AUGUST 30, 2017

ROCK HEALTH

Demystifying AI in Healthcare

RESEARCH PREVIEW

You probably don't need a reminder—it's been the summer of AI hype.

> "We are now witnessing a new shift in computing: the move from a mobile-first to an AI-first world."
>
> Sundar Pichai
> CEO
> Google

A MASSIVE OPPORTUNITY FOR HEALTHCARE

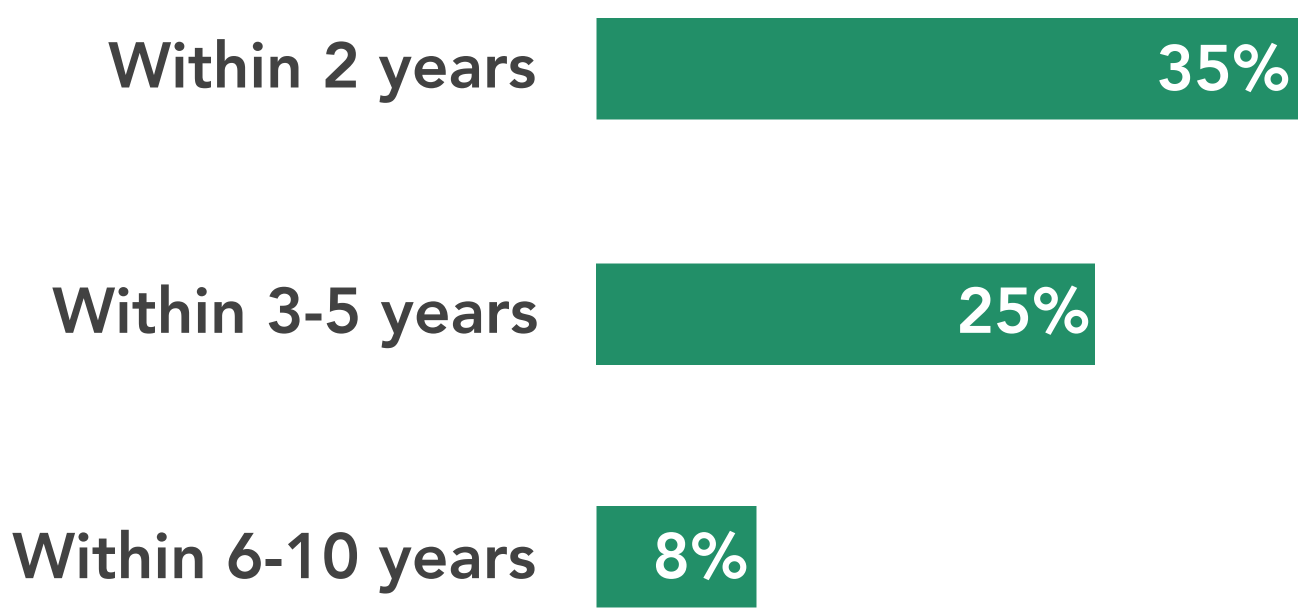
$150B

by 2026

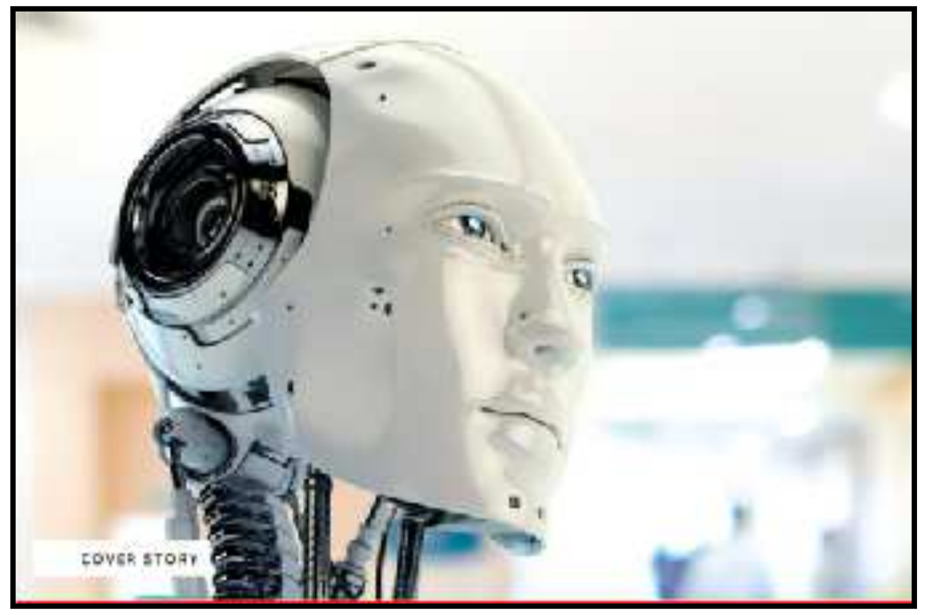
Accenture analysis predicts clinical health AI applications can create $150 billion in annual savings to the US healthcare system by 2026.

WHEN HEALTH SYSTEMS EXPECT TO LEVERAGE AI TECHNOLOGY[1]

2017



AI PRESS COVERAGE MAKES BIG PROMISES



How Artificial Intelligence Will Cure America's Sick Health Care System"

Newsweek cover

June 2017

1: Survey by Healthcare IT News and HIMSS Analytics survey includes responses from CEOs, CIOs, CFOs, COOS, chief medical information officers, chief clinical officers, and professionals working at the IT_director level and above.

Source: Pichai, Sundar, "Making AI work for everyone," https://www.blog.google/topics/machine-learning/making-ai-work-for-everyone/ ; "AI: An Engine for Growth," Accenture, https://www.accenture.com/us-en/insight-artificial-intelligence-healthcare; Sullivan, Tom, "Half of hospitals to adopt artificial intelligence within 5 years," April 11, 2017; "How Artificial Intelligence will cure America's sick health care system," Newsweek, http://www.newsweek.com/2017/06/02/ai-cure-america-sick-health-care-system-614583.html; Rock Health analysis.

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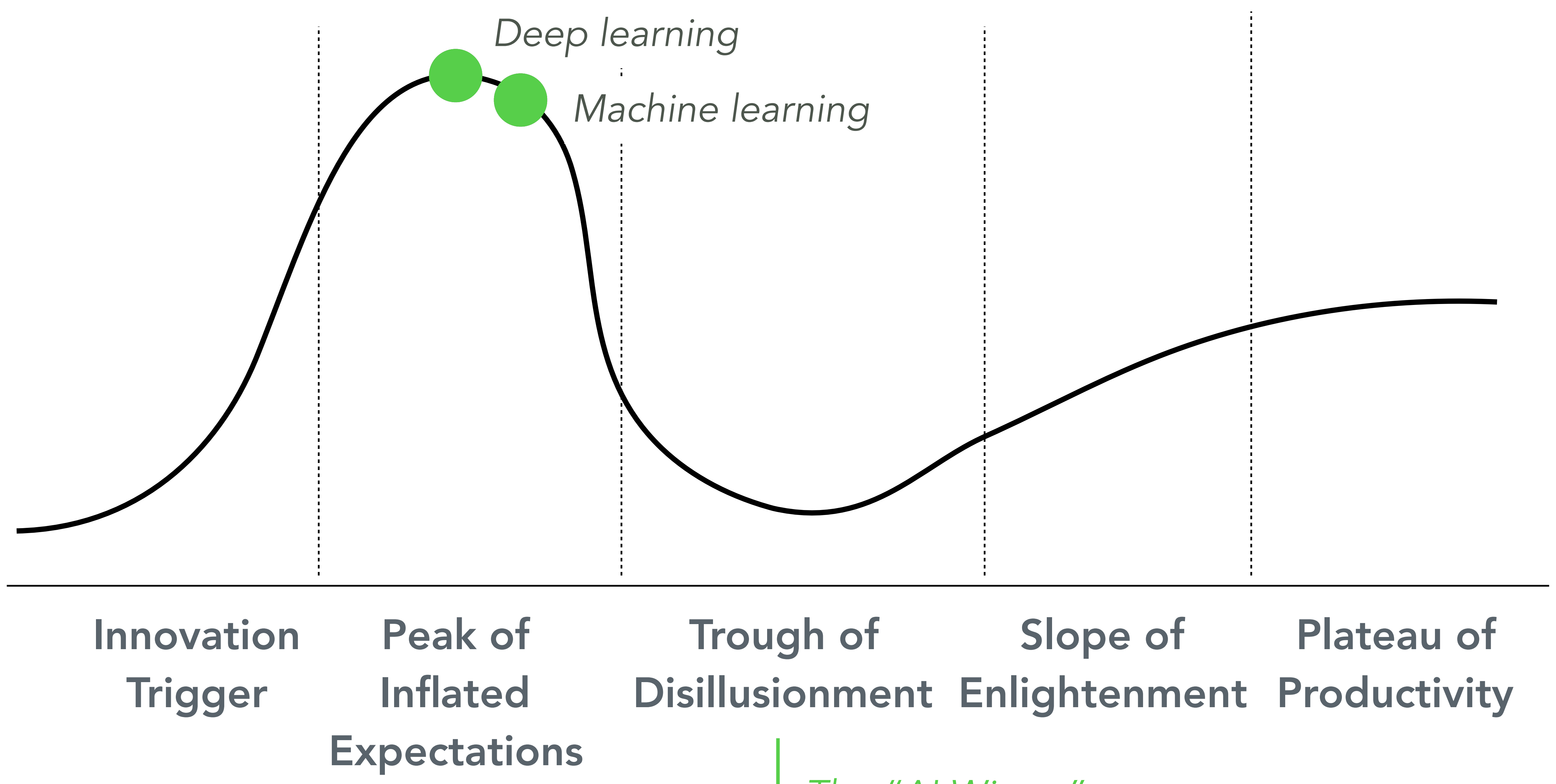
With machine and deep learning at the "peak of inflated expectations," backlash to AI hype anticipates a potential move to the "trough of disillusionment."

WE'RE AT PEAK HYPE

Gartner Hype Cycle for Emerging Technologies



The "AI Winter" was a backlash to hype in the late 1970s-early 1980s when AI interest and funding dwindled

ADOPTION STILL LAGGING

5%

Health systems self-reporting they already leverage AI[1]

> "I think there is more hype and buzz than reality. I've seen these bubbles burst. I am concerned."

Digital Health Entrepreneur, PhD

> The huge increase in startups [...] all claiming to offer AI products without any real differentiation is confusing buyers.

Gartner

1: Survey by Healthcare IT News and HIMSS Analytics survey includes responses from CEOs, CIOs, CFOs, COOS, chief medical information officers, chief clinical officers, and professionals working at the IT_director level and above.

Source: "Top Trends in the Gartner Hype Cycle for Emerging Technologies, 2017," August 15, 2017; http://www.gartner.com/smarterwithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017/, Sullivan, Tom, "Half of hospitals to adopt artificial intelligence within 5 years," April 11, 2017, http://www.healthcareitnews.com/news/half-hospitals-adopt-artificial-intelligence-within-5-years; "Gartner Says AI Technologies Will Be in Almost Every New Software Product by 2020," July 18, 2017, http://www.gartner.com/newsroom/id/3763265; Rock Health analysis.

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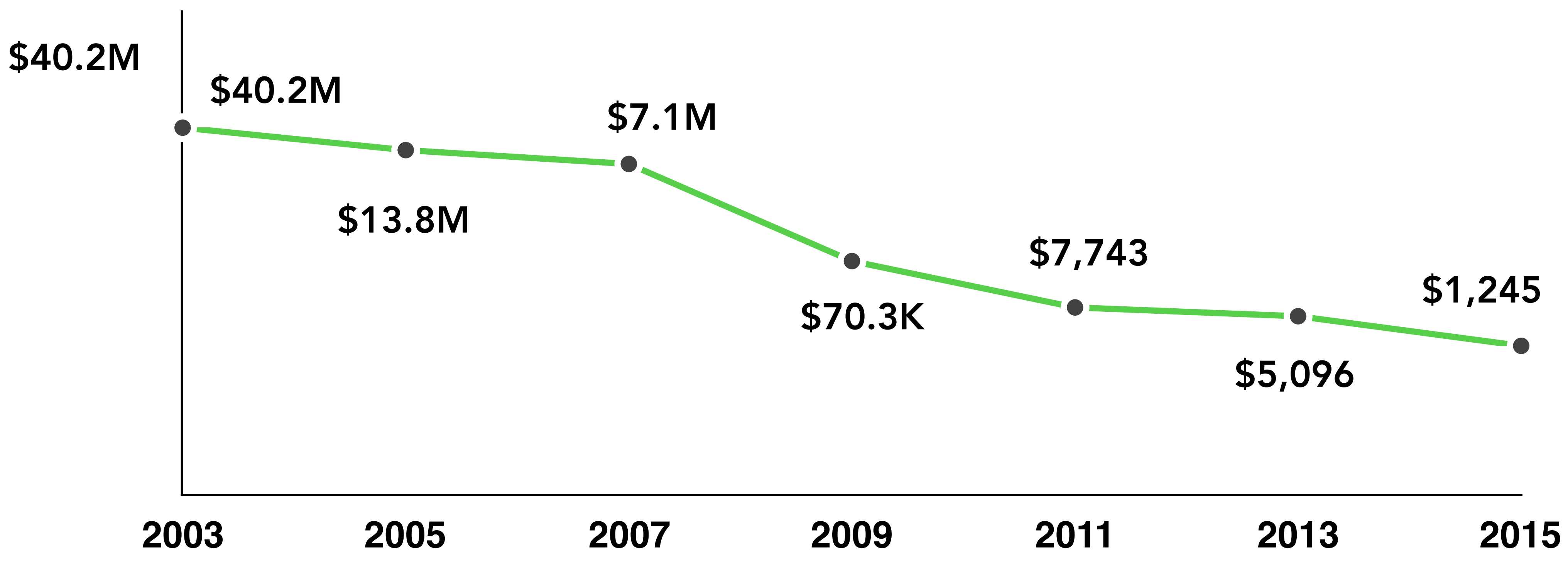
With key developments advancing machine learning, there is reason to believe we won't have another "AI Winter."

FOUR MACHINE LEARNING ACCELERANTS

		ADVANCES
1	BETTER ALGORITHMS	Advances in deep learning such as convolutional neural networks and recurrent neural networks have led to computer systems that have human-level (or better) image and speech recognition
2	MORE INFRASTRUCTURE	Cloud-based machine learning infrastructure and services, such as that provided by Google, Amazon, Microsoft and IBM, reduces the cost and difficulty of developing ML capabilities
3	FASTER PROCESSING	Graphical processing units (GPUs) are electronic circuits cutting the time required to train neural networks—and the cost of GPUs has been dropping.
4	MORE HEALTH-RELATED DATA	• Genetic data • EHR, lab, imaging data • Patient-generated data (e.g., wearables)

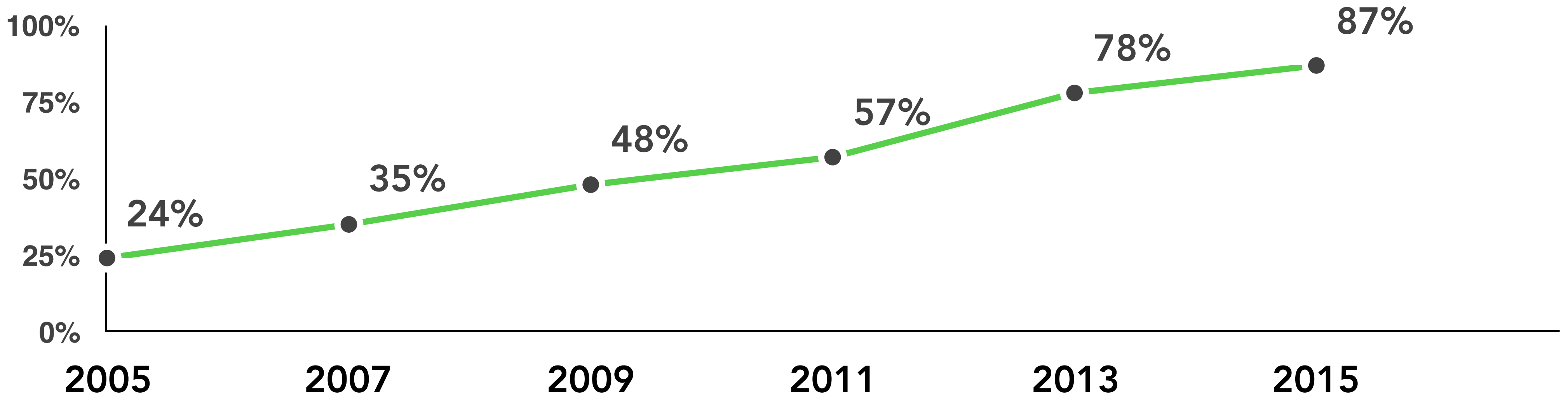
COST OF SEQUENCING A HUMAN GENOME

2003-2015 (reported for October of each year)



OFFICE-BASED PHYSICIAN EHR ADOPTION

2005-2015



Source: Kelnar, David, "The fourth industrial revolution: a primer on Artificial Intelligence (AI)," December 2, 2016, https://medium.com/mmc-writes/the-fourth-industrial-revolution-a-primer-on-artificial-intelligence-ai-ff5e7fffcae1?welcomeRedirect=true; "DNA Sequencing Costs: Data," National Human Genome Research Institute, https://www.genome.gov/sequencingcostsdata/; "Office-based Physician Electronic Health Record Adoption," The Office of the National Coordinator for Health Information Technology, https://dashboard.healthit.gov/quickstats/pages/physician-ehr-adoption-trends.php; Rock Health analysis.

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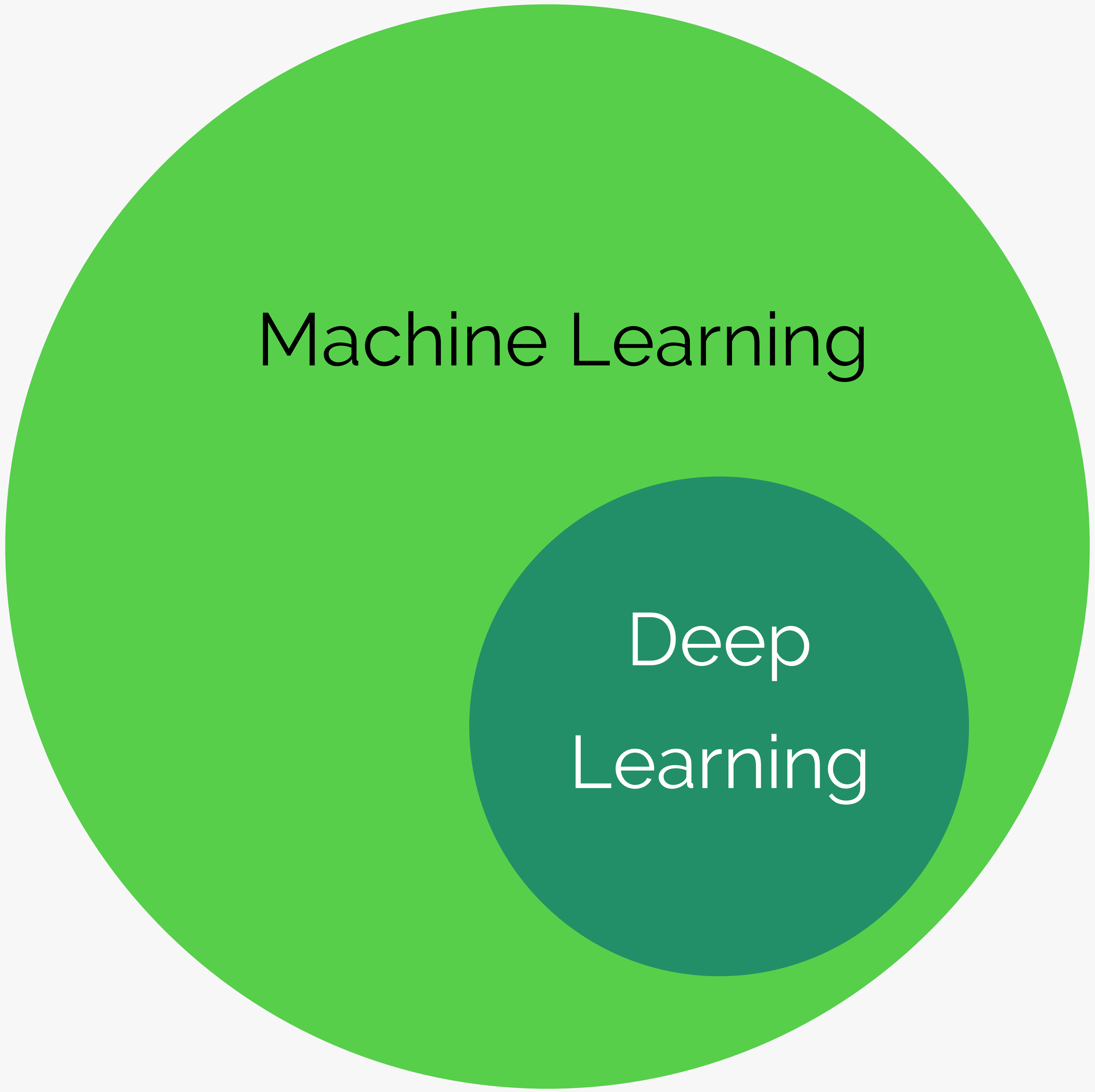
ROCK HEALTH'S ASSESSMENT

There is no single, agreed-upon definition of "artificial intelligence." Debating the merits of various definitions is a distraction from a couple more important questions.

What are the use cases that are transforming—and will transform—the healthcare industry? What are the underlying mathematical models that enable transformation?


Machine Learning
Deep
Learning

Our goal is not to define AI, but we want to provide a framework for thinking about the various mathematical methods underpinning "AI" applications.

SPECTRUM OF ALGORITHMS UNDERPINNING AI

CATEGORY	EXPERT SYSTEMS	MACHINE LEARNING (1)		MACHINE LEARNING (2)
REPRESENTATIVE ALGORITHMS	*Human-defined ontologies* *Human-coded boolean expressions*	*Generalized linear models*	*Random Forests* *Support Vector Machines* *Ensembles*	*Deep Learning* *Reinforcement Learning*
SUMMARY	Human-programmed, static program to perform a deterministic task	Model capable of learning from training data such that the quality of its predictions improves with experience		Models learn independently through practice and feedback via data; the resulting model lacks a mathematical "solution" (e.g., a set of equations) that can be understood and analyzed
EXAMPLES	Old-fashioned natural language processing (NLP) defined by linguists who helped programmers write code that represented human grammars	Ranges from simple models that can be implemented in Excel to more complex models that require advanced statistics. E.g., a linear regression analysis performed on data from a clinical trial submitted to the FDA to demonstrate the degree to which age, gender, and race contributed to an observed clinical effect		Most common deep learning includes "neural networks" which are essentially stacks of machine learning models. E.g., algorithm is trained via images to recognize and interpret differences in medical images, such as those on a radiology scan

1: "Explainability" refers to the degree to which the internal structure of the model can be examined in order, for example, to allow better understanding of which factors (variables) most influenced the prediction (output) generated by the model. A predictive model with high explainability for predicting heart attacks, for example, would provide both a prediction of the future probability of a heart attack and also show the degree to which high blood pressure, cholesterol levels, and age contributed to the prediction of a future heart attack. A model with low explainability would only provide a probability for a heart attack with no easy way to see which variables contributed to the prediction.
Source: Rock Health interviews and analysis.

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Each algorithm has hallmark characteristics which make them well-suited (or not well-suited) for solving particular challenges.

SPECTRUM OF ALGORITHMS UNDERPINNING AI (CONT.)

	EXPERT SYSTEMS	MACHINE LEARNING (1)	MACHINE LEARNING (2)
SUMMARY	Human-programmed, static program to perform a deterministic task	Program capable of learning from training data such that the quality of its predictions improves with experience	Models learn independently through practice and feedback via data; the resulting model lacks a mathematical "solution" (e.g., a set of equations) that can be understood and analyzed
PERIOD OF MAJOR BREAKTHROUGHS	1980s-1990s	2000s	2010s-present
TRAINING REQUIREMENTS	Requires domain expert for programming	Moderate volume of data is sufficient, but the more the better.	Significant volume of data; well-equipped for text, image, audio
HUMAN GUIDANCE REQUIRED	High, program is entirely dependent on human-provided information	Medium, generally humans guide the model to take into account certain features[2] and to remove "noisy" outlier data	Low, generally the model decides on feature selection and weighting and has to account for outlier data independently
PREDICTIVE POWER	Limited to human rules	High	High
EXPLAINABILITY[1]	High	Medium	Low, "black box"
LIMITING FACTOR	Cannot manage scenarios or data outside of explicit rules from training	Clean data requirements	Large data requirements; low explainability; extensive processing power required

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Source: Rock Health interviews and analysis.
2: Feature selection consists of the decision to include or exclude variables from a mathematical model. A model to predict heart attacks might include blood pressure measurements, cholesterol levels, age, etc. Other factors thought to be "not relevant" - like hair color, a person's month of birth, etc. - would not be selected as features (variables) of a model.

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We want to help you understand where AI is breaking through—and how to be a smart participant in the ecosystem.

FIVE TIPS TO DEMYSTIFY AI

1. DON'T EQUATE MODEL SOPHISTICATION WITH BUSINESS VALUE.
2. DATA IS THE BIG BARRIER TO ENTRY—EVEN MORE SO THAN THE ALGORITHMS.
3. ALGORITHMS WILL ONLY GET YOU SO FAR. DON'T EXPECT BEHAVIOR CHANGE WITHOUT AN OPTIMIZED USER EXPERIENCE.
4. KNOW HOW READY YOUR BUSINESS REALLY IS.
5. BE A MACHINE LEARNING PROMOTER AND A HYPE SKEPTIC.

Source: Rock Health interviews and analysis.

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1. Don't equate model sophistication with business value. Most companies should be assessing—and using—a variety of techniques.

> "Most ML implementations are not deep learning or neural networks. There are many cases where if you know what to optimize, statistical machine learning can take you really far and there's no reason to shy away from that. It's incredibly powerful in the right domain."
>
> Entrepreneur
> a16z podcast
> "The Product Edge in Machine Learning"

CASE STUDY: amino

AMINO'S ITERATIVE APPROACH ENSURES OPTIMAL TECHNIQUE SELECTION

	SET GOAL	TEST NEW ALGORITHM	ASSESS VALUE
Example:	Physician specialties are not always accurate. Is there a better way to categorize physicians based on experience, procedures, etc.?	Data science team applies deep learning method and surfaces interesting trends	Due to high cost of method, team distills technique to a simpler, less costly method with sufficient accuracy

2 month evaluation cycle

AMINO'S GUIDING "VALUE" QUESTIONS

- What degree of accuracy is necessary to make the product successful?
- What is the incremental improvement from using a more expensive, sophisticated method? Is a simpler technique available?

Source: a16z podcast, "The Product Edge in Machine Learning," March 17, 2017; Rock Health interviews and analysis.

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2. Data is THE big barrier to entry—even more so than the algorithms.

> "Clean data beats more data. And more data beats better algorithms."
>
> Abe Gong
> Founder, Superconductive Health

DATA-CENTRIC PARTNERSHIPS

A look at three approaches to access sufficient training data

SELF-DRIVEN DATA CLEANUP

Select providers report spending two or more years "readying" data for use with machine learning techniques.

Major biopharma company spends significant time and money to standardize, clean data for breast cancer cases.

PARTNERSHIP

Google Deep Mind partners with the NHS to use a million anonymized eye scans to train a neural network to identify early signs of degenerative eye conditions.

Partners HealthCare and GE Healthcare launched 10-year collaboration to integrate deep learning across the patient journey, starting with diagnostic imaging.

MISSION-DRIVEN CONSORTIUM

The government-funded Cancer Moonshot encourages collaboration among the government, academics, providers, data scientists and others to lead innovations in oncology. Machine learning is leveraged to find patterns among genomic and molecular data sets, patient records, family histories, and other complex information related to cancer.

Source: Moniz, Ernest, "Supercomputers Join the Fight Against Cancer," June 15 2016, https://medium.com/cancer-moonshot/supercomputers-join-the-fight-against-cancer-724fcc9910ce; Hern, Alex, "Google DeepMind pairs with NHS to use machine learning to fight blindness," July 5, 2016, https://www.theguardian.com/technology/2016/jul/05/google-deepmind-nhs-machine-learning-blindness; Rock Health interviews and analysis.

Data sets (especially in healthcare) are prone to many types of bias—ensure an expert identifies and accounts for any relevant bias.

REAL-WORLD PHENOMENA EVOLVE OVER TIME

Access to dynamic, recent data is critical.

- *Relevance of clinical data decays with an effective half-life of about four months*[1]
- *CDS algorithms learning from EHRs have found that accumulating years of historical data is worse than using the most recent year of data.*

CASUAL INFERENCE REQUIRES AN EXPERIMENT (NOT JUST OPERATIONAL DATA)

In looking for correlations, algorithms can find misleading patterns.

- *Eg.: High utilization led an algorithm to identify seemingly unrelated predictors of stroke such as abnormal breast finding.*
- *Eg.: palliative care consults and norepinephrine infusions are highly predictive of patient death, but it would be irrational to conclude that we should stop either.*

OUTCOME—DATA THAT SHOWS A "RESULT" IS THE HOLY GRAIL

Algorithms benefit from a variety of data that provides a more comprehensive picture (e.g., sensors, genomics, socioeconomic, etc.), but arguably the most critical clinical data—patient outcomes—are not consistently tracked.

- *Eg.: evaluating pain and function post-surgery*
- *Tracking outcomes usually requires follow-up with patients—one of the most expensive aspects of a clinical trail*

STATISTICAL BIAS

If trained with operational data, algorithms can suffer from unintended biases in the data (e.g., relative rates of diagnosis, overrepresentation of subpopulations, etc.)

- *Non-human generated data, such as labs and images, will yield more precise predictions in the short-term*

These sophisticated data challenges require an on-staff expert to evaluate data validity and uncover any potential biases.

1: Sendhil Mullainathan and Ziad Obermeyer, "Does Machine Learning Automate Moral Hazard and Error?" American Economic Review: Papers & Proceedings, 2017
Sources: Jonathan Chen and Steven Asch, "Machine Learning and Prediction in Medicine—Beyond the Peak of Inflated Expectations," NEJM, June 29, 2017; Rock Health interviews and analysis.

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3. Algorithms will only get you so far. Don't expect behavior change without an optimized user experience.

> An accurate prediction of a patient outcome does not tell us what to do if we want to change that outcome [...]. The last mile of clinical implementation thus ends up being the far more critical task of predicting events early enough for a relevant intervention to influence care decisions and outcomes.

Jonathan Chen and Steven Asch
New England Journal of Medicine

CASE STUDY: Qventus

SOMETIMES, PREDICTIONS ARE COUNTERPRODUCTIVE

1 QVENTUS MAKES PREDICTION → **2 NURSE MANAGER IN DECISION PARALYSIS**

"There's a 40% chance the ED will reach capacity in the next two hours."

"Should I call in more staff? Should I turn over beds? Is this information correct?"

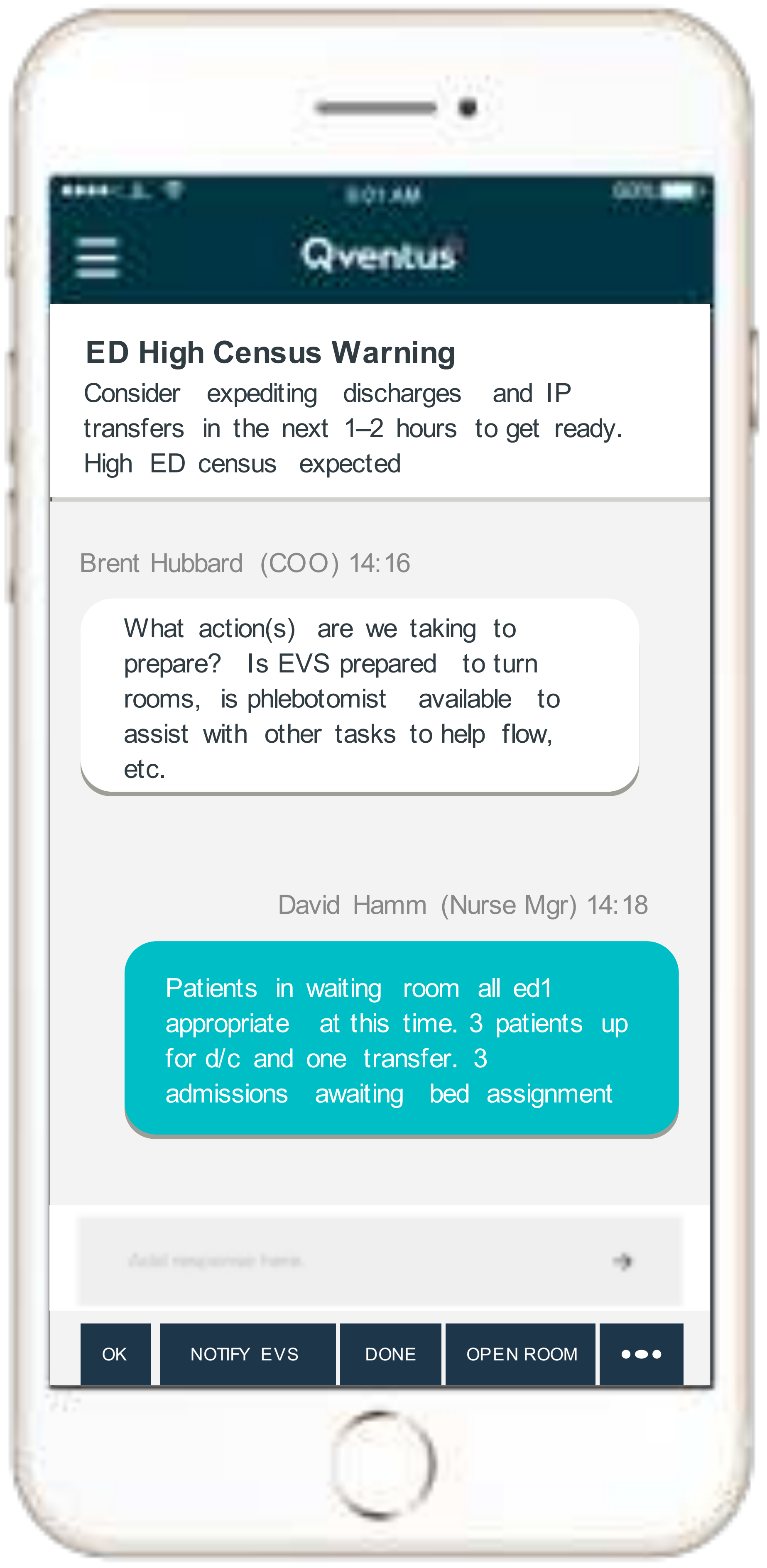
> What if I was driving and the GPS told me there was a 40% chance the road would be busy soon. I would throw it out the window!

Nurse Manager
Qventus customer

Source: Jonathan Chen and Steven Asch, "Machine Learning and Predictions in Medicine—Beyond the Peak of Inflated Expectations," NEJM, June 29, 2017; Rock Health interviews and analysis.

Qventus moves beyond providing predictions to delivering clear, actionable recommendations for frontline staff in real-time.

CASE STUDY (CONT.): Qventus



PREDICT

- Uses machine learning to predict issues before they occur

PRESCRIBE

- Courses of action instantly evaluated
- Course correction identified based on cost/benefit considerations

PERSUADE

- Sends recommendation to right team member via any device
- Provides clear action for frontline staff and promotes collaboration

> "The cognitive capacity of clinicians cannot keep up with the change being asked of them. Qventus reduces that cognitive load. We take the more mundane, boring stuff and make it much easier."
>
> Mudit Garg
> CEO, Qventus

COMPANY IN BRIEF: QVENTUS

- Real-time decision management platform to optimize hospital efficiency, patient experience and clinician satisfaction
- Founded in 2013; have raised $13M in venture capital
- Largely relies on machine learning; data sources include EHR, labs, call light systems, staffing, scheduling, billing
- Select results include: 39% reduction in patient falls at El Camino Hospital; 24% reduction in door-to-doc time and 30% reduction in patients who leave without being seen at Mercy Fort Smith; 18% increase in patient satisfaction scores within two months at Lucile Packard Children's Hospital

Source: Rock Health interviews and analysis.

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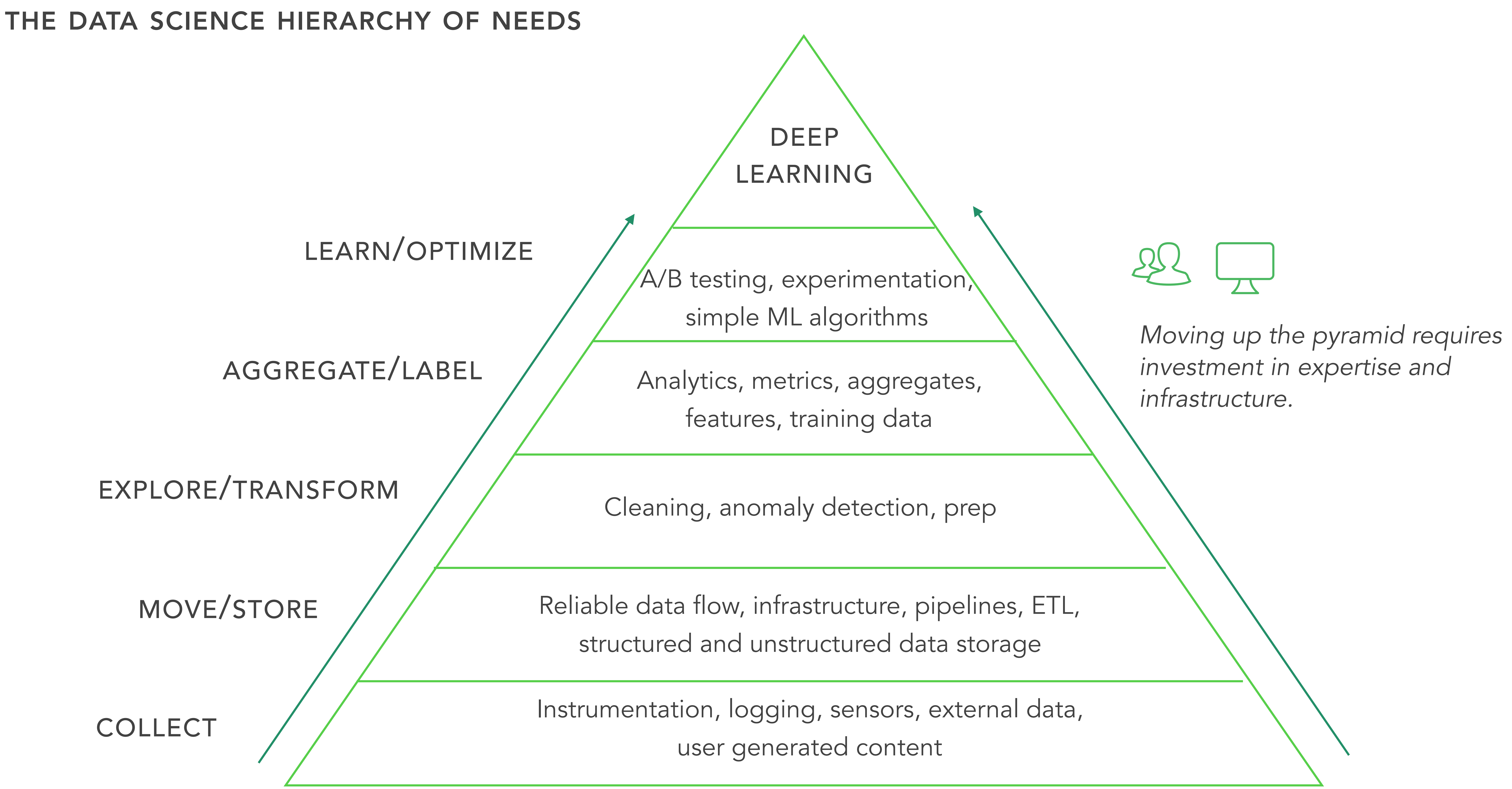
4. It takes a lot to get ready: know how ready your business really is.



Moving up the pyramid requires investment in expertise and infrastructure.

Source: Rogati, Monica, "The AI Hierarchy of Needs," Hackernoon, August 1, 2017, https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007; Rock Health analysis.

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5. You can be a machine learning promoter AND a hype skeptic by smartly assessing potential partners.

QUESTIONS
Vetting "AI" Technology

- Can the company explain, in layperson terms, what distinguishes their technology from basic, traditional business intelligence methods and why their approach is necessary (or at least better)?
- Can the company tell you what methods they're using—and where these methods fall on the Spectrum of Algorithms Underpinning AI? Do we have a plan for ETL (extract, transfer, load)?
- Can the company help you establish your position in the Data Science Hierarchy of Needs?
- Is there public proof that their product/technology works?
- How was the data generated that was used to train the algorithm (watch out for bias!)?
- Who are their referenced customers?
- How does the company consider trade-offs between attributes such as real-time responsiveness, cost and accuracy of their algorithms?
- Is there a technology comparable(s) outside the domain of healthcare?
- Has a technical expert on our team vetted their demo/product?

RED FLAGS
What to watch out for

- ❏ Companies that claim to be using a new form of machine learning. ML is largely a commodity.
- ❏ Companies claiming total replacement of humans in clinical settings—augmentation should be the goal.
- ❏ Have an expert check out the companies' engineers on LinkedIn to see the sophistication of methods they're trained in.
- ❏ Their product requires data sets your organization does not have—or—they cannot concretely (and simply) explain to you the kind of data needed for their methods to work.

Source: Rock Health interviews and analysis.

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@rock_health

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