INTERNATIONAL INSTITUTE FOR ANALYTICS™

COMPLIMENTARY EDITION

DELTA Plus Model & Five Stages of Analytics Maturity: A Primer

ADAPATED FROM *ANALYTICS AT WORK: SMARTER DECISIONS, BETTER RESULTS* (DAVENPORT, HARRIS, MORISON, 2010) AND *COMPETING ON ANALYTICS: THE NEW SCIENCE OF WINNING* (DAVENPORT AND HARRIS, 2017 & 2007)

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Big Ideas

- The DELTA Plus Model Framework encompasses the five foundational elements of a successful analytics program (Data, Enterprise, Leadership, Targets, and Analysts) and introduces two new elements (Technology and Analytical Techniques) required for high performance.
- Enterprises committed to using analytics and data to transform their businesses progress through the Five Stages of Analytical Maturity, from 'Analytically Impaired' to 'Analytical Competitor.'
- As organizations build capabilities across the DELTA Plus elements, they become more analytically mature and competent.

Introduction

As enterprises of all shapes and sizes commit to harnessing the power of data and analytics to transform all aspects of their businesses, leadership will inevitably ask these questions:

- *How good are we at using data and analytics throughout our enterprise? Are we actually as good as we think?*
- *Are we ahead of or behind our nearest competitors? Are other industries ahead of ours?*
- *Are we moving toward becoming an analytical competitor?*
- *How can we set a path forward without knowing where we stand today?*

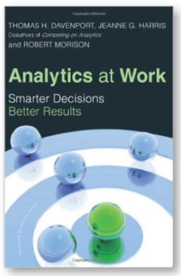
The Five Stages of Analytics Maturity and the DELTA Model have become the industry standard frameworks for assessing analytics maturity. The five stages of analytics maturity were introduced in 2007 by Tom Davenport and Jeanne Harris in their book, *Competing on Analytics: The New Science of Winning*. The DELTA Model was introduced in 2010 by Tom Davenport, Jeanne Harris and Bob Morison in their book, *Analytics at Work: Smarter Decisions*, Better Results. Both frameworks were updated by Tom Davenport and Jeanne Harris in their 2017 revision of *Competing on Analytics*. Two new components were added to the DELTA model, creating the DELTA Plus model.

The purpose of this research brief is to summarize the key elements of DELTA Plus and five stages of analytics maturity, and discuss how these two frameworks can be used to understand analytical maturity in your organization. For additional discussion on these topics, IIA recommends reading *Analytics at Work: Smarter Decisions, Better Results* (2010) and *Competing on Analytics: The New Science of Winning (2017).*

DELTA Plus Model

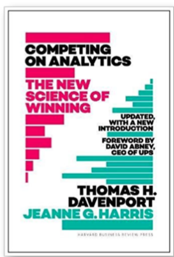
The original DELTA model featured five elements that must be in alignment for organizations to succeed with their analytics initiatives. Without alignment, organizations run the risk of poor or limited results. To make real progress and become a data-driven organization, the capabilities and assets of these five elements must evolve and mature.

Δ DELTA PLUS MODEL



D	DATA	BREADTH, INTEGRATION, QUALITY
E	ENTERPRISE	APPROACH TO MANAGING ANALYTICS
L	LEADERSHIP	PASSION AND COMMITMENT
T	TARGETS	FIRST DEEP THEN BROAD
A	ANALYSTS	PROFESSIONALS AND AMATEURS

Adapted from *Analytics at Work*, Davenport, Morrison and Harris, 2010



T	TECHNOLOGY	APPROACH, ORIENTATION, VELOCITY
A	ANALYTICS TECHNIQUES	SOPHISTICATION, DIVERSITY

Adapted from *Competing on Analytics*, Davenport and Harris, 2017

The five elements of a successful analytics program, as stated in *Analytics at Work*, are:

D for accessible, high quality *data*

E for an *enterprise* orientation to managing analytics

L for analytical *leadership*

T for strategic *targets*

A for *analysts*

The continued growth of big data, coupled with the introduction of new analytics techniques like machine learning, means there are two additional elements (the Plus factors) that should also be considered:

T for *technology*

A for *analytics techniques*

Data

For meaningful analytics, data must be organized, unique, integrated, accessible, and of high quality. Of course, not all organizations have an environment that encompasses all the important elements of data, but it's important to know what to pursue to create the largest opportunity. The way an organization's data is structured influences the type of analysis that can be done. The ability of an organization to structure and leverage unstructured data also influences the type and value of analytics that is done. The same is true for data uniqueness – if an organization can also gather unique data outside what other companies have access to, then they have an analytical edge and more opportunity in their analyses. Organizations also need to integrate their data across organizational silos and boundaries. Most organizations have multiple transaction systems in different business units and functions, and to fully understand organizational performance data from all of them needs to be combined and harmonized.

It is also no secret that many organizations face data-quality issues. Once data has been cleaned and integrated, it must be made accessible to the organization for analytical purposes. Simply put, analysis cannot be done if the data cannot be located and accessed. Data warehouses or Hadoop-based data lakes are the primary means to allow analysts and non-analysts to access data. These repositories can be deployed on premise, in the cloud or in a hybrid mix of the two. Finally, if an enterprise is becoming more mature within all aspects of its data environment, it implements a dynamic governance strategy to ensure high-quality and well-managed data across the organization.

Enterprise

Analytical competitors take an enterprise approach to managing systems, data and people. They have coordinated approaches relying on enterprise-level organizational structures, resource allocations and plans.

To embrace this approach a company must advocate a single and consistent perspective for analytics across the organization. This is accomplished by setting an analytics strategy and building a road map for strategy implementation. Integrating data and managing a unified data and analytics platform are key components of an analytics road map, as is cultivating a culture of analytics across the organization. Perspectives from individual managers and business units/functions that do not support or advance the enterprise view must be discouraged and replaced with a single, enterprise wide view of analytics.

If analytics goals are not centrally established, organizational silos can develop and lead to duplicated efforts and tools, errors in analysis, ineffective use of resources, conflict among different groups, and increased complexity with analytics projects. An enterprise approach to analytics will greatly increase the organization's competitiveness.

> *"Without a broad business perspective, a company cannot address the strategic issues at the core of business performance and organizational competitiveness."*
>
> *-Tom Davenport*

Leadership

Analytical organizations have leaders who fully embrace analytics and lead company culture toward data-driven decision-making. Beyond the CEO or other top executives, all levels of leadership within the organization should support analytics. This is important for cultural acceptance of analytics across the enterprise, as well as the accomplishment of analytics initiatives. In *Analytics at Work*, authors Davenport, Harris and Morison note 12 traits that analytical leaders exhibit in analytically competitive organizations.

1. Possess people skills
2. Push for more data and analysis
3. Hire smart people, and give them credit
4. Set a hands-on example
5. Sign up for results
6. Teach
7. Set strategy and performance expectations
8. Look for leverage
9. Demonstrate persistence over time
10. Build an analytical ecosystem
11. Work along multiple fronts
12. Know the limits of analytics

Targets

Virtually no organization can afford to be equally analytical in all parts of its business. Analytics efforts must be aligned with specific, strategic targets that are also aligned with corporate objectives. Organizations will get lost in all the business opportunities that analytics can support if they do not focus on a few initial and purposeful use cases and applications. Choosing these targets based on the organization's strategic plan is helpful, but not always easy. What is typically required is a group of executives that understands both the business and the analytical possibilities for improving it. Enterprises can also survey internal employees for ideas, as well as external groups to help understand industry and analytical trends. Looking beyond one's industry is also helpful to find opportunities in common, cross-industry applications.

When determining what targets to choose, leaders should narrow in on the best options. This often requires several steps. Leaders need to think about the big picture for where the business is going, create a systematic inventory of possibilities, and then prioritize potential uses of analytics based on the benefit for and capabilities of the organization. Once an enterprise is mature, its targets become embedded in the strategic planning process, and are considered business initiatives, not just analytics initiatives. If the organization is successful with analytics, its targets can broaden over time.

Analysts

Organizations require analytical talent that covers a range of skills from employees capable of basic spreadsheets to accomplished data scientists. In *Analytics at Work,* four analytical types of people are defined, all of whom play an important role in an organization: analytical champions, analytical professionals (now often known as data scientists), analytical semiprofessionals, and analytical amateurs. Recruiting analysts and data scientists can be quite difficult today and retaining these employees even more challenging. Such professionals must have quantitative and technical skills, business knowledge, interpersonal skills, and the ability to coach others who may not understand analytics. They also must be adept at navigating new analytics techniques such as machine learning and AI. Once the right people are in place, keeping them motivated with creative and challenging projects is crucial.

Of course, the perfect analyst or data scientist with all the necessary skills for a specific project may be practically impossible to find. Some may hire business people with the potential to be great analysts, and others may hire analysts and develop their business acumen along the way. Other companies employ teams to marshal the required range of skills. Because analytical skills are often in short supply, organizational structures and processes are critical for using them effectively. Both organizing and hiring analysts will have an impact on how the analytics strategy is deployed across the organization, and on recruiting and retention approaches.

Technology

As the technology for analytics rapidly evolves, an organization's ability to deploy and manage the underlying infrastructure, tools and technologies becomes increasingly important. Technology was stable for several decades in analytics, but is changing rapidly today. With the advent of big data, AI, cloud and open source options, creating an effective technology strategy for analytics is a critical prerequisite for success. Companies are also increasingly expecting "citizen data scientists" to do self-service analytics and reporting. Self-service data science platforms can accelerate productivity and deployment for all types of analytical professionals and semiprofessionals.

"Architectures must support experimentation and flexibility while making it feasible to integrate analytics with production systems and processes."

As analytics and AI become more critical to an organization's success, many will need to develop sophisticated architectures for them. The architecture must support experimentation and flexibility while making it feasible to integrate analytics with production systems and processes. The relative proportions of cloud versus on-premises, open source versus proprietary, structured versus unstructured data capabilities, and other key decisions should be specified in the architecture. Companies with relatively specialized data and analytics AI environments — for deep learning-based image recognition issues, for example — may need specialized hardware capabilities like graphics processing units.

Analytical Techniques

At one time, most commercial organizations primarily undertook simple regression analysis. Today, however, the plummeting costs of compute and storage, coupled with widespread adoption of open source development by Google, Amazon, Microsoft and others, have resulted in an explosion of analytical methods and techniques. Some machine learning platforms may automatically evaluate hundreds of different algorithms. "Ensemble" methods employ multiple techniques within a particular model. AI methods such as deep learning raise important issues of the transparency and interpretability of models. And more traditional approaches to analytics such as reporting and visual analytics haven't gone away.

"Organizations wishing to succeed with analytics need to assess what types of models they are most likely to need and ensure that the relevant tools and skills are available to use them."

Organizations wishing to succeed with analytics need to assess what types of models they are most likely to need and ensure that the relevant tools and skills are available to use them. An informal "technique survey" can compare methods currently used within an organization to what is available externally. Increasingly, the most sophisticated tools will determine which (among a large variety) of techniques to employ in analyzing data, which may lessen the need for an organization-specific approach to technique selection.

Five Stages of Analytics Maturity

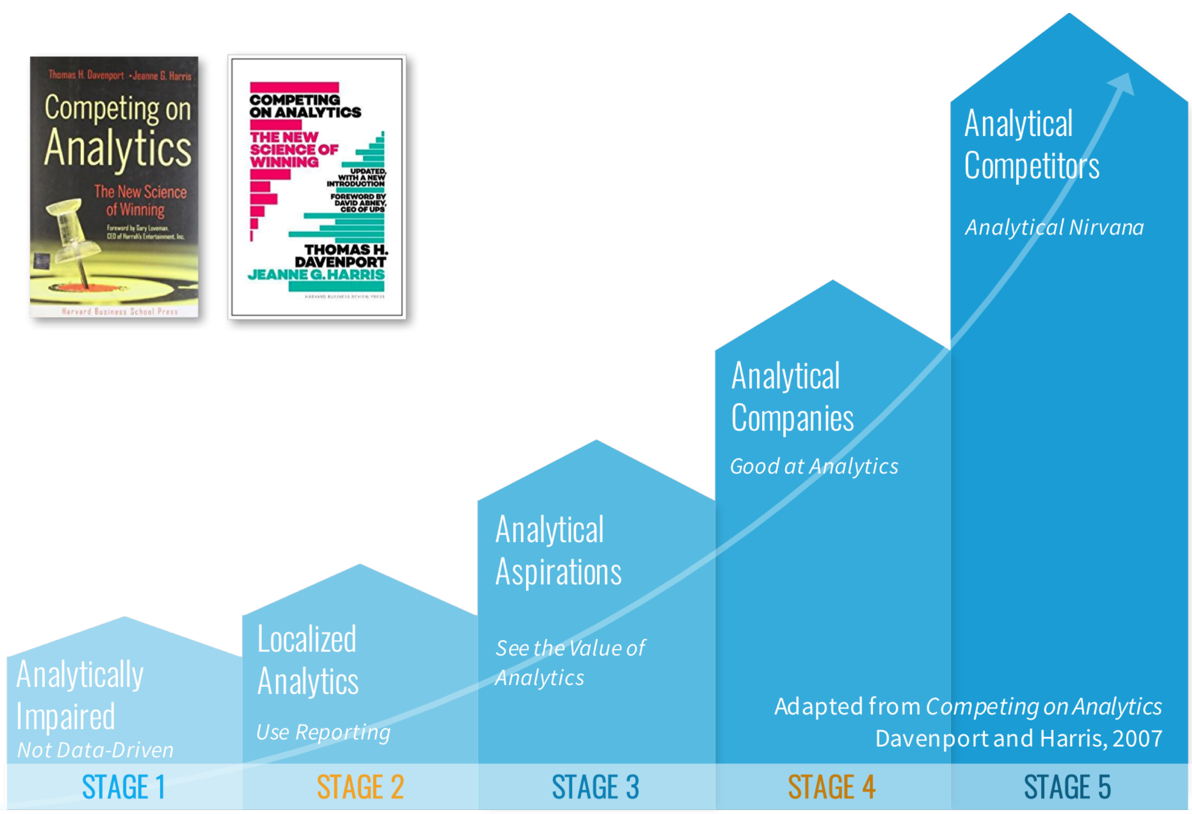
Organizations mature their analytical capabilities as they develop in the seven areas of DELTA Plus. The maturity model, described in *Competing on Analytics* and developed in *Analytics at Work*, helps companies measure their growth across the seven DELTA elements. This model enables an organization to assess which elements are strengths and which are weaknesses. For example, an organization may achieve a stage 4 in analytics leadership maturity, but achieve only a stage 3 in its management and use of data. This assessment enables targeted investment to mature analytics weaknesses based on the DELTA Model.

Stage 1: Analytically Impaired. These companies rely primarily on gut feel to make decisions, and they have no formal plans for becoming more analytical. They aren't asking analytics questions and/or they lack the data to answer them. Their leaders may be unaware of analytics and what can be done with them.

Stage 2: Localized Analytics. Analytics or reporting at these companies exist within silos. There is no means or structure for collaborating across organizational units or functions in the use of analytics. This often leads to "multiple versions of the truth" across a company.

Stage 3: Analytical Aspirations. These companies see the value of analytics, and intend to improve their capabilities for generating and using them. Thus far, however, they have made little progress in doing so.

Stage 4: Analytical Companies. Companies in this category are good at multiple aspects of analytics. They are highly data-oriented, have analytical tools and make wide use of analytics with some coordination across the organization. However, there



remains a lack of commitment to fully compete on analytics or use them strategically.

Stage 5: Analytical Competitors. These companies use analytics strategically and pervasively across the entire enterprise. They view their analytical capabilities as a competitive weapon, and they already seen some competitive advantage result from analytics.

DELTA Plus Elements Across the Five Stages of Maturity

The factors described above drive the relative maturity and sophistication levels of an organization's approach to analytics. In the tables below are described typical attributes of each DELTA element for a given maturity level, and the types of changes that typically accompany a move from one maturity level to the next.

Organizations that desire to increase their maturity level can use this figure as a guideline for capabilities and improvements to pursue. Of course, circumstances will vary across companies, but these descriptions are illustrative of the most common attributes and change types.

DELTA Plus Transitions

Table 2 outlines the conditions that are typically in place at each stage of progress in building an analytics program.

Study this table with your current conditions and analytical ambitions in mind. What do you need to do to leverage your strengths, shore up your weaknesses, become more DELTA Plus ready, and increase the business impact and value of analytics? As you consider your course of action, be sure to avoid these common pitfalls:

- *Focusing too much on one dimension of analytical capability (most often technology and data) at the expense of others*
- *Devoting too much time, energy and money to analytical initiatives that have low business impact (less valuable targets - even if that's what the business is asking for)*
- *Attempting to do too much at once.*[1]

[1] Davenport, Harris, Morison, Analytics at Work: Smarter Decisions, Better Results, 2010 (Harvard Business School Publishing), 185 – 188.

Table 1 Success Factors	Stage 1: Analytically Impaired	Stage 2: Localized Analytics	Stage 3: Analytical Aspirations	Stage 4: Analytical Companies	Stage 5: Analytical Competitors
Data	Inconsistent, poor quality and organization; difficult to do substantial analysis; no groups with strong data orientation; basic reporting tools and descriptive analytics.	Much data useable, but in functional or process silos; senior executives don't discuss data management; BI and basic analytics tools.	Identifying key data domains and creating data warehouses or data lakes; expansion into unstructured NoSQL data.	Integrated, accurate, common data in central warehouse; data still mainly an IT matter; little unique data: use of unstructured NoSQL data analysis.	Relentless search for new data and metrics; organization separate from IT oversees information; data managed as strategic asset.
Enterprise	No enterprise perspective on data or analytics. Poorly integrated systems.	Islands of data, technology and expertise deliver local value.	Process or business unit focus for analytics. Infrastructure for analytics beginning to coalesce.	Key data, technology and analysts are managed from an enterprise perspective.	Key analytical resources focused on enterprise priorities and differentiation.
Leadership	Little awareness of or interest in analytics.	Local leaders emerge, but have little connection.	Senior leaders recognizing importance of analytical capabilities.	Senior leaders developing analytical plans and building analytical capabilities.	Strong leaders behaving analytically and showing passion for analytical competition.
Targets	No targeting of opportunities.	Multiple disconnected targets, typically not of strategic importance.	Analytical efforts coalescing behind a small set of important targets.	Analytics centered on a few key business domains with explicit and ambitious outcomes.	Analytics integral to the company's distinctive capability and strategy.
Analysts	Few skills, and those are attached to specific functions.	Disconnected pockets of analysts; unmanaged mix of skills.	Analysts recognized as key talent and focused on important business areas.	Highly capable analysts explicitly recruited, deployed and engaged.	World-class professional analysts; cultivation of analytical amateurs across the enterprise.
Technology	Desktop technology, standard office packages, poorly integrated transactional systems.	Individual analytical initiatives, statistical packages, descriptive analytics, database querying, spreadsheets.	Enterprise analytical plan, tool and platforms; predictive analytical packages.	Enterprise analytic plan and processes, cloud-based big data.	Sophisticated, enterprise-wide big data and analytics architecture, cognitive technologies, prescriptive and autonomous analytics.
Analytical Techniques	Simple visual analytics, measures of central tendency, exploration, trending.	Correlation and linear regression, segmentation, database querying, use of ranges, confidence intervals.	Simple predictive analytics, logistic regression, classification and clustering; dynamic forecasts.	Advanced predictive methods deployed to discover insights; advanced optimization, sentiment analytics, text and image analytics.	Neural nets and deep learning, automated machine learning, ensemble models.

Table 2 DELTA Plus Transitions	Stage 1 to Stage 2 Analytically Impaired to Localized Analytics	Stage 2 to Stage 3 Localized Analytics to Analytical Aspirations	Stage 3 to Stage 4 Analytical Aspirations to Analytical Companies	Stage 4 to Stage 5 Analytical Companies to Analytical Competitors
Data	Gain mastery over local data of importance, including building functional data marts.	Build enterprise consensus around some analytical targets and their data needs. Build some domain data warehouses (e.g. customer) and corresponding analytical expertise. Motivate and reward cross-functional data contributions and management.	Build enterprise data warehouses or data lakes and integrate external data. Implement self-service data science platforms. Engage senior executives in EDW plans and management. Monitor emerging data sources.	Educate and engage senior executives in competitive potential of analytical data. Exploit unique data. Establish strong data governance, especially stewardship. Form a BICC if you don't have one yet.
Enterprise	Find allies for small-scale analytics projects that nonetheless suggest cross-functional or enterprise potential. Manage data risk at local level. Partner with IT on common tool selection and data standards.	Select applications with relevance to multiple business areas. Keep scope manageable, but with an eye to future expansion. Establish standards for data privacy and security. Begin building enterprise analytical infrastructure incrementally. Plan and lay groundwork for enterprise analytics strategy and priorities.	Develop and implement analytics IT roadmap for the entire enterprise. Conduct risk assessments of all analytical applications. Establish enterprise governance of technology and architecture for analytics.	Manage analytical priorities and assets at the enterprise level. Implement enterprise-wide model review and management. Extend analytics tools and infrastructure broadly and deeply across the enterprise.
Leadership	Encourage the emergence of analytical leaders in functions and business units.	Create a vision of how analytics will be used in the organization in the future and begin to identify specific capabilities that are necessary.	Engage senior leaders in building analytical capabilities, particularly in the areas of data, technology and analytical human resources.	Encourage leaders to be visible with their analytical foci, and to communicate with internal and external stakeholders about how analytics contribute to success.
Targets	Work wherever there is sponsorship and some decent data. Target "low hanging fruit."	Work with business areas that are already somewhat analytical or can benefit greatly from analytics. Identify likely business processes or cross-functional applications. Start taking systematic inventories of analytical opportunities by business area.	Work with major business processes and their owners. Focus on high value and high impact targets. Initiate an enterprise-wide approach to finding and evaluating targets. Formalize the process of targeting as collaboration among business executives, IT and analytics leaders.	Work with the executive team. Focus on strategic initiatives, value creation, and building distinctive capability that will enhance competitive differentiation. Infiltrate the strategic planning process so analytics can shape (not just respond to) business strategy.
Analysts	Identify pockets of analysts and skills. Offer analytical skills training. Encourage analytical components of systems projects. Enlist managers to appreciate and engage analytical employees. Create analyst group "beachheads" in business units or functions with specific need and some appetite for analytics.	Define analytical positions and use specialty recruiting sources to fill them. Begin collaboration among analyst groups, first for experience exchange, then for work on a cross-functional and strategic initiative. Promote rotational deployment of analysts. Provide coaching and support, especially for analytical professionals.	Evaluate analytical expertise of all information workers, develop relationships with universities and associations, and provide advanced training for analysts. Focus on developing business acumen in analysts and analytical expertise in business executives. Integrate the development and deployment process. Establish a central analytics function to supplement local analytics groups.	Hire analytically minded employees in all business roles. Formalize an analyst-role/business-rotation program. Consolidate the organization and management of analysts so that all key initiatives and objectives are coordinated, and analysts are deployed with their development in mind. Regularly recognize analytical employees in all roles and ensure that analysts are constantly challenged in their work.

Table 2 DELTA Plus Transitions	Stage 1 to Stage 2 Analytically Impaired to Localized Analytics	Stage 2 to Stage 3 Localized Analytics to Analytical Aspirations	Stage 3 to Stage 4 Analytical Aspirations to Analytical Companies	Stage 4 to Stage 5 Analytical Companies to Analytical Competitors
Technology	Adopt predictive analytics tools and encourage their use. Make visual analytics tools available. Put important data into a warehouse or lake. Encourage early adopters to experiment with analytical technologies.	Identify a suite of analytics tools for use throughout the enterprise. Experiment with cloud-based analytics and data management, and with a few big data applications.	Embrace cloud, big data, and predictive and prescriptive analytics on structured and unstructured data. Move toward Hadoop-based data lakes. Develop some machine learning applications. Experiment with other forms of AI. Employ open source tools in some cases.	Identify AI toolset for the enterprise for all types of data. Explore automated machine learning tools. Move big data analytics to the cloud. Adopt model management approaches and treat algorithms as key assets. Heavy use of open source tools.
Analytical Techniques	Encourage some departments to adopt predictive models. Begin to move toward statistical significance analyses and range-based forecasts. Explore optimization, web analytics, and other special-purpose tools.	Ensure that a central analytics organization is well-trained in predictive and prescriptive models. Experiment with statistical machine learning. Undertake some “test and learn” experiments. Try out text and sentiment analysis.	Employ broad mix of model types around the organization. Move toward a combination of discrete simple and complex machine learning approaches. Explore commercial and open source AI tools for applications like image and voice recognition.	Make extensive use of automated and semi-automated machine learning models with a variety of algorithms to select among. Use commercial or open source tools for neural networks and deep learning. Employ ensemble modeling approaches.

About the Author

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Tom Davenport is a co-founder and advisor of IIA. He is the President's Distinguished Professor of IT and Management at Babson College, and a research fellow at the MIT Center for Digital Business. Tom's "Competing on Analytics" idea was named by Harvard Business Review as one of the twelve most important management ideas of the past decade and the related article was named one of the ten 'must read' articles in HBR's 75 year history. His most recent book, co-authored with Julia Kirby, is *Only Humans Need Apply: Winners and Losers in the Age of Smart Machines*.