The Impact of AI as an Employer in the Health Care and Life Sciences Sectors

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Introducing Braintrust AIR – the world's first AI recruiter (Apr. 29, 2024), https://youtu.be/wHgL7ShWOLo

Case Study: The Home Healthcare Matching Tool

Evaluating an operational AI tool prior to deployment

- **The Tool:**
A homegrown AI tool developed by a home healthcare company.

- **The Function:**
Designed to match caregivers to patients based on care needs, qualifications, and location/proximity.

- **The Risk:**
The algorithm decides which caregivers receive higher-value, more stable, or desirable work assignments.

Caregivers
Skills & Expertise Certifications & Qualifications Availability (Day/Time)

Patients
Specific Care Needs Patient Location

Methodology: Navigating the Cold Start

Proactive bias testing without historical deployment data

The Challenge

- **Requirement:**
Before scaling and implementation, the client needed to evaluate the tool under both NYC Local Law 144-style bias audit requirements and the broader Title VII framework.

- **Constraint:**
The tool had never been deployed in New York City.

- **Missing Variables:**
No historical outcome data, no demographic data (race/gender), and no prior NYC applicant or patient records to analyze.

Use of Synthetic Data

- **Approach:**
Rather than waiting for actual adverse impacts to occur, the team developed a methodology based on synthetic data to simulate the NYC deployment environment.

- **Data Inputs:**
  - Historical ATS data & expected caregiver quals
  - Public data on commuting distances
  - Census data for potential patient locations
  - Industry reports on labor-market patterns

- **Analyses Conducted:**
  - NYC Local Law 144-style impact-ratio calculations
  - Multiple-pools adverse-impact analysis
  - Sensitivity testing

Insights & Takeaways

Redefining AI Employment Risk

- **The Insight:**

The employment decision is rarely just a simple hire/no-hire binary.

- **The Context:**

In healthcare and shift-based industries, AI drives matching, scheduling, assignment allocation, and workforce planning.

The Conclusion:

Algorithms that allocate opportunity, assign shifts, or determine patient coverage carry similar legal and ethical risks as traditional recruitment tools. Adverse-impact risk applies to assignment stability and quality.

The Geographic Proxy Risk

- **The Insight:**

Facially neutral data points can quietly introduce demographic disparities.

- **The Context:**

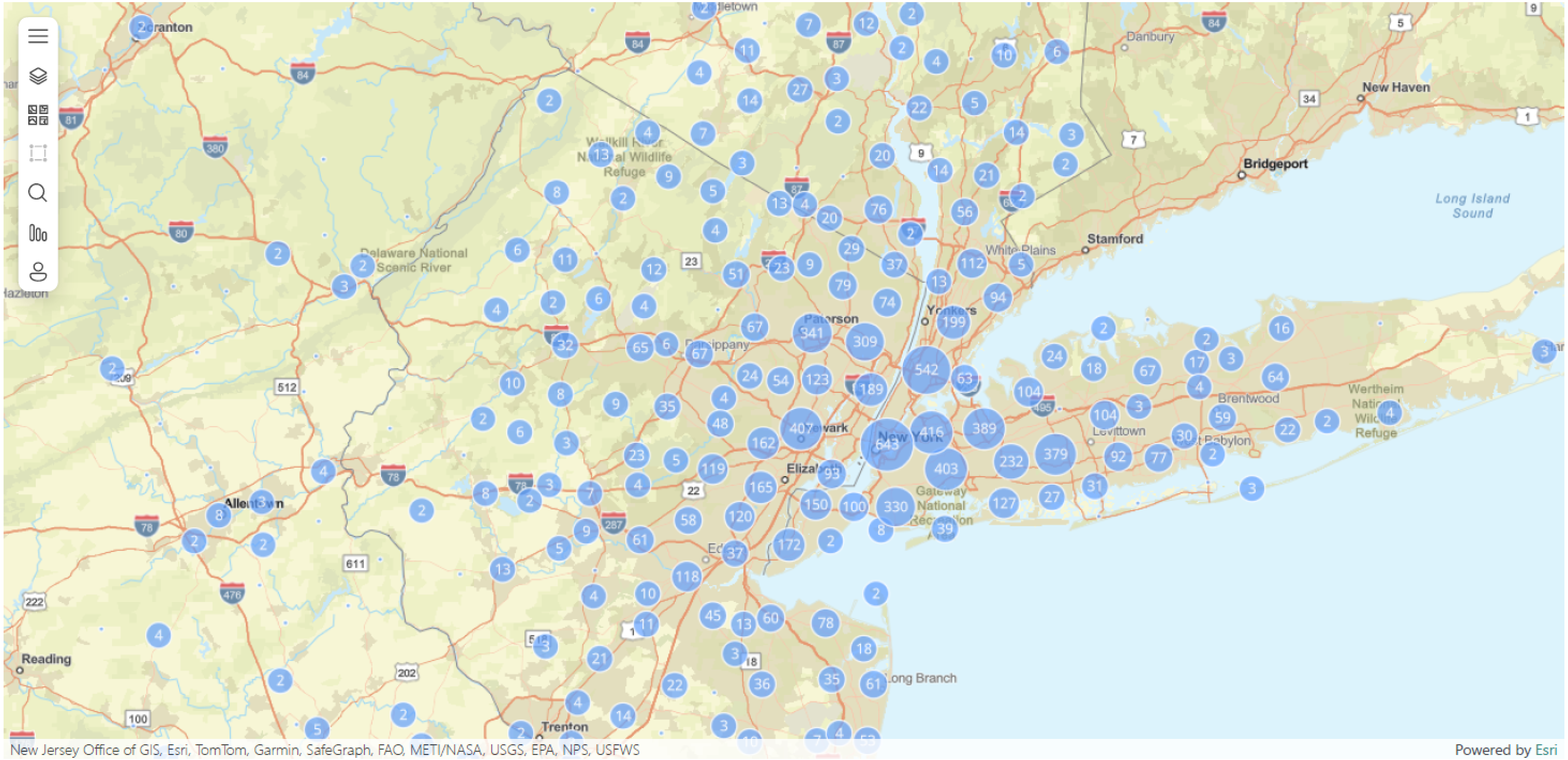
Geography was a legitimate business factor in this case-caregivers physically needed to reach patients' homes.

- **The Conclusion:**

Logistical constraints often mask demographic disparities. A ZIP code, travel distance, or commuting route can inadvertently function as a proxy for race, ethnicity, and socioeconomic status, requiring rigorous pre-deployment sensitivity testing.

Candidate Locations

Attorney-Client and Attorney-Work-Product Privileged
Exempt from Disclosure Pursuant to Subpoena or
Discovery Request, or Under the F.O.I. and Privacy Acts
XYZ AEDT



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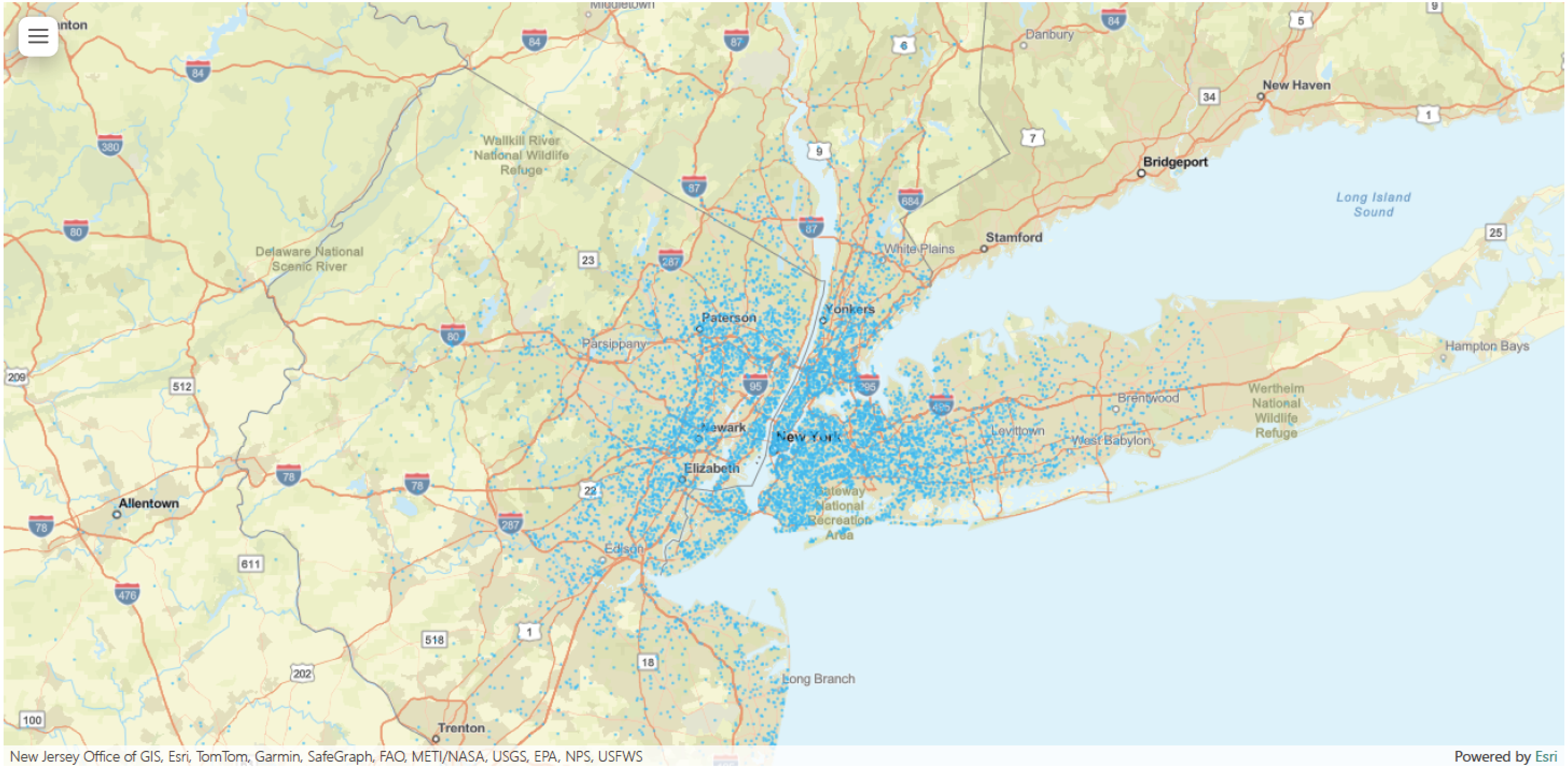

Phase I: Impact Ratio (NYC AEDT Bias Audit)

Match Score Above v Below the Cutoff

Company-wide

Gender	# of Applications	% of Overall Applications	Cutoff Score	# Applications Above Cutoff	Passing Rate	Impact Ratio
Female	5,738	43.5%	50	3,443	60.0%	92.3%
Male	**7,446**	**56.5%**	**50**	**4,840**	**65.0%**	**100.0%**
Overall	***13,184***		***50***	***8,283***	***62.8%***	

Phase I: Impact Ratio

Match Score Above v Below the Cutoff

RN-1

Gender	# of Applications	% of Overall Applications	Cutoff Score	# Applications Above Cutoff	Passing Rate	Impact Ratio
Female	695	51.9%	50	392	56.4%	69.7%
Male	**644**	**48.1%**	**50**	**521**	**80.9%**	**100.0%**
Overall	***1,339***		***50***	***913***	***68.2%***	

Phase II: Multiple Pools Analysis

Match Score Above v Below the Cutoff by Requisition

RN-1

Req ID	# Applicants	# Applicants Above Cutoff	# Female Applicants	# Male Applicants	# Female Applicants Above Cutoff	# Male Applicants Above Cutoff	Expected # Female Applicants Above Cutoff	Difference (Actual-Expected)	# S.D.	Significant
All Reqs	**1,339**	**913**	**695**	**644**	**392**	**521**	**450.1**	**-58.1**	**-4.14**	**Adverse**
287197	283	220	188	95	130	90	146.1	-16.1	**-2.31**	Adverse
287221	116	74	41	75	20	54	26.2	-6.2	**-1.50**	Neutral
292104	**197**	**126**	**106**	**91**	**101**	**25**	**67.8**	**33.2**	**5.93**	**Favorable**
298563	248	100	193	55	50	50	77.8	-27.8	**-6.70**	Adverse
304776	20	20	10	10	10	10	10.0	0.0	**0.00**	Neutral
264720	207	174	57	150	40	134	47.9	-7.9	**-1.34**	Neutral
264773	101	75	57	44	31	44	42.3	-11.3	**-2.64**	Adverse
265408	167	124	43	124	10	114	31.9	-21.9	**-4.50**	Adverse

Phase III: Regression Analysis

Match Score Above v Below the Cutoff by Requisition

RN-1

Req ID	# Female Applicants	# Male Applicants	# Female Applicants Above Cutoff	# Male Applicants Above Cutoff	Expected # Female Applicants Above Cutoff	Difference (Actual-Expected)	Odds Ratio	# S.D.	Significant
All Reqs	**695**	**644**	**392**	**521**	**450.1**	**-58.1**	**0.92**	**-0.98**	**Neutral**
287197	188	95	130	90	146.1	-16.1	0.84	**-1.38**	Neutral
287221	41	75	20	54	26.2	-6.2	0.94	**-0.42**	Neutral
292104	106	91	101	25	67.8	33.2	1.79	**3.64**	Favorable
298563	193	55	50	50	77.8	-27.8	0.65	**-2.42**	Adverse
304776	10	10	10	10	10.0	0.0	1.03	**1.16**	Neutral
264720	57	150	40	134	47.9	-7.9	0.90	**-1.09**	Neutral
264773	57	44	31	44	42.3	-11.3	0,96	**-0.33**	Neutral
265408	43	124	10	114	31.9	-21.9	0.72	**-2.05**	Adverse

Logistic regression model

Dependent variable: Above Cutoff Score (Yes/No)

Control variables: Care Type, Caregiver Certifications, Availability, Special Care Indicator, Commute Distance

Analysis of all requisition IDs also includes controls for requisition.