

VERO AI

A Non-Technical Guide to Using AI Safely and Effectively in Hiring

Eric Sydell, Ph.D.

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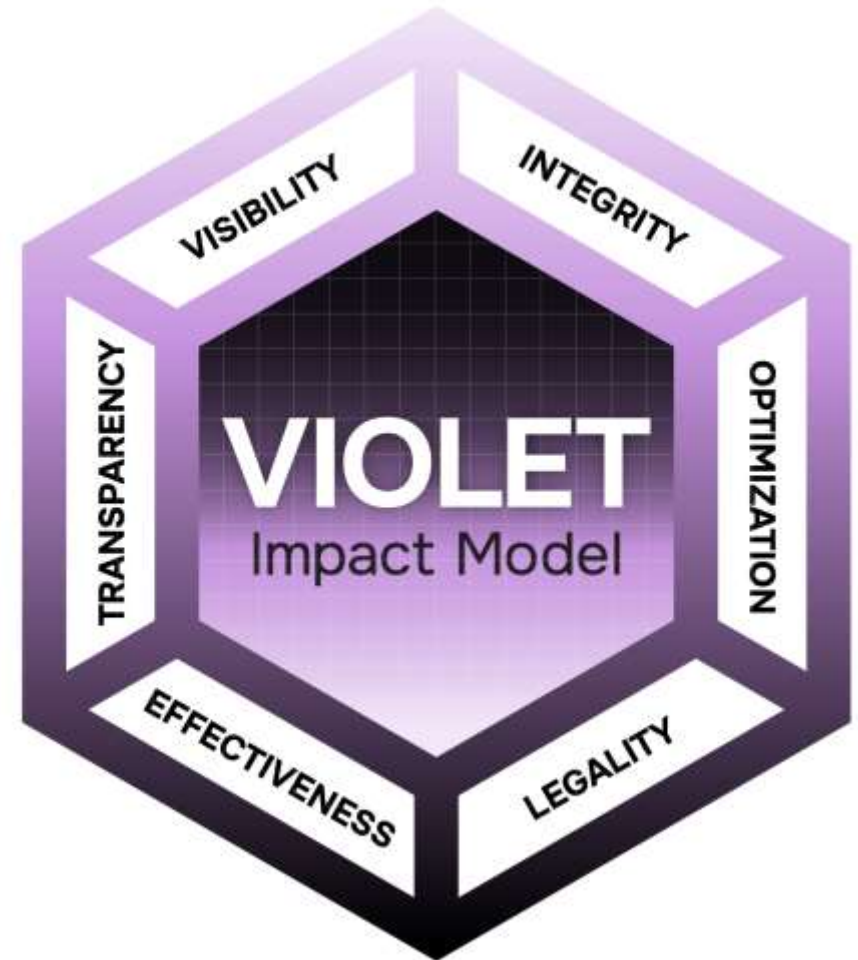
Who am I? What is Vero AI?

Eric Sydell

- IO psychologist, cofounder of Shaker/Modern Hire and Vero AI

Vero AI

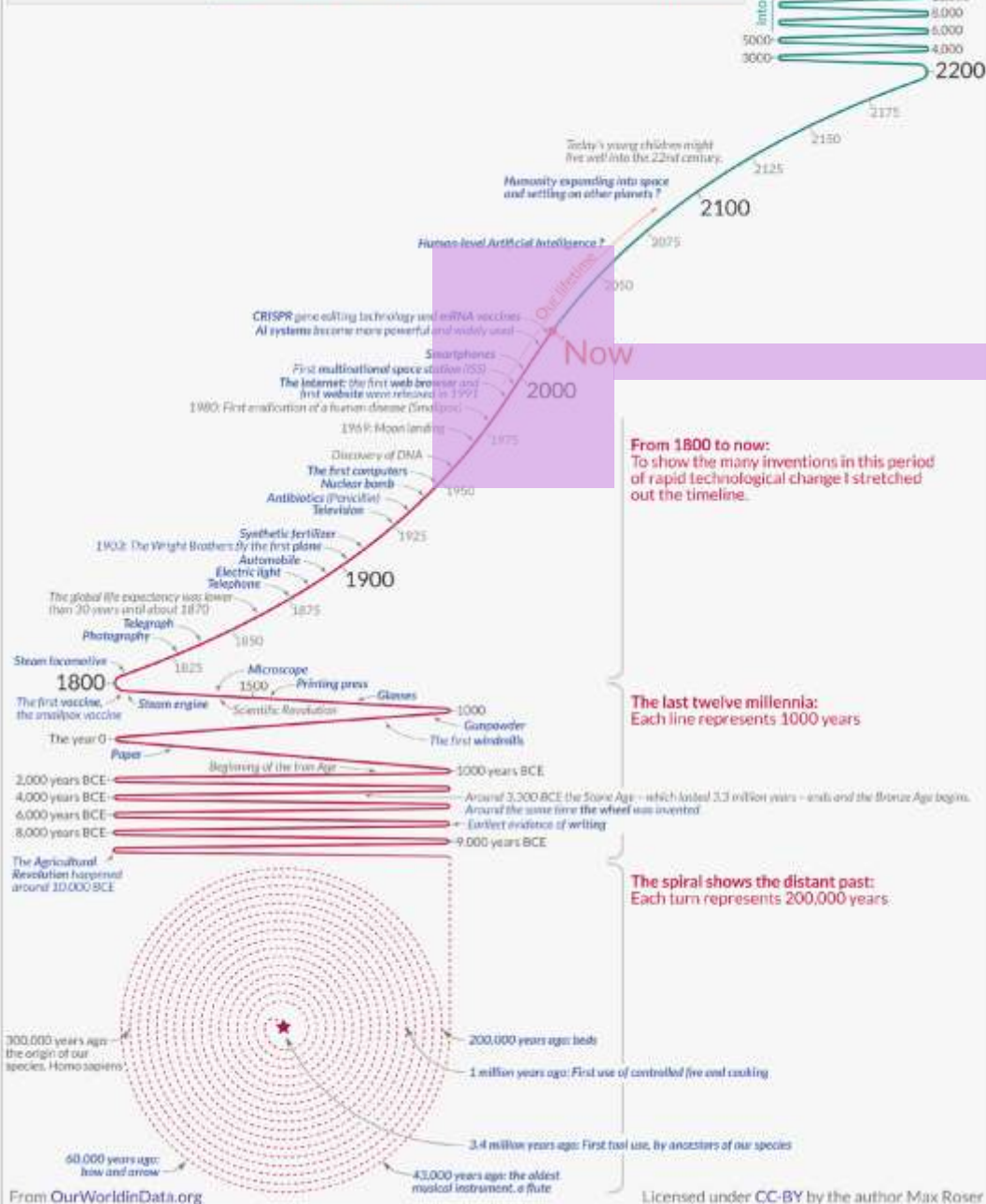
- New firm designed to objectively evaluate algorithms
- Goal is to deploy scaled scientific solutions
- Working to get beyond hype, to show objective truth



A long-term timeline of technology

Our World in Data

From the distant past, to our lifetime, and into the distant future.



In the 4 million years covered by this timeline, our lives are in the steepest part.

Explosive Growth of Generative AI

Time it took to reach 100 million monthly users:



Source: UBS

@TheRunDownAI

What is AI?



“A.I. is the science of how to get machines to do the things they do in the movies.”

-Astro Teller, CEO of X

“Who cares?”

-Me

But seriously...

I think of AI as just statistical analysis tooling that is uniquely good at processing unstructured (text, imagery, video, complex/messy) information.

Some Opinions on AI

“I’ve always thought of A.I. as the most profound technology humanity is working on—more profound than fire or electricity or anything that we’ve done in the past.”

-Sundar Pichai

“Artificial intelligence is the future...for all humankind. It comes with colossal opportunities, but also threats that are difficult to predict. Whoever becomes the leader in this sphere will become the ruler of the world.”

-Vladimir Putin

Techno-discombobulation

- What exactly is AI?
- Can algorithms be powerful without being AI?
- Should I use AI in my business?
- How do I know if AI is working?
- How do I know if it is biased?
- Is it legal?
- How do candidates feel about it?
- How do I begin?
- Where am I???



Wrong Answers

It's simple!

We have the most/best AI

Trust us!

It's validated...

Marketing vs Science

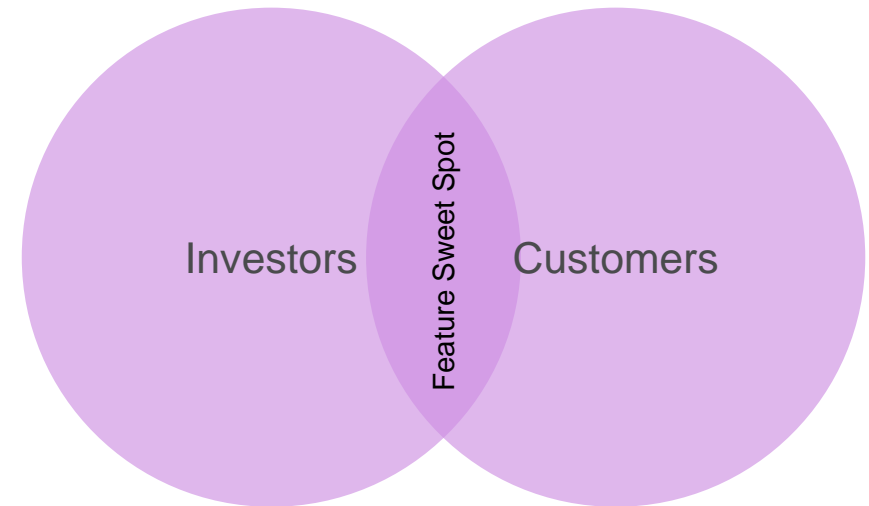
Not all marketing is wrong or bullsh!t.

But you should **assume it is** until you verify its accuracy.



What Investors Want vs What You Want

- Financial backers want tech that is:
 - Exciting (such anything AI-related)
 - Scalable (can be automated)
 - SaaS, one-size-fits-all
 - Appears to have a steep growth curve
- Organizations want:
 - Solutions that improve the company
 - Customization, not one-size-fits-all
 - Interoperability, easy of use/updating



Some Actual Marketing Claims

- We match employees with the right jobs
- Improve hiring speed, development, and retention
- Improve efficiency, cut costs, and create a great candidate experience
- 2.5x improved retention
- Proven to optimize organizations

Consider What Isn't Said

Common Claims

- Improve retention
- Enhance diversity
- Better candidate experience
- Increase speed to hire
- Optimize stuff
- AI-powered

Missing Elements

- Effectiveness/validity
- Transparency
- True ROI
- Legality

I/O Perspective on Validity

Is it good enough to do a small sample criterion-related validation study and document it in a test manual that collects dust on a shelf?





Validation Samples vs Real World Data

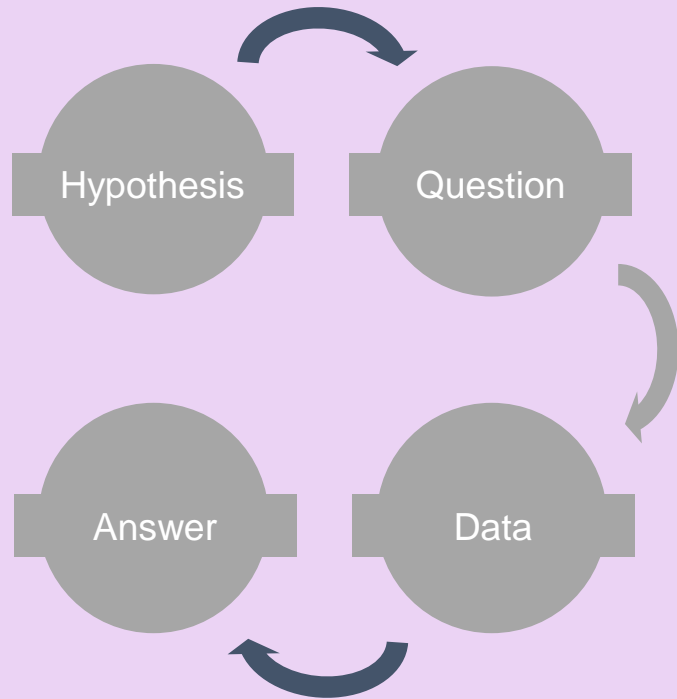


A Skilled Statistician, Probably

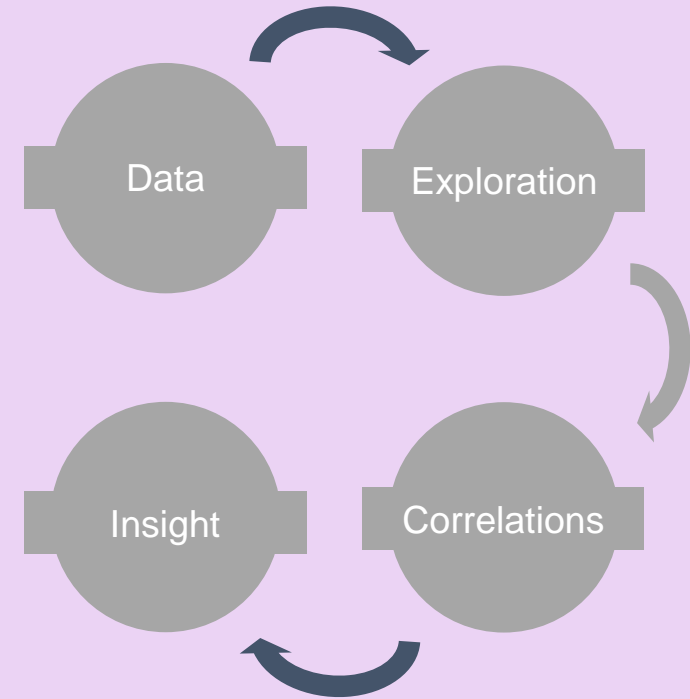
- A skilled statistician get almost anything to validate in a small local sample
- Getting it to revalidate in a live sample is another story
- However, even small correlations can lead to large ROI

Thinking Differently About Science

Traditional Approach



Big Data Approach



Based on Ryan & Herleman, 2016. Big Data Platform, in Big Data At Work

Questions that Traditional Statistics Struggles to Answer

- How does information other than standardized test data predict organizational outcomes?
 - Background checks?
 - Interview responses?
 - Resume data?
 - Social media posts?
 - Written responses?
- How does all of that information interact to predict performance?
 - Can we find the predictive overlap?
 - Can we combine data across sources, even if some are structured and some are unstructured?

Statistics Two Ways

- 1. Traditional statistics** – correlations, regressions, etc. are good for predicting outcomes with quantitative data
- 2. AI** – strength is in making sense of unstructured data...messy, incomplete, complex, qualitative information





How do we make sense of all this?

Our Field Knows The Answer!

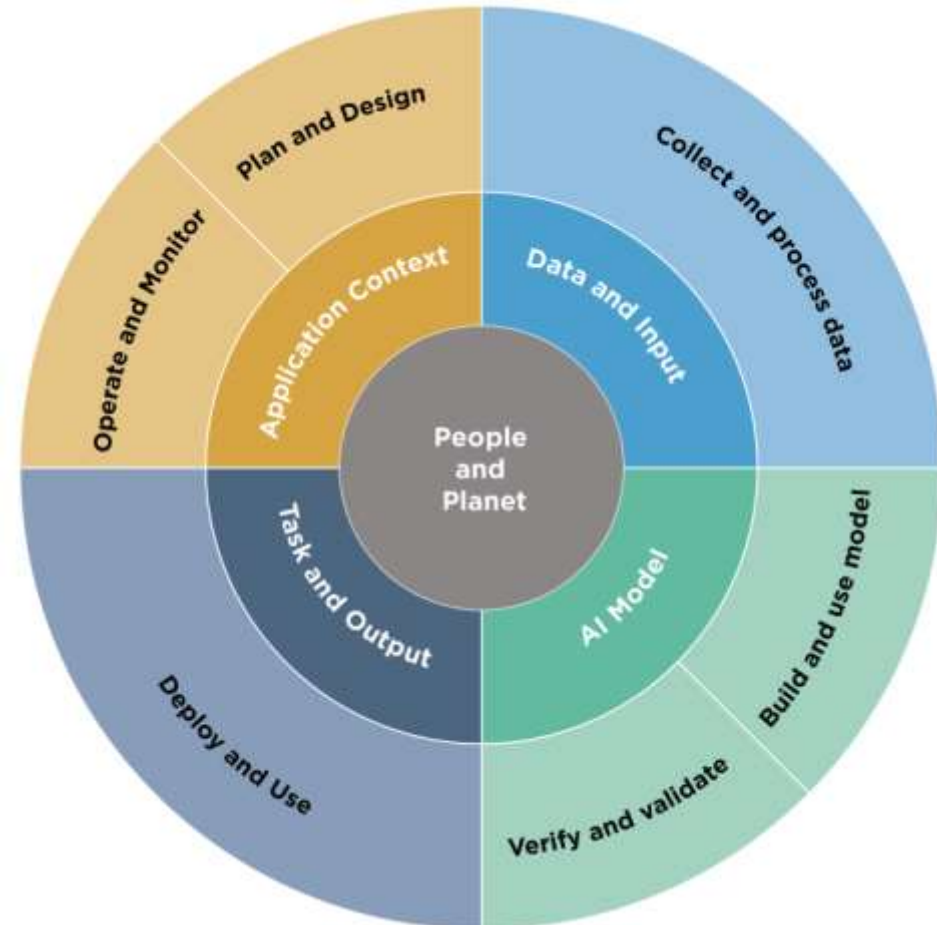
- It's the scientific method!
- Uniform Guidelines, SIOP Principles, etc.
- Your skills and perspective is extremely valuable in this problem space!



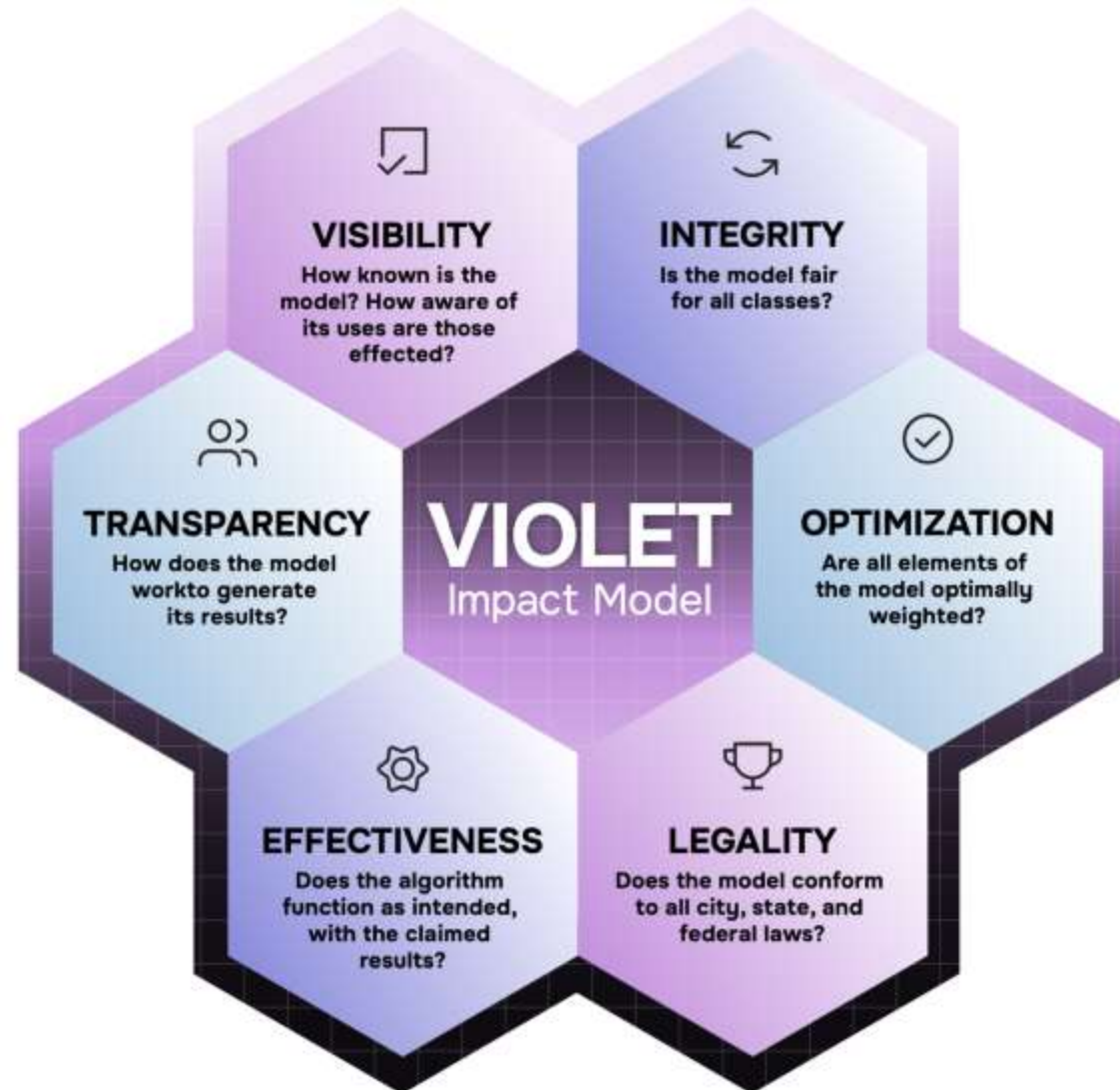
Ethical AI Frameworks

- NIST
- OECD
- WEF
- Private companies

NIST AI Risk Management Framework



The VIOLET Impact Model



Generative AI Strengths and Limitations

Strengths	Limitations
New, human-like output	Accuracy
Ability to learn quickly	Bias
Massive integration across modalities	Resource intensive
Fast technology growth/adoption	Ethical concerns
	Creativity limit

Generative AI Questions to Consider

- How can it help your business today?
- What about in the future as the tech is developed?
- What ethical/moral problems could it create?
- How would we go about learning more?

Beneficial AI in Hiring

- Chatbots for answering simple questions
- Scoring interview responses (just words, not audio/video)
- Resume scanning / job matching
- Background checks
- Scoring assessments

Questionable AI in Hiring

- Scoring interview video/audio
- Chatbots that impersonate humans
- Privacy violations
- Dehumanizing the hiring experience
- Opaque scoring/automation
- Unnecessary AI

Decoding Talent

BOOK LAUNCH

- Presenting a comprehensive vision of the future of talent management in the age of big data and AI
- Introducing a talent analytics maturity model to help truly decode talent organization wide
- Released in February, 2022

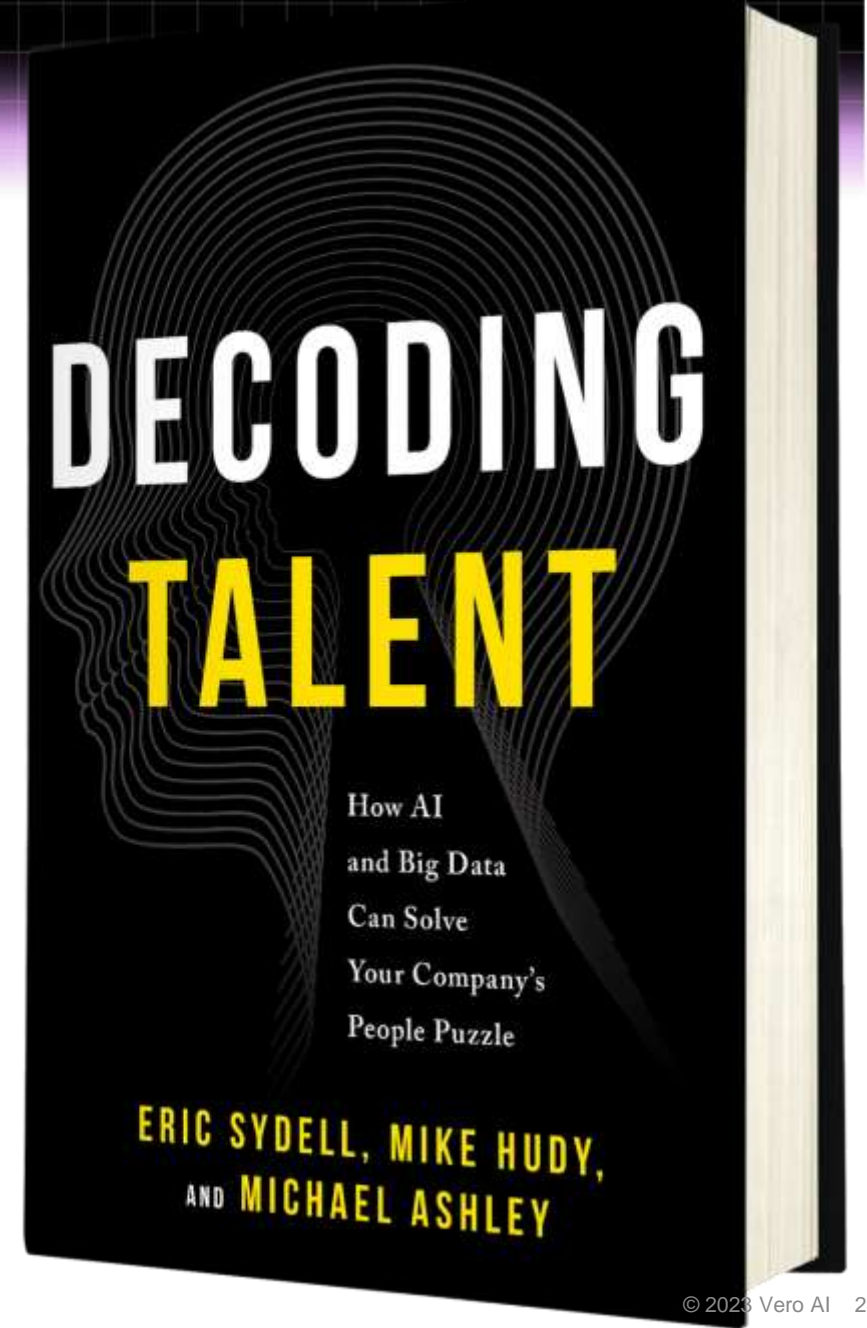


**FAST
COMPANY**
Press

A clear and powerful plan for how to leverage tech, data, and AI to finally and truly revolutionize HR and talent management

—Jim Livingston, chief people officer, Rock Central

VEROAI



Talent Analytics Maturity Model

Level 5: Decoded Talent/Automated Analytics

Ubiquitous human data collection including pre- and post-hire data; automatic AI-driven analytics

Level 4: Predictive Analytics

Integration of outcome data; predictive modeling; differential prediction
Reports can drive strategy, but analytics process is primarily manual

Level 3: Benchmarks & Normative Analytics

Comparison of results across groups, both internally and externally
Reports used for decision making and issue identification

Level 2: Coordinated Reporting

Consistent, consolidated reporting using dashboards
Reports are tactical; used primarily for operations management




Level 1: Basic Operational Reporting




Operational reporting for measurement of efficiency, compliance, and EEO needs
Dependent on ad-hoc processes; uncoordinated across units; spreadsheet-based

The Decoding Talent Model



Example VIOLET Report

Element	Results	Score
 Visibility	<p>Highs: Clear candidate messaging present with opt-out option; algorithm use is apparent to both candidates and recruiters interacting with the hiring software.</p> <p>Lows: Approximately 40% of higher level talent acquisition leaders are not aware of the use of algorithms; unclear to candidates what happens to their applications if they opt out.</p> <p>Actions: Educate talent leaders on the use of algorithms and their risks and benefits; clarify candidate messaging to include statement on opt out ramifications.</p>	4
 Integrity	<p>Highs: Available data showed that the size of protected class differences was practically insignificant, though some large sample comparisons resulted in significant differences.</p> <p>Lows: Missing data prevented the calculation of differences for American Indians as well as several intersectional groups.</p> <p>Actions: Build process to monitor differences continually; investigate alternate sources of data on low volume protected classes and intersectional groups.</p>	3
 Optimization	<p>Highs: Algorithm runs optimally in training dataset; comprehensive set of parameters taken into account during development.</p> <p>Lows: Significant loss of predictive power in various geographies; wide fluctuation in group differences across regions.</p> <p>Actions: Retrain model using multiple outcome optimization or similar techniques; investigate alternate scoring that could reduce variation in group differences.</p>	3

 Legality	<p>Highs: Algorithm is currently in compliance with NY Local Law 144 and other major regulations; technical documentation is detailed and thorough.</p> <p>Lows: Compliance with emerging legislation is not guaranteed; stricter EU regulations may result in non-compliance regarding privacy issues.</p> <p>Actions: Monitor emerging legislation; review data privacy approach and determine whether to revise standards in advance of new regulations.</p>	8
 Effectiveness	<p>Highs: Strong evidence of effectiveness in training datasets; broad availability of criterion/performance indicators.</p> <p>Lows: Low and insignificant relationships between algorithm output and performance indicators in live data.</p> <p>Actions: Retrain algorithm on live data and test it with a live data hold out sample; if not effective, revise further or discontinue use.</p>	2
 Transparency	<p>Highs: Technical documentation presents a heat-map that explains algorithm operation at a conceptual level.</p> <p>Lows: Some model elements do not fit theoretical understanding, and other elements are opaque in operation.</p> <p>Actions: Revalidate model on live data and confirm workings of all model elements.</p>	4

AI is the (Utopian or Dystopian?) Future

It is up to us to decide!



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eric.sydell@vero-ai.com

www.vero-ai.com