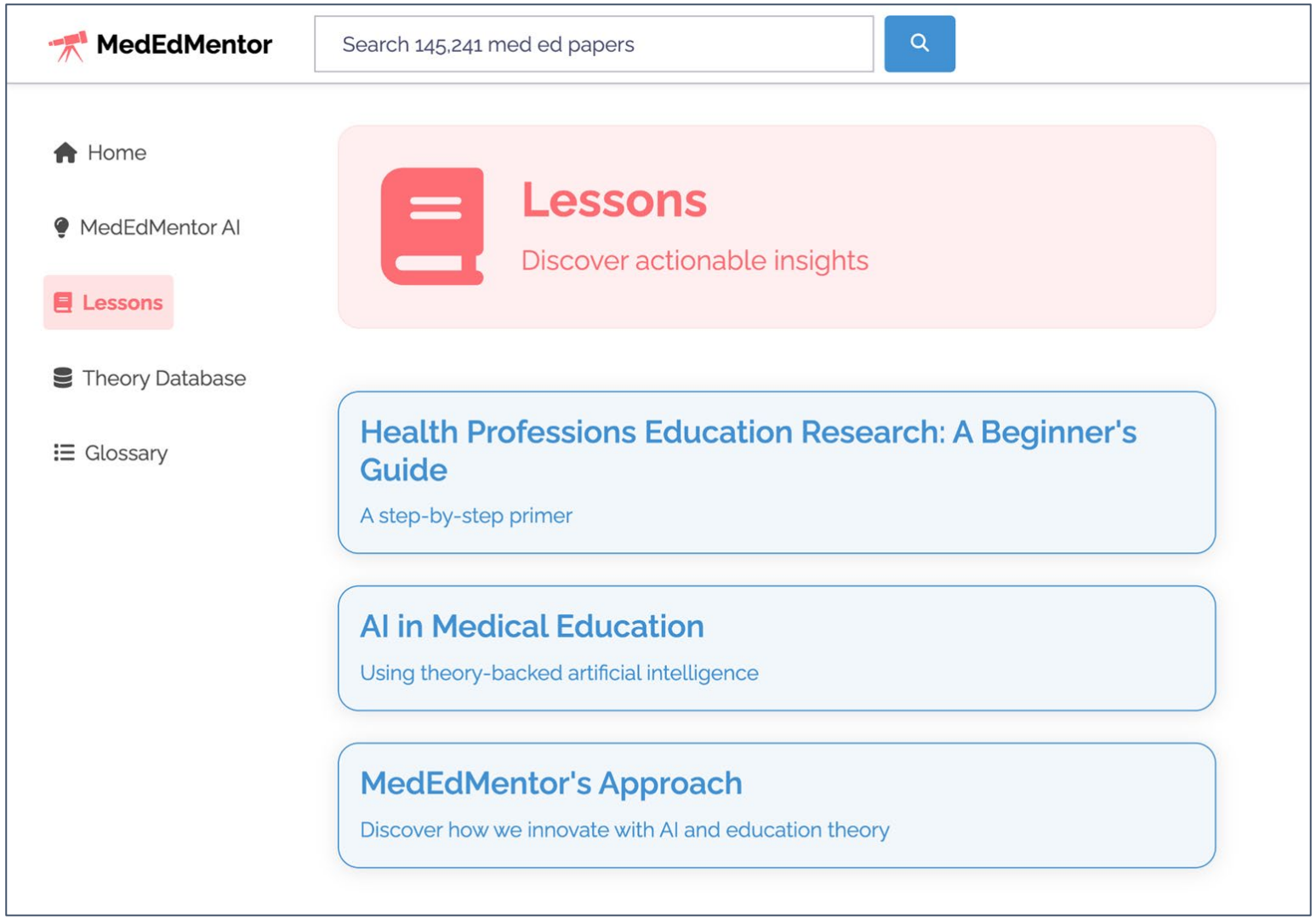
Static Content



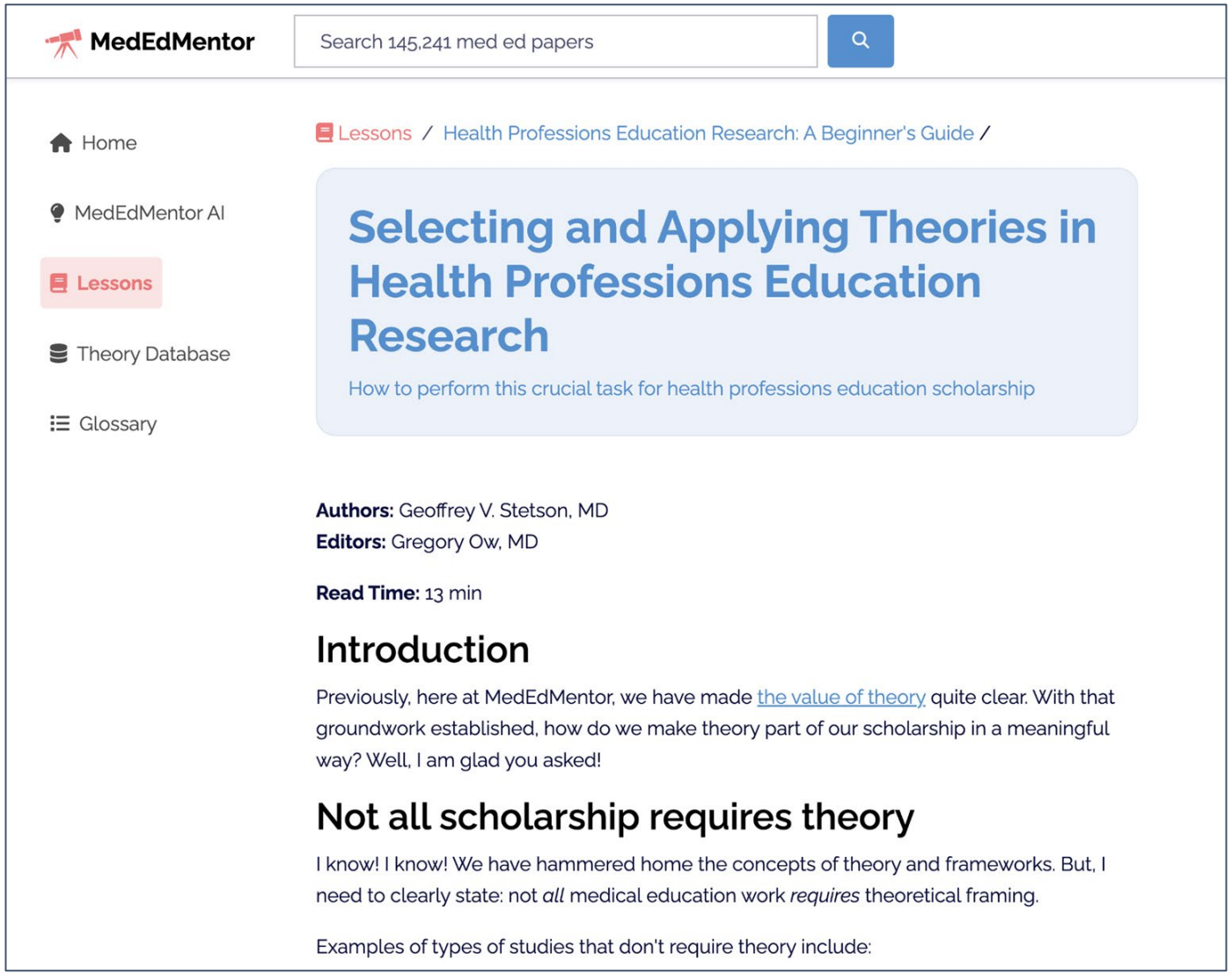
Lessons



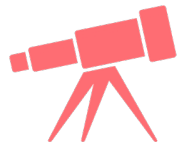
Lessons


MedEdMentor
Search 145,241 med ed papers
Home
MedEdMentor AI
Lessons
Theory Database
Glossary
Lessons
Discover actionable insights
Health Professions Education Research: A Beginner's Guide
A step-by-step primer
AI in Medical Education
Using theory-backed artificial intelligence
MedEdMentor's Approach
Discover how we innovate with AI and education theory

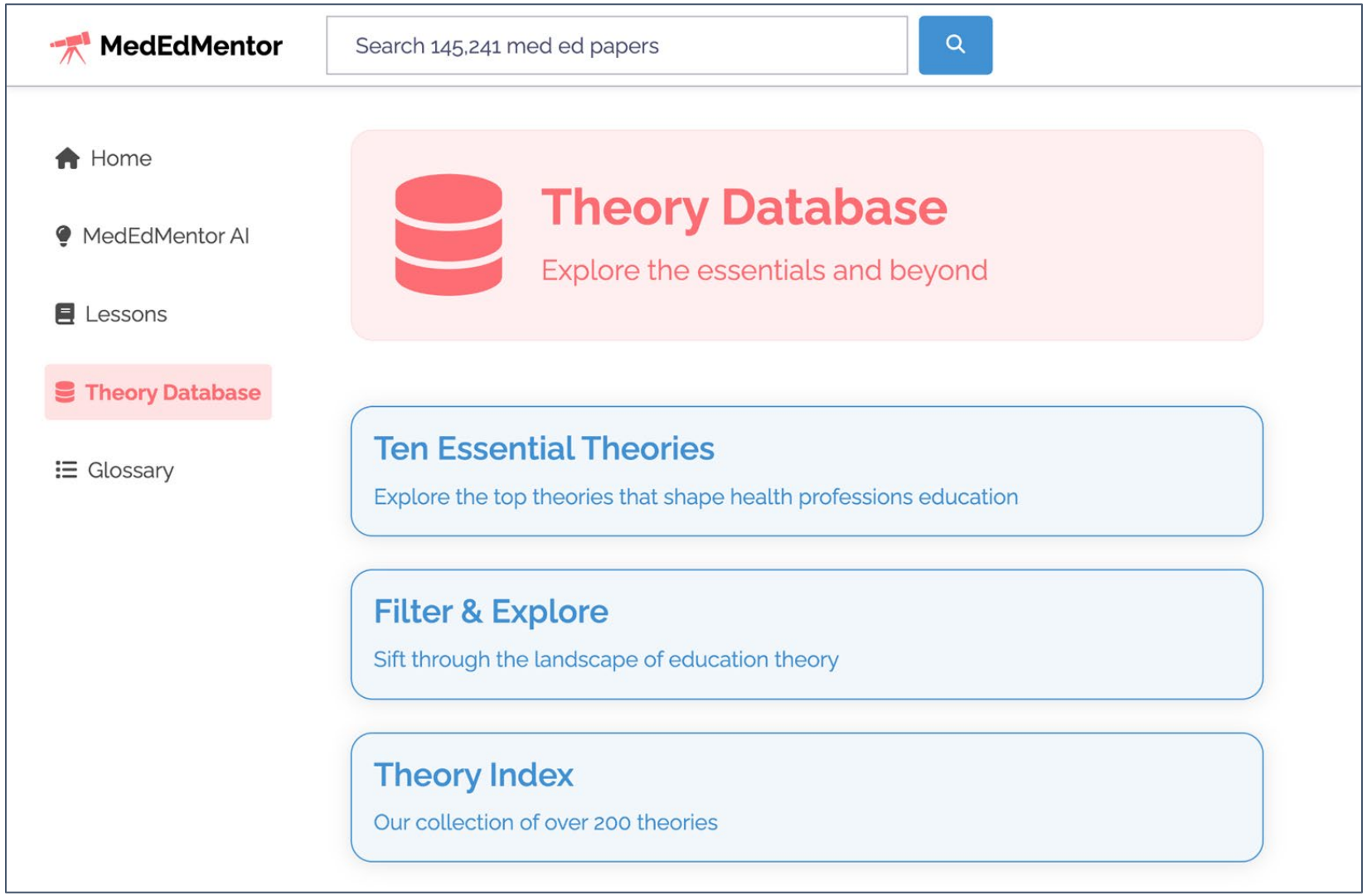
Sample Lesson from MedEdMentor



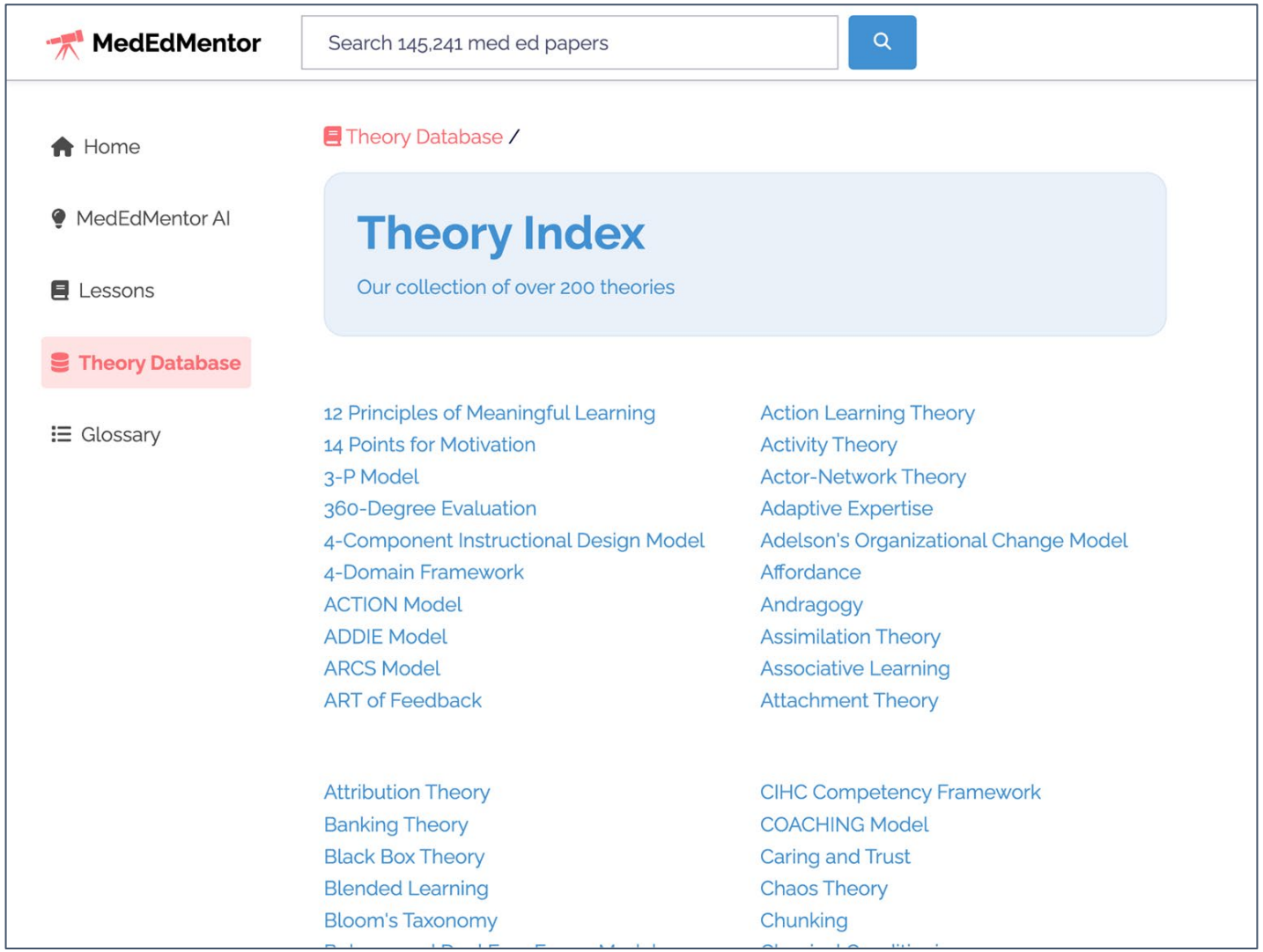
Theory Database



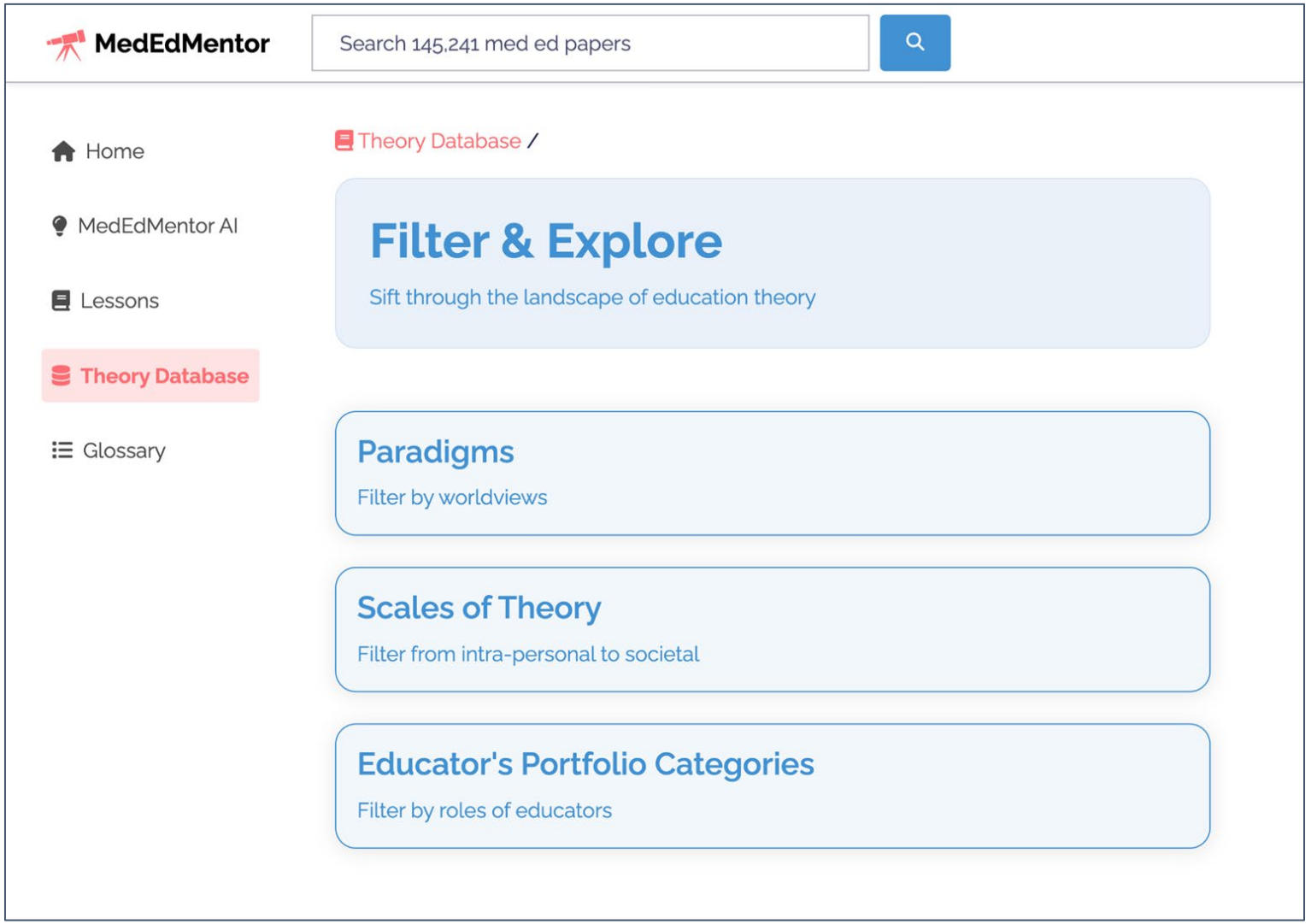
Theory Database



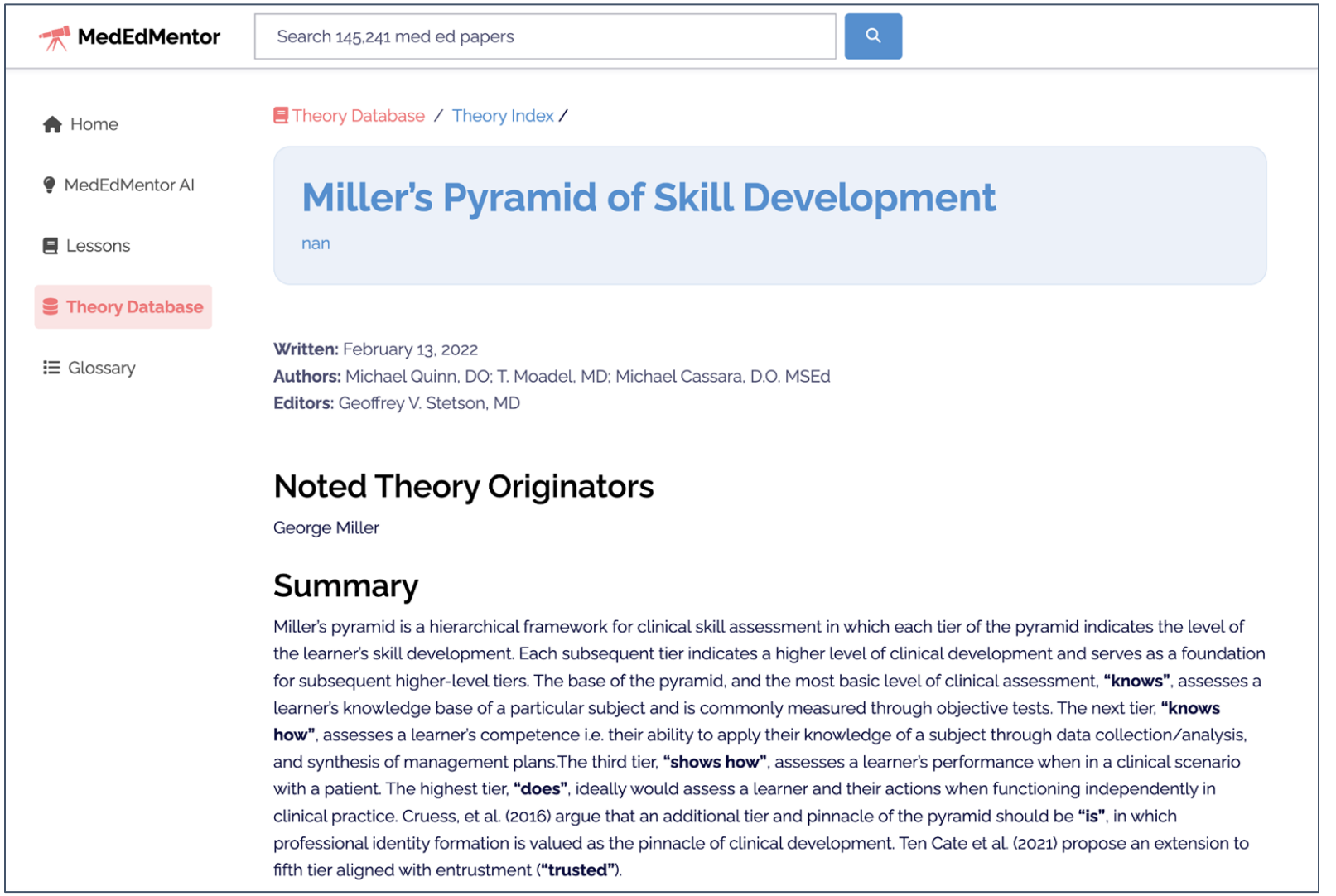
Index of 200+ theories



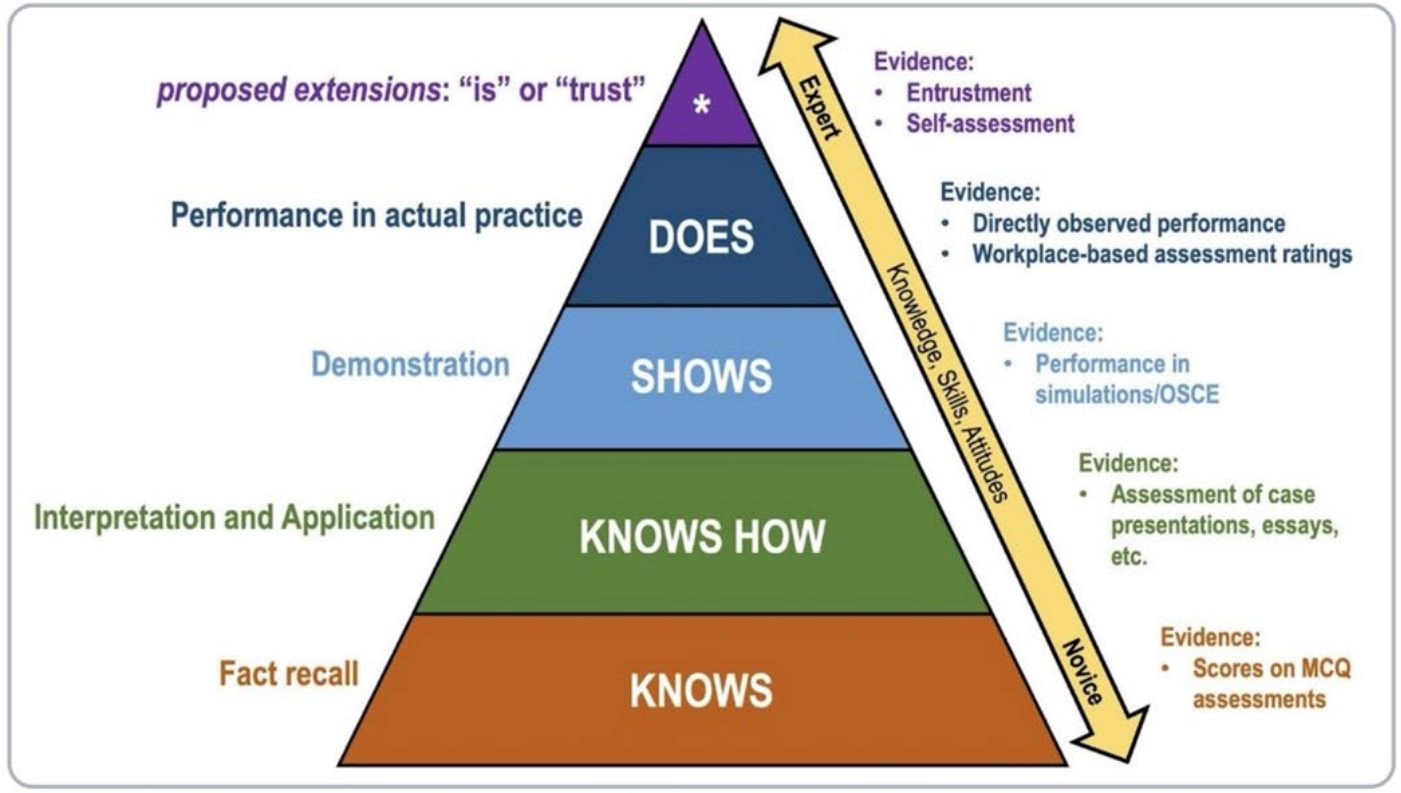
Find theories by paradigm, scale, and more



Theory Summaries



Example diagram from a Theory Summary



Original Diagram by Michael Quinn and Michael Cassara. Adapted from: Miller's pyramid of clinical competence. (n.d.). In The iDea Book. University of Saskatchewan. Retrieved February 16, 2022, from https://openpress.usask.ca/ideabook/chapter/millers-pyramid-of-clinical-competence/, based on Ramani & Leinster (2008); also includes extension ideas from Creuss et al. (2016) and ten Cate et al. (2021).

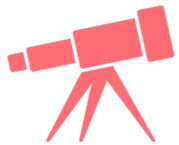
Where the theory was described / applied

Described In

1. Miller G. E. (1990). The assessment of clinical skills/competence/performance. *Academic Medicine: Journal of the Association of American Medical Colleges*, *65*(9 Suppl), S63–S67. https://doi.org/10.1097/00001888-199009000-00045
2. Cruess, R. L., Cruess, S. R., & Steinert, Y. (2016). Amending Miller's Pyramid to Include Professional Identity Formation: *Academic Medicine*, *91*(2), 180–185. https://doi.org/10.1097/ACM.0000000000000913
3. Ten Cate, O., Carraccio, C., Damodaran, A., Gofton, W., Hamstra, S. J., Hart, D. E., ... & Schumacher, D. J. (2021). Entrustment decision making: extending Miller's pyramid. *Academic Medicine*, *96*(2), 199-204.
4. Ramani, S., & Leinster, S. (2008). AMEE Guide no. 34: teaching in the clinical environment, Medical Teacher, 30:4, 347-364. https://doi.org/10.1080/01421590802061613

Applied In

1. Witheridge, A., Ferns, G., & Scott-Smith, W. (2019). Revisiting Miller's pyramid in medical education: the gap between traditional assessment and diagnostic reasoning. *International journal of medical education*, *10*, 191–192. https://doi.org/10.5116/ijme.5d9b.0c37
2. Williams, B. W., Byrne, P. D., Welindt, D., & Williams, M. V. (2016). Miller's pyramid and core competency assessment: a study in relationship construct validity. *Journal of Continuing Education in the Health Professions*, *36*(4), 295-299.https://journals.lww.com/jcehp/fulltext/2016/03640/Miller_s_Pyramid_and_Core_Competency_Assessment__.11.aspx
3. Al-Eraky, M., & Marei, H. (2016). A fresh look at Miller's pyramid: assessment at the 'Is' and 'Do' levels. *Medical education*, *50*(12), 1253-1257.



Categorization of the theory & similar theories

Paradigm

Interpretivist

Post-positivist

Educator's Porfolio Category

Approaches to Teaching and Learning

Learner Assessment

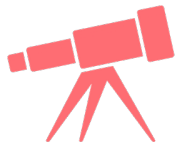
Curriculum Development and Evaluation

Scale of Theory

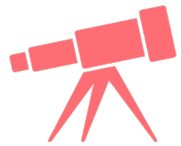
Individual

Similar Theories

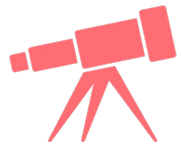
Dreyfus (Five-Stage) Model of Skill Acquisition, Peyton/Burch/Broadbent conscious-competence model, Bloom's Taxonomy, Competency-Based Education, Entrustable Professional Activities



AI-Enhanced Features

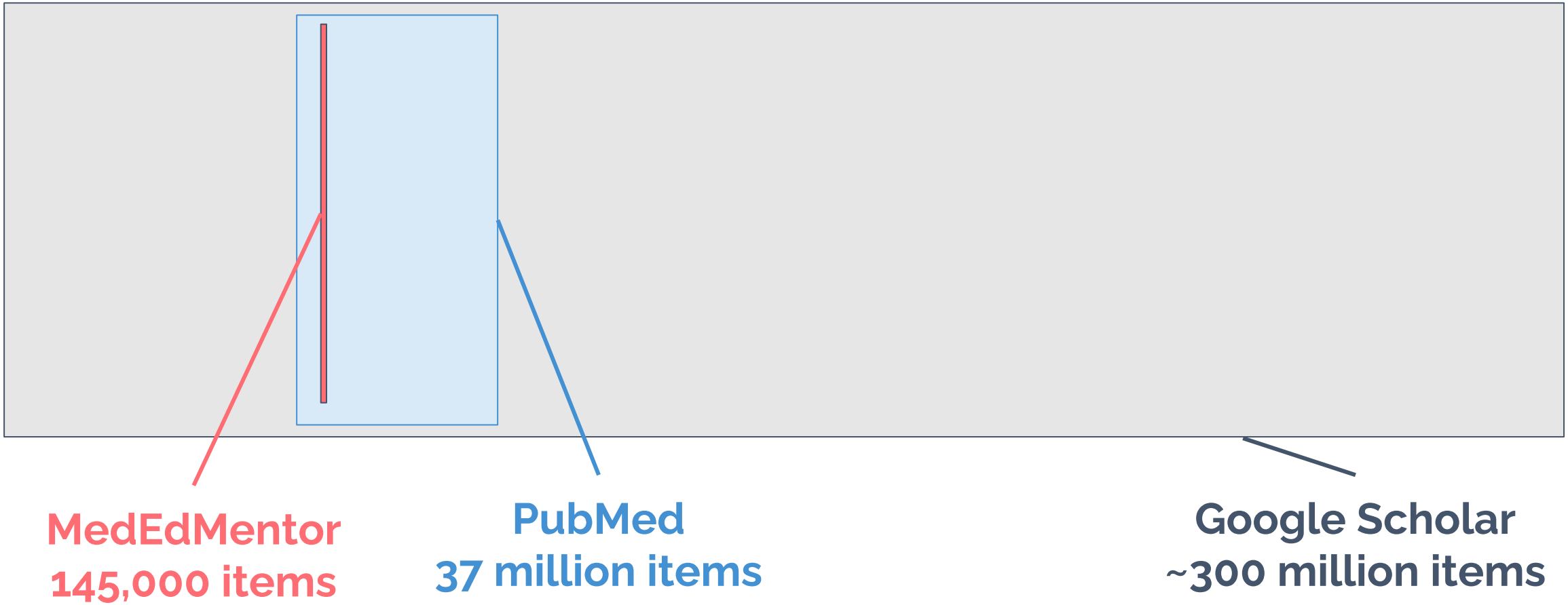


HPE-Specific Literature Search

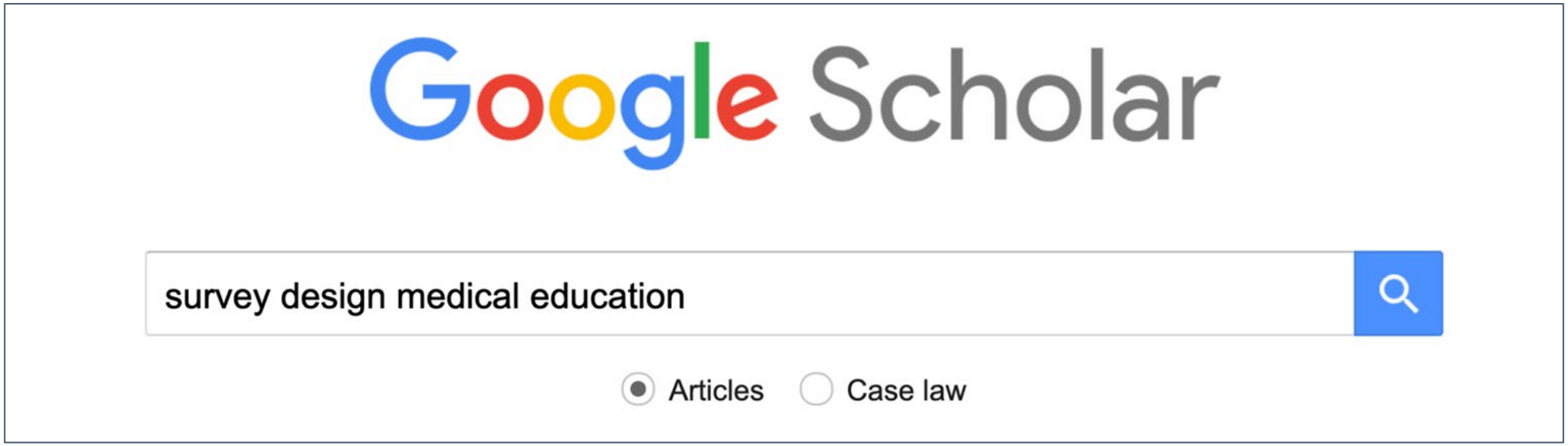


HPE-Specific Literature Search

A much more focused search



Let's search Google Scholar



Google Scholar Result #1 — ✓

Tracing the steps of **survey design**: a graduate **medical education** research example [PDF] alle

C Magee, G Rickards, L A. Byars… - … **Medical Education**, 2013 - meridian.allenpress.com

… the quality of GME **surveys** and increase the likelihood of collecting **survey** data with evidence … in **medical education** may operationalize this framework with examples from a **survey** we …

☆ Cited by 50 Related articles »

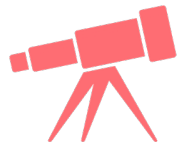
Google Scholar Result #2 — ✓

What do our respondents think we're asking? Using cognitive interviewing to improve **medical education surveys** [PDF] alle

GB Willis, AR Artino Jr - … of graduate **medical education**, 2013 - meridian.allenpress.com

… **medical education** (GME) educators and researchers to use more systematic and rigorous **survey design** … a 6-step decision process for questionnaire **designers** to use. In this article, we …

☆ Cited by 561 Related articles »



Google Scholar Result #3 — ✓

You can't fix by analysis what you've spoiled by **design**: developing **survey** instruments and collecting validity evidence [PDF] alle

G Rickards, C Magee… - … **medical education**, 2012 - meridian.allenpress.com

… or best practices in **survey design**.2 As a result, the reliability and validity of many **medical education surveys** are uncertain. When **surveys** are not well **designed**, the data obtained from …

☆ Cited by 247 Related articles »

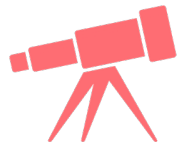
Google Scholar Result #4 — Not quite

National **survey** on anatomical sciences in **medical education** [PDF] wil

JM McBride, RL Drake - Anatomical sciences **education**, 2018 - Wiley Online Library

… **medical** schools wishing to gain or maintain accreditation through the Liaison Committee on **Medical Education** … After a review of LCME decisions on full **survey** reports from 2004–2012, …

☆ Cited by 243 Related articles »



Now, an HPE-Specific Literature Search

MedEdMentor Result #1, #2 — ✓

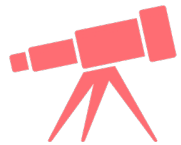
Survey research design: Questionnaire development

Michael J. Peeters , K. Janke - Currents in Pharmacy Teaching and Learning - 2022

Educator's blueprint: A how-to guide for survey design

Jeffery Hill , K. Ogle , S. Santen , M. Gottlieb , A. Artino - AEM Education and Training

Abstract Surveys are ubiquitous in medical education. They can be valuable for asse across a wide … Expand



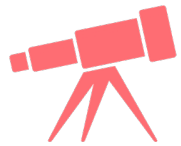
MedEdMentor Result #3 — ✓

Tracing the steps of survey design: a graduate medical education research exa

Charles Magee , G. Rickards , Lynn A Byars , A. Artino - Journal of Graduate Medical Education - 2013

tldr This article illustrates how researchers in medical education may operationalize framework for developing survey instruments with examples from a survey developed the recent integration of 2 independent internal medicine residency programs.

Expand



MedEdMentor Result #4, #5 — ✓

Mastering Survey Design and Questionnaire Development.

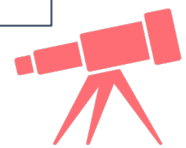
Meigan Robb , T. Shellenbarger - Journal of Continuing Education in Nursing: Continuing Competence for the Future - 2020

tldr Individuals creating surveys should follow survey design and item development guidelines, such as those described in this article, to ensure the accuracy of the data gathere Expand

Lies, Damned Lies, and Surveys.

A. W. Phillips , A. Artino - Journal of Graduate Medical Education - 2017

Abstract S urveys are a common research method used in medical education. For example, retrospective … Expand



Different # of results ⇒ different purposes

Google Scholar

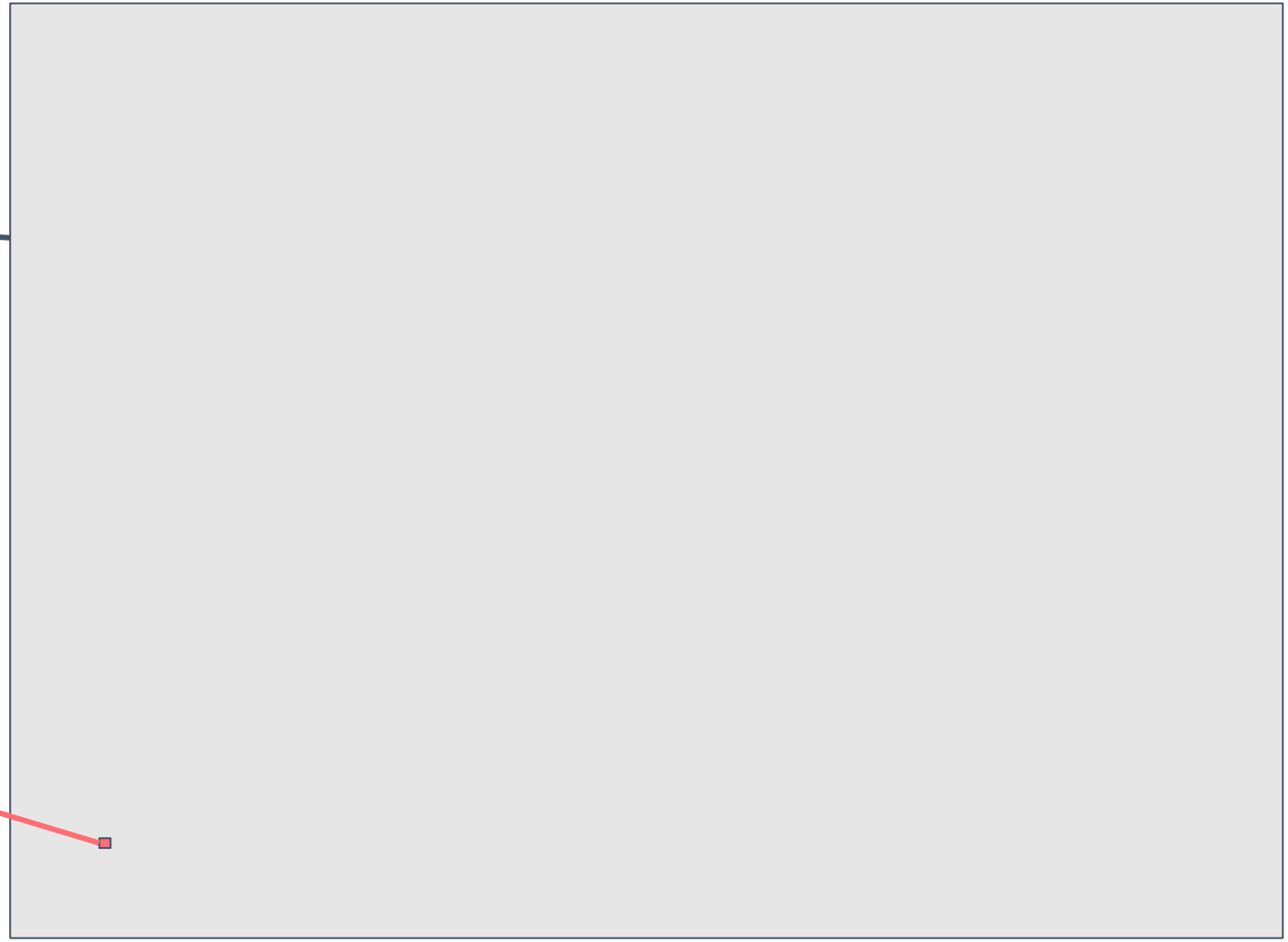
5,940,000 results

Ideal for broad, thorough searches

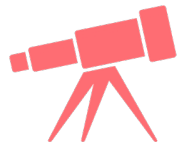
MedEdMentor

40 results

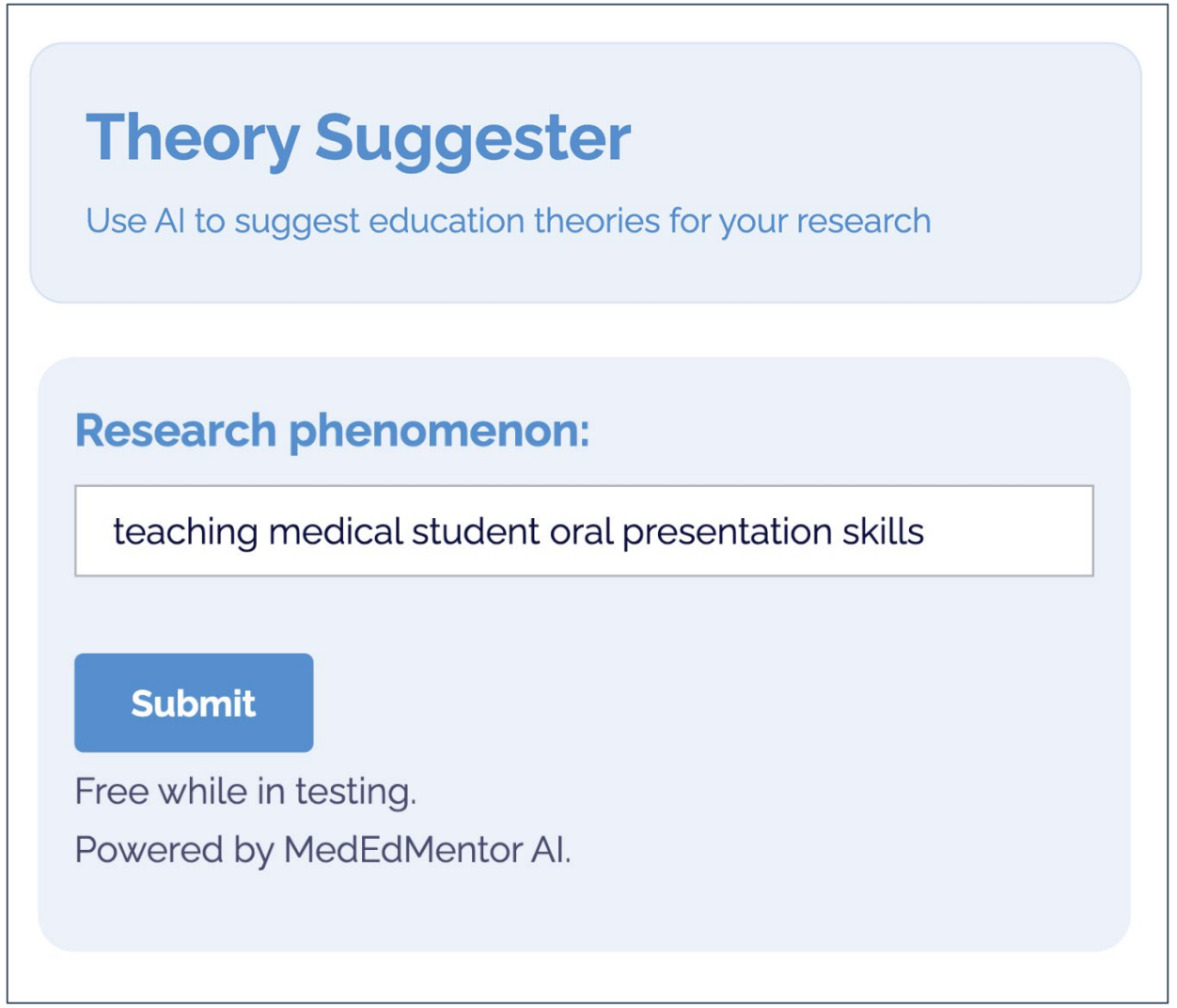
Ideal for focused overviews



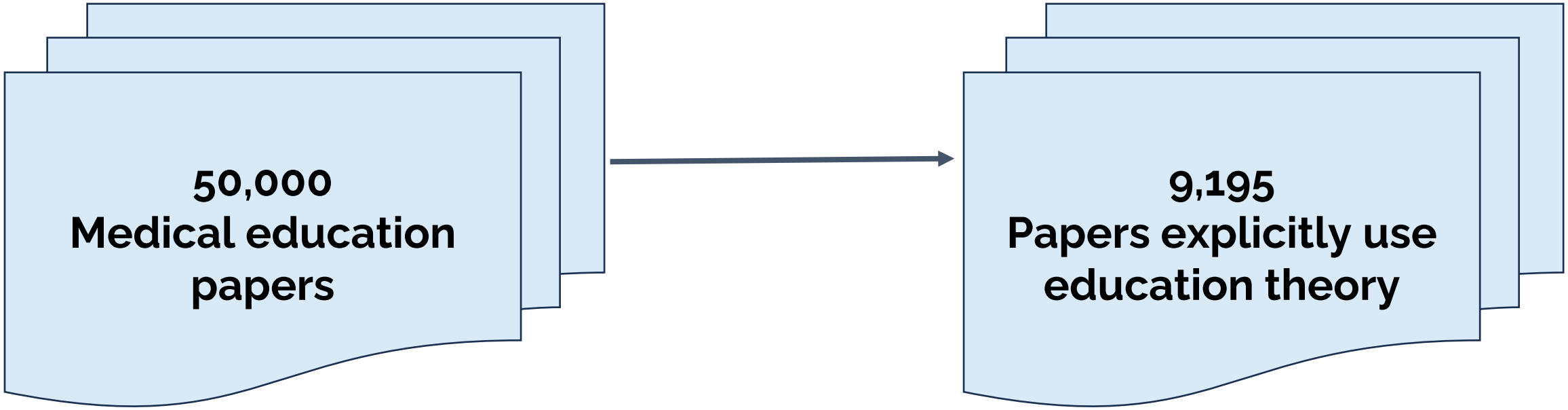
Theory Suggester



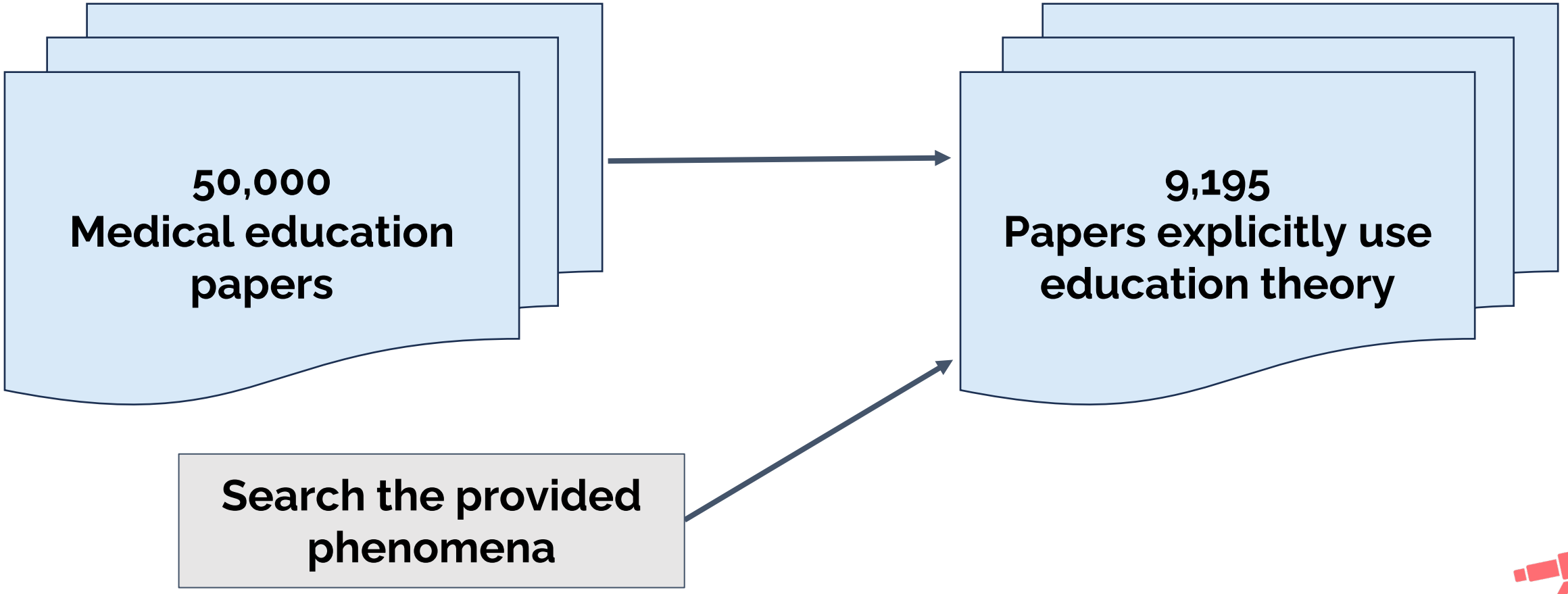
Enter a phenomenon into Theory Suggester



Then MedEdMentor finds relevant theories



Then MedEdMentor finds relevant theories



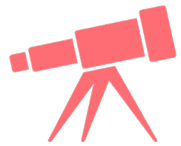
Receive a list of theories to consider

MedEdMentor AI

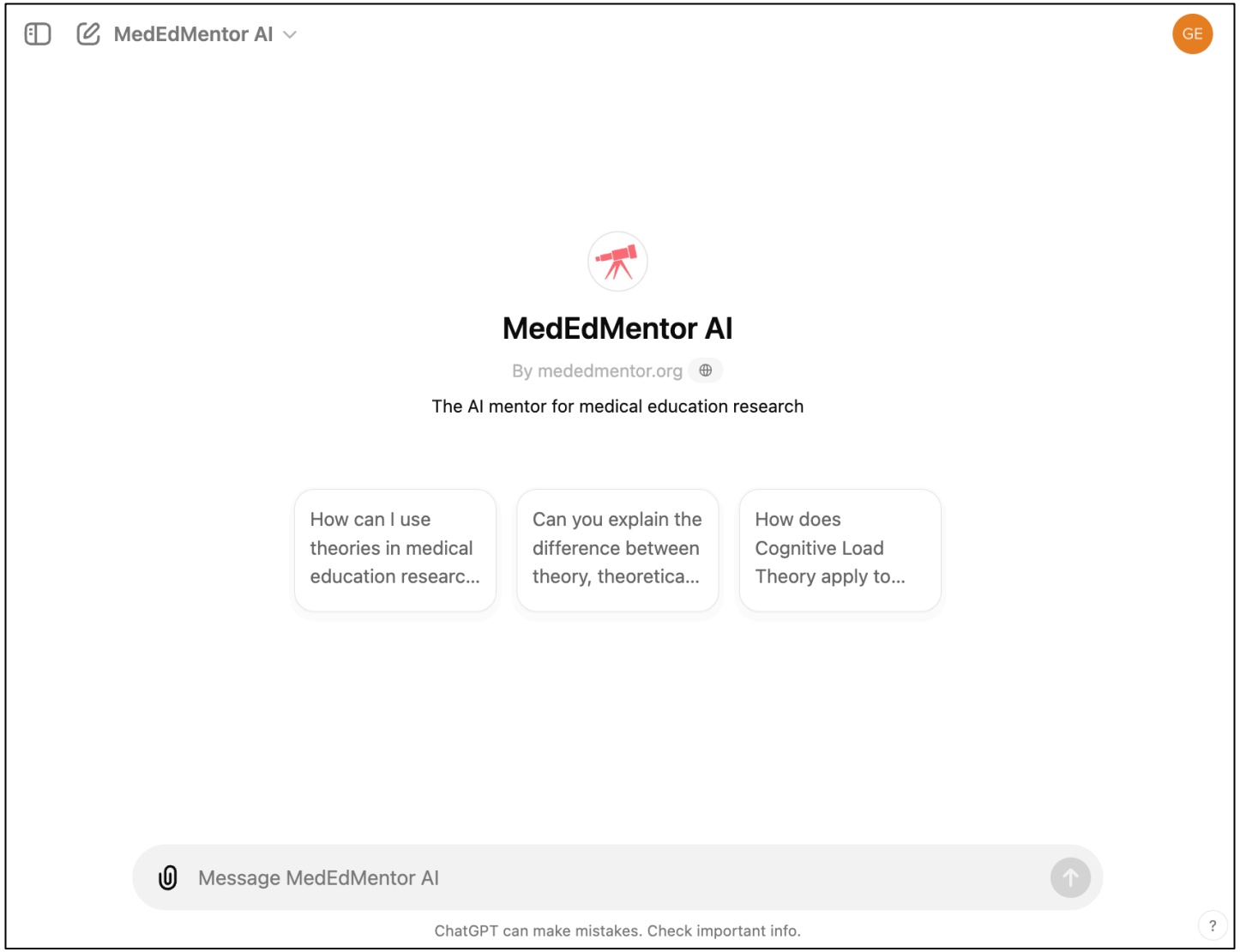
Here are some theories for you to consider:

- Experiential Learning Theory - 3 papers
- Rhetorical Theory - 2 papers
- Genre Knowledge - 2 papers
- Active Learning Theory - 2 papers
- Feedback Theory - 2 papers
- Deliberate Practice Theory - 1 paper
- Social Learning Theory - 1 paper
- Formative Assessment - 1 paper
- Hidden Curriculum Theory - 1 paper
- Sociolinguistic Theory - 1 paper
- Effective Communication Theory - 1 paper
- Role Theory - 1 paper

MedEdMentor AI



MedEdMentor AI



MedEdMentor is meeting a global need

High organic usage:

- 1750 Users
- 13,000 Minutes
- 1,000 Suggestions
- 5,000 Searches
- 95 Countries

MedEdMentor is meeting a global need for accessible mentorship

Next, more mentorship domains in progress

Human Mentor	MedEdMentor
Recommending literature	Expand paper database to other HPE fields
Writing research questions	Offer critiques for research questions
Suggesting methodologies	Methodology Suggester
Networking	Community of Practice
Moral support	Project reminders and encouragement

Partnership, Collaboration, and Support

MedEdMentor

UIC

UNIVERSITY OF ILLINOIS
COLLEGE OF MEDICINE

Implications of no partnership

- All MedEdMentor business after-hours
- Academic caveats
- No university resources
  - No students, residents, fellows, graduate students
  - No collaboration with colleagues

Budding Collaboration

MedEdMentor

HARVARD MACY INSTITUTE
HARVARD MEDICAL SCHOOL

Support from Macy Foundation

Meet Our Scholars

Geoff Stetson, MD

UNIVERSITY OF ILLINOIS CHICAGO COLLEGE OF MEDICINE

VIEW PROFILE

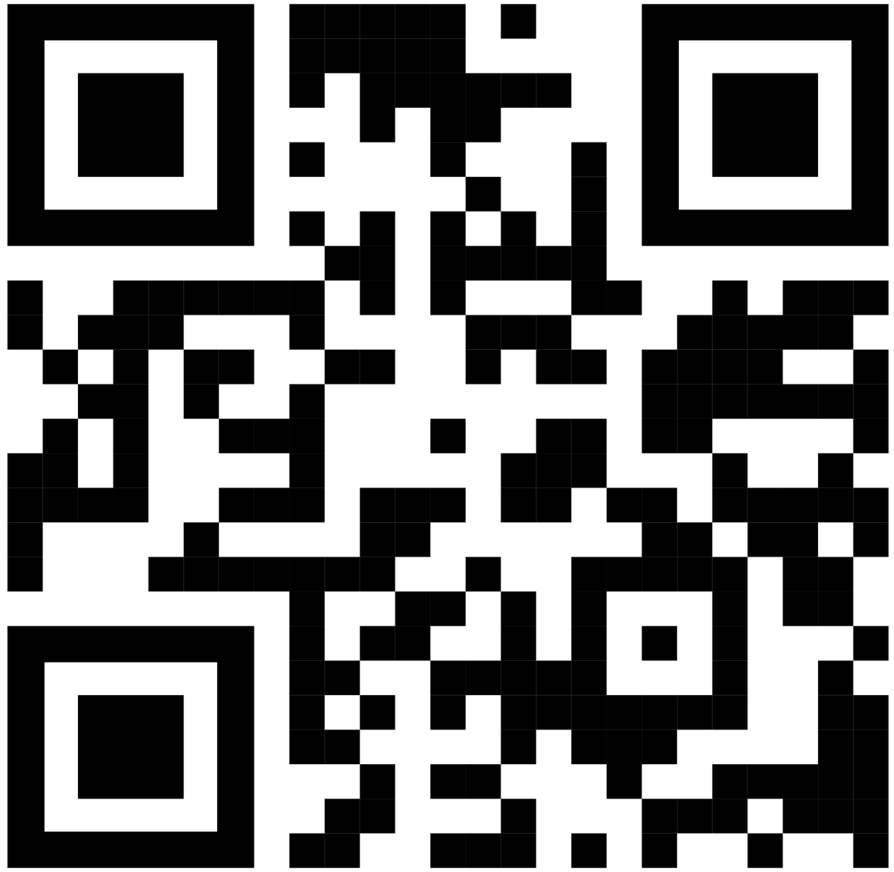
Geoff Stetson is an Associate Professor of Clinical Medicine and Medical Education at the University of Illinois Chicago (UIC) College of Medicine. Until 2022, Dr. Stetson worked at the University of California San Francisco.

Through his role as Director of Clinical Faculty Development at UIC, Dr. Stetson works to optimize learning in clinical environments with an emphasis on diversity and inclusion. Additionally, he is an expert in technology-enhanced education.

Dr. Stetson's Macy Faculty Scholars project investigates how master researchers in health professions education utilize theoretical frameworks and make them accessible to mentees. Lessons learned will inform the creation and study of an interactive website for novice scholars from diverse backgrounds, geographies, and institutions, to foster scholarship, mentorship, and community. You can find that website at: www.MedEdMENTOR.org.

Alan Schwartz, PhD, the Michael Reese Endowed Professor of Medical Education in the Department of Medical Education at the UIC College of Medicine, serves as Dr. Stetson's mentor.

Thank you!



MedEdMentor.org

BUILDING AI PARTNERSHIP ACROSS MEDICINE, INDUSTRY, & GOVERNMENT: Lessons Learned from the Harvard Data Science Initiative

The Harvard Data Science Initiative is a **Harvard-wide initiative** that connects and galvanizes Harvard's data science ecosystem **to make meaningful progress on issues of societal impact.**

CONTEXT –
ABOUT THE HARVARD DATA SCIENCE INITIATIVE

CHALLENGE:

DATA SCIENCE EXISTS IN ALL SPACES AT HARVARD

SINCE LAUNCHING IN 2017, OUR COMMUNITY HAS GROWN TO INCLUDE:

- 160+ FACULTY MEMBERS
- 10 HARVARD SCHOOLS
- 13 RESEARCH CENTERS

DEPARTMENTS AND AREAS:
Applied Math (SEAS)
Astronomy (FAS)
Bioengineering (SEAS)
Biomedical Informatics (HMS)
Biostatistics (SPH)
Computer Science (SEAS)
Design (GSD)
Earth and Planetary Sciences (FAS)
Economics (FAS)
Education (GSE)
Electrical Engineering (SEAS)
Environmental Health (SPH)
Epidemiology (SPH)
Global Health and Pop (SPH)
Global Health Social Med (HMS)
Government (FAS)
Health Care Policy (HMS)
International Dev (HKS)
Law/International Law (HLS)
Marketing (HBS)
Mathematics (FAS)
Molecular and Cell Biology (FAS)
Nutrition (SPH)
Physics (FAS)
Psychiatry (HMS)
Psychology (FAS)
Public Policy (HKS)
Romance Languages (FAS)
Sociology (FAS)
Statistics (FAS)
Tech and Operations Mgmt (HBS)

CENTERS AND PROGRAMS:
Berkman Klein Center for Internet & Society (HLS)
Boston Area Research Initiative (Harvard/NEU)
Center for Geographic Analysis (CGA)
Center for Intl Development (HKS)
Center for Research on Computation and Society (SEAS)
Center on the Legal Profession (HLS)
CrisisReady.io (SPH/HMS)
Digital, Data, and Design (D^3) Institute (HBS)
Harvard Business Analytics Program (HBS/SEAS)
Institute for Applied Computational Science (SEAS)
Institute for Quantitative Social Science (FAS)
metaLab (FAS/GSD)
Wyss Institute (SEAS/HMS)

HDSI FACULTY DIRECTOR
Francesca Dominici (Biostatistics)

HDSI FACULTY CO-DIRECTOR
Stratos Idreos (Computer Science)

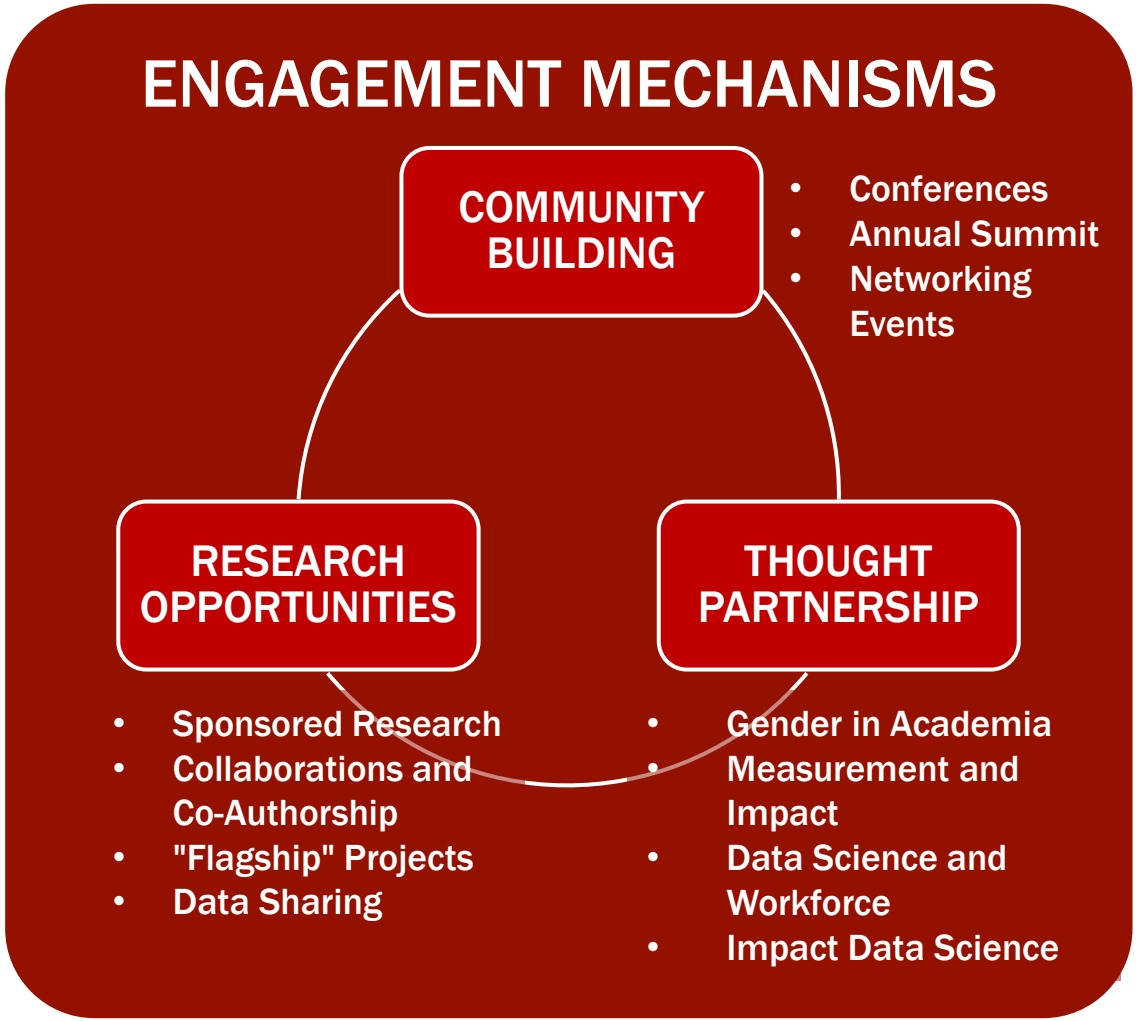
WHY DO WE INTERACT WITH INDUSTRY?

VALUE TO ACADEMIA:

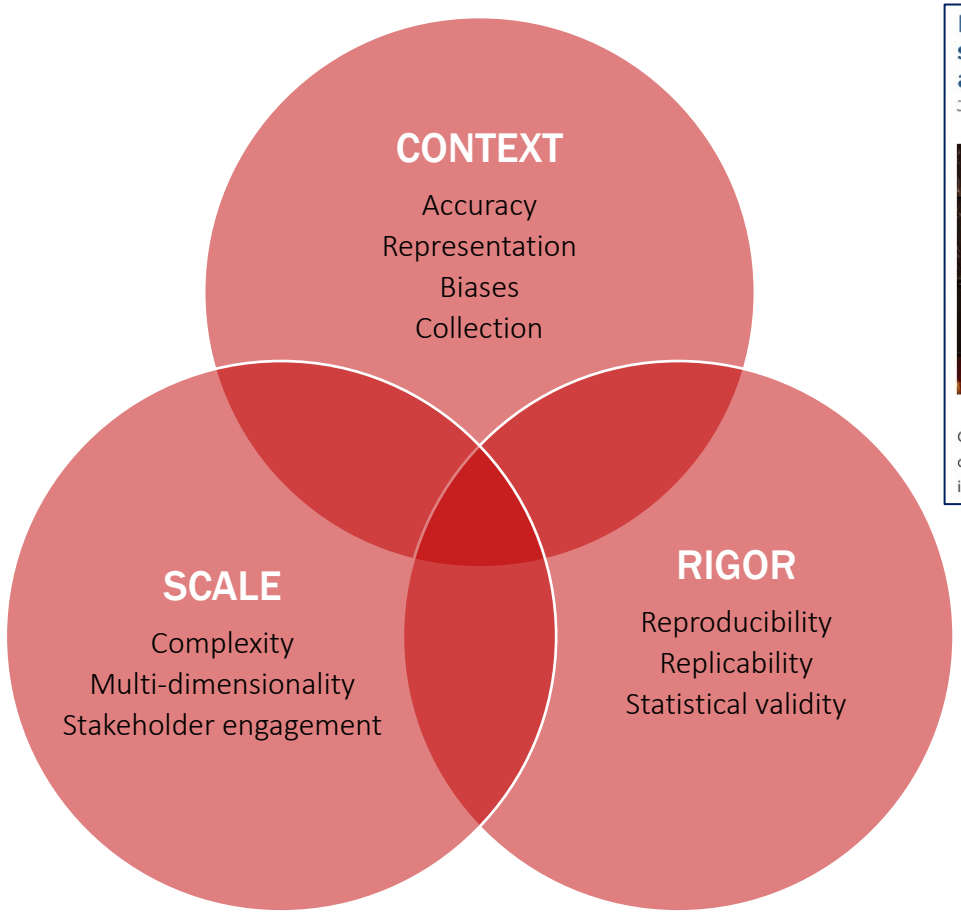
- Industry is innovating data science and AI in real time, at scale
- Amplify impact of academic research
- Research resources and support

VALUE TO INDUSTRY:

- Workforce / hiring / access to talent
- Executive education / continuing education
- Collaborative research / thought partnership
- Branding



HDSI WORKS WITH INDUSTRY ON URGENT, PRE-COMPETITIVE TOPICS



Harvard and Elsevier are using data science to improve gender equality in academia

January 16, 2020

Colleagues from H
data science proje
in academia

Harvard Data Science Initiative Announces the AWS Impact Computing Project at the HDSI

November 8, 2022

New alliance between Harvard Data Science Initiative and Amazon Web Services set to transform how faculty use data to solve the world's biggest problems.

Bayer to support Harvard Research Study to Evaluate Trust in Science, Including in COVID-19 pandemic

May 26, 2020

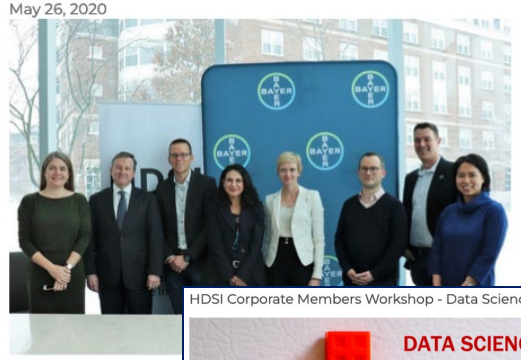


Image Courtesy of Bay

With seed funding fro
launches a research eff

HDSI Corporate Members Workshop - Data Science and Our Workforce

Image Credit: Aldo Gonzalez

ABOUT

With the continued growth of predictive analytics and ever increasing access to data, both structured and unstructured, we see new opportunities and challenges for understanding workforce dynamics. How can data science methods be used in recruitment? What can data science tell us about teams and team members? How should we approach performance metrics while remaining sensitive to human elements? How do we achieve a diverse and inclusive workforce? And, for all of the above, what are the limitations and biases of a quantitative approach and how do we overcome them? Are there places where a quantitative approach is never appropriate? In this half-

QUESTIONS TO ASK

WHY?	HOW?	WHO?	WHAT?	WHEN?
• What is valuable about collaboration? • Is it tangible or intangible? • Who decides?	• Know what mechanisms are available: sponsored research, philanthropy, something else? • How to decide? • How will you incentivize faculty?	• What is the administrative cost of managing the collaboration? • Who are your champions on either side? How will they help unstick challenges?	• Define, define, define. • “What does that mean?”	• The agreement is only the beginning. • How will you sustain momentum?

CASE STUDY: AWS IMPACT COMPUTING PROJECT AT THE HARVARD DATA SCIENCE INITIATIVE

SCIENCE & TECHNOLOGY

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Harvard Data Science Initiative, Amazon Web Services join to boost research, unlock solutions to health, climate, economic challenges

WHY?

- Using HPC to overcome roadblocks for data-driven solutions
- First-hand experience in building workflows and pipelines

HOW?

- Faculty research - sponsored
- Field-building and education - philanthropy

WHO?

- Alliance management
- Our internal stakeholders - Vice Provost for Research, Tech Development, Fundraising (Development), General Counsel

WHAT?

- Ongoing communication
- Getting to know corporate culture

WHEN?

- Entering Year 3.
- Continued connection – advisory groups, events, etc.

GETTING STARTED - KEY TAKEAWAYS

1. Industry relations requires an investment in resources (PEOPLE!)
2. If you can, start local. Who is in your region?
3. Communication, communication, communication!

Thank you!

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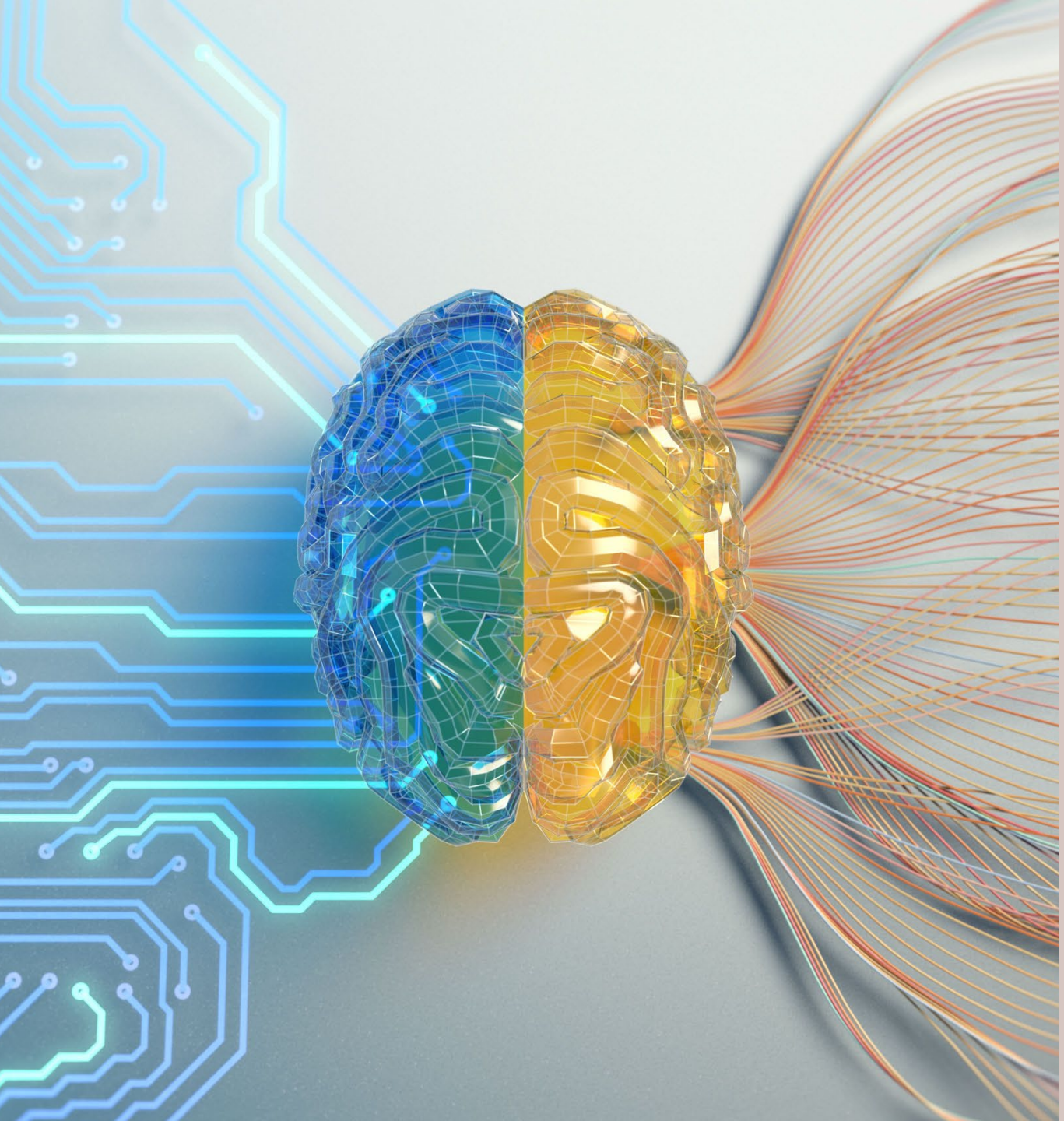
- Accreditation
- Application of AI tools
- Clinical skills assessment
- Competencies
- Content delivery
- Content development
- Curriculum mapping
- General assessments
- Simulation
- Student Support Services



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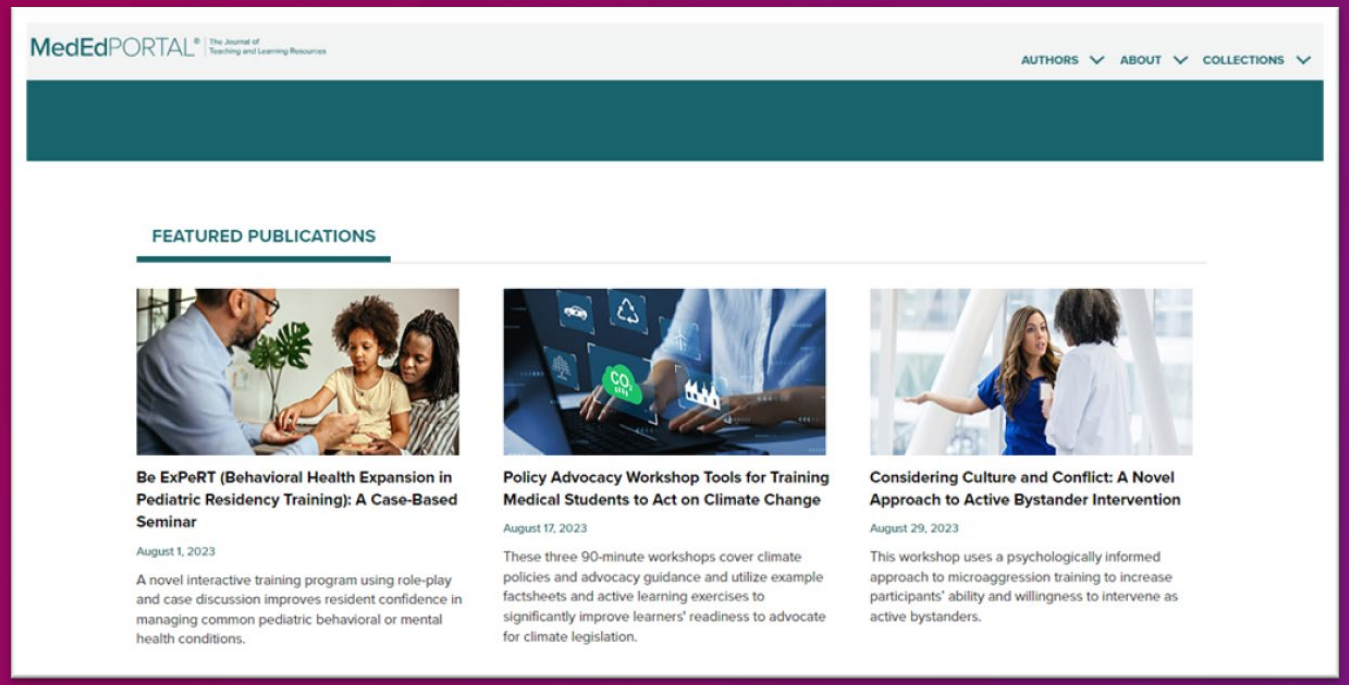

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