



# Turn Data Science into Value: The Four Key Requirements

**Delivering Value with Research-Based  
Data Science and Predictive Analytics**

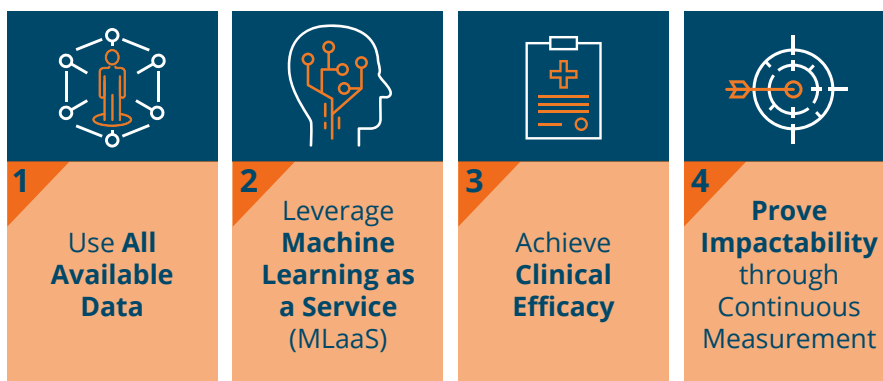
## Judging by the buzz at HIMSS 2017, predictive analytics is reaching the peak of the hype cycle.

Buzzwords used to describe it — like “cognitive computing,” “artificial intelligence (AI)” and “machine learning” — are often only brochure-level deep. But data science is science, after all, and must be validated through rigorous research and vetted by the academic community. The data science behind any predictive analytics model should go beyond marketecture, and be tested and proven through continuous research and critical peer review.

Predictive analytics solutions must offer research-driven data science, clinical actions and demonstrable results in order to deliver maximum value. But healthcare organizations struggle to understand how predictive analytics can be effectively used to drive these clinical and financial results.

To help healthcare organizations select an analytics partner, vendors need to show them what's under the hood. Vendors should publish their work in leading medical journals to transparently detail the data science methods used and statistical results, and how their models improve health outcomes in real clinical settings. This type of rigor will not only curb skepticism, but also help ensure that predictive analytics is adopted in meaningful ways to optimize care and improve outcomes.

**To do this and turn data science into value, a predictive analytics solution must meet four requirements.**



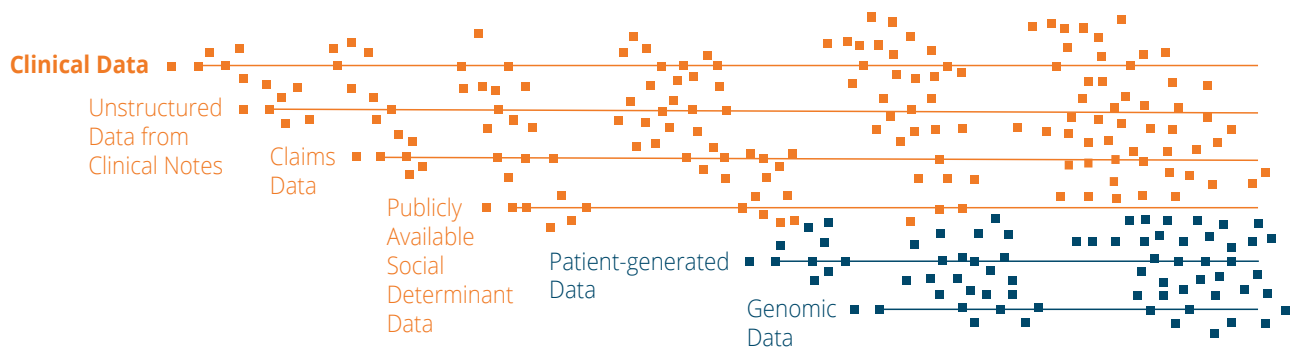
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# 1

## Requirement One: Use All Available Data

Using all available data provides the richest data set to develop better risk algorithms, which results in fewer false positives and false negatives. That means more at-risk patients are identified and clinicians are not wasting time reaching out to patients who are not truly at risk. The combination of clinical data from the EHR, claims data, unstructured data from clinical notes and publicly available social determinants of health data provides rich patient profiles to develop the best possible real-time predictive risk scores. With the addition of new emerging data types like patient-generated and genomic data, predictions will improve even further. And to provide the most value, the data should be aggregated and harmonized in as close to real time as possible.

**As the variety and volume of data increases, so does the value.**



# 2

## Requirement Two: Leverage Machine Learning as a Service (MLaaS)

Predictive models using machine learning techniques must be organic. In other words, models should be specifically trained on the uniqueness of the data set and patient population they're analyzing. This process is called "Machine Learning as a Service." It allows you to continuously refine each risk algorithm to consider new data sets and incorporate new population-specific evidence of risk. This constant monitoring and tuning produces the highest-performing models for a given population and data set.

## Requirement Three: Achieve Clinical Efficacy

Great data science is meaningless without clinical efficacy. Clinical efficacy is the ability of an intervention or action to produce the desired health outcome(s). The outputs of the machine learning process are algorithms that run inside the real-time risk engine and produce clinical actions for workflow and clinical improvement. The algorithms first identify patients at risk for negative outcomes like high cost, the onset of disease or mortality. When backed by valid and credible data science, they often identify patients that clinicians alone or inferior algorithms miss.

Next is identification and statistical evaluation of the relationships among the underlying health risk factors, disease, interventions and outcomes. Moreover, these relationships must be weighted to optimize end-user decision making at both the population and individual patient levels.

Clinical efficacy is then enabled through identification and grouping of patients in specific cohorts or micro-cohorts to focus on those likely to benefit most from care management or a preventive intervention. For example, by effectively targeting patients in a cohort at risk for high cost, high utilization or undesirable clinical outcomes, providers can identify and realize the following performance improvements:



Reduction in hospital readmissions and ED visits



Prevention of the onset of chronic conditions such as diabetes and COPD



Reduction in hospital adverse events



Reduction in unnecessary utilization and clinical variation



Reduction in acute episodes such as AMI and stroke



Reduction of nursing hours required for care management

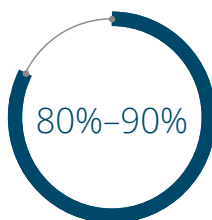
## Requirement Four: Prove Impactability through Continuous Measurement

If data science and medical efficacy were the only factors, reducing cost and improving population health would be far less challenging. Impactability — the degree to which the medical research and data science lead to actual results — remains a significant challenge. The following table from the Jefferson School of Population Health describes the myriad of factors, many of which are non-clinical, that influence adherence to interventions intended to improve population health.

### FACTORS AFFECTING ADHERENCE TO INTERVENTIONS

Socioeconomic	Therapy Related	Patient Related	Condition Related	Health System + Health Care Team
<ul style="list-style-type: none"> <li>• Cost of co-payment or coinsurance</li> <li>• Lack of health insurance</li> <li>• Medication cost</li> <li>• Access restrictions (e.g., formulary, utilization management)</li> <li>• Lack of family or social support</li> </ul>	<ul style="list-style-type: none"> <li>• Complexity of treatment (e.g., pill burden, changes in schedule, duration of therapy)</li> <li>• Side effects</li> <li>• Lack of immediate therapy benefit</li> </ul>	<ul style="list-style-type: none"> <li>• Lacks belief in benefit of treatment</li> <li>• Lacks insight into the illness</li> <li>• Health literacy</li> <li>• Poor relationship between patient and provider</li> <li>• Missed appointments</li> <li>• Access to care (hospital or pharmacy)</li> </ul>	<ul style="list-style-type: none"> <li>• Asymptomatic disease</li> <li>• Disease states with social stigma</li> <li>• Number of comorbid conditions</li> </ul>	<ul style="list-style-type: none"> <li>• Poor relationship between patient and provider</li> <li>• Inadequate follow-up, discharge planning or continuity of care</li> <li>• Knowledge or health literacy issues</li> <li>• Lack of empathy and/or positive reinforcement</li> <li>• Amount of prescribed medications and complexity of treatments</li> </ul>

[www.jefferson.edu/content/dam/university/population-health/research/newsletters/Prescriptions-for-Excellence-Winter2016-Issue25.pdf](http://www.jefferson.edu/content/dam/university/population-health/research/newsletters/Prescriptions-for-Excellence-Winter2016-Issue25.pdf)



of health determinants are not related to healthcare delivery.<sup>1</sup>

According to HealthIT.gov, 80%–90% of health determinants are not related to healthcare delivery.<sup>1</sup> These include factors such as patient motivation, compliance, transportation needs and activity level. To be fully impactful and to deliver real value, a predictive analytics solution must be able to consume and process these behavioral and social determinants of health — which are often found only in unstructured case notes.

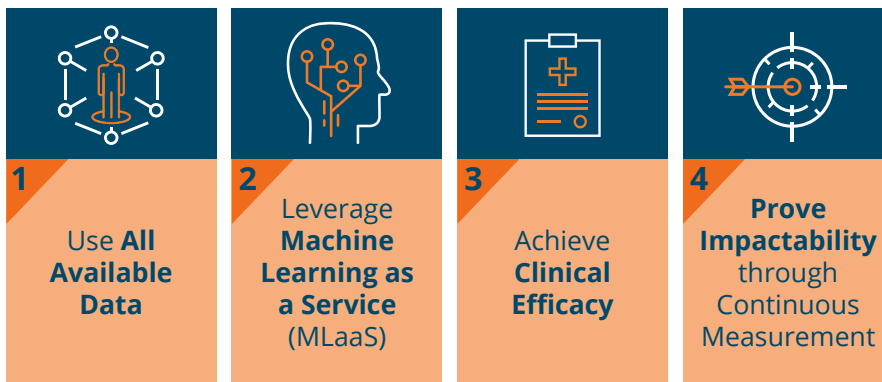
To prove impactability, longitudinal performance must be continuously measured against benchmarks such as aligned MIPS, HEDIS and other key performance measures, creating a feedback loop to adjust and refine interventions based on risk and ability to impact that risk.

<sup>1</sup><https://www.healthit.gov/sites/default/files/shared-nationwide-interoperability-roadmap.png>

# What to Remember

The best predictive analytics companies don't hide behind the buzzwords. Instead, they openly share their data science methods and rigorously test them to demonstrate meaningful outcomes. And they turn that data science into value by meeting four essential requirements: They use all available data, they offer machine learning as a service, they enable clinical efficacy, and they prove impactability.

## 4 Requirements to Turn Data Science into Value



To better understand how HBI Solutions delivers serious data science and predictive analytics, read our peer-reviewed journal publications at [hbisolutions.com/publications](http://hbisolutions.com/publications) or get in touch by emailing [aeisman@hbisolutions.com](mailto:aeisman@hbisolutions.com).

### About HBI Solutions Inc.

HBI Solutions Inc. offers a proven suite of predictive analytics and performance analysis solutions to healthcare organizations worldwide. HBI's Spotlight Data Solution, applications, and risk models use real-time clinical, billing, and claims data to provide healthcare organizations with actionable information to improve patient care at a lower cost. Flexible and easy to install, it can fit into any business intelligence, data warehouse, EHR, or interoperability system. HBI's customers include health systems, physician practices, federally qualified health centers, accountable care organizations, payers, health information exchanges, and technology vendors. The company incorporated in 2011 and is headquartered in Palo Alto, CA.



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