

Taking Charge of the Miracle:

Actively Guiding Expectations into Outcomes

2019 Naval Intelligence Essay Contest:
“Achieving High Velocity Outcomes”

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*“I think you should be more explicit here
in step two.” ¹*

Introduction

The CNO's *Design for Maritime Superiority* is by definition, a plan to affect and improve a long-term strategy of maritime success. Specifically, Version 2.0 redesigned the *Achieve High Velocity Learning* Green Line of Effort (LOE) to focus on outcomes rather than processes.² The updated LOE, renamed *Achieve High Velocity Outcomes*, provides better links between strategy and expectations. Yet even with those stronger identified linkages, truly effective execution must be supported by a culture of self-assessment and connections throughout all levels of the enterprise.

Within the Naval intelligence enterprise there is a targeted need for the empowerment and execution of business analytics to help streamline our analytic resources and alignments toward identified intelligence outcomes. Just as analytic tradecraft is vital for proper intelligence analysis, Naval intelligence must also embrace the tradecraft associated with assessing business performance toward specific intelligence outcomes. This paper explores emerging concepts and lessons learned in industry and government for honing and strengthening business evaluations and tradecraft, and the parallels for implementing outcomes-driven self-assessments for Naval intelligence.

Breaking Down the Steps

Overwhelming complexity and lack of resources are common inhibitors of success for many well-defined efforts, projects, and processes. Yet these limitations can often mask a truer root cause: skipping steps needed for useful evaluations.

Even where business evaluation is well known and valued as a key middle step, organizations can skip the meatiest parts of implementation: actively maturing an overall culture of self-assessment and associated evaluation tradecraft skills.

In other words, we can have refined strategic goals (the “why”) and the expected outcomes (the “what”) in place, but we will not have truly successful outcomes without the paths or knowledge for our workforce to actively analyze and connect local progress to our complex or large-scale efforts (the “how”).

This assertion will sound intuitive enough to outcome-oriented professionals: you can't expect miraculous success if you can't identify the path to it or truly understand the obstacles. And at many levels within Naval Intelligence these aspects of business performance assessments

already exist: professionals leading naval intelligence programs are asking the right questions and providing accurate evaluations of their progress to program managers. However, closer inspection reveals areas with inconsistent expectations of progress assessment that aren't translated or framed well across middle managing organizations, or more importantly for broader upper echelon interests.

“Like a tree falling in a forest with no one to hear it, if analysts are putting out analyses but no one takes notice, if they don't influence decision makers' decisions, which are still based on gut and opinion, it is not data-driven. Analytics has to inform and influence the influencers.” [3](#)

For Naval Intelligence specifically, we must improve these meaty middle steps by:

- (1) Ensuring a culture of self-assessment at all levels
- (2) Identifying translatable connections between each level's assessments to adequately inform the overall mission goals.

Culture of Self-Assessment: Art and Science

What is a “culture of self-assessment”? It means consistent practices and expectations through an organization to provide an evidentiary basis for decision making at any level.

How are do we get there? A first step is to realize that assessment is a collaborative approach of both art and science. Next is to realize that we already have the tools we need to actively support this collaboration.

Organizations throughout industry and government often respond to growing customer demands and complexities by increasing resources for the latest technical skills and tool licenses. In the era of big data, data science technologies and practitioners have risen to meet many of those growing needs. For each of these disciplines, the art of data science is just as valuable as the technologies and algorithms.

While it is most often associated with artificial intelligence and machine learning (AI/ML), data science actually encompasses a wide variety of specialties – including, but not limited to, machine learning, robotics, data engineering, data storage, data visualization, data analytics, and business analytics. In the business analytics discipline, also called business intelligence (BI), the analytic questions themselves concern the functioning of the business.

“Business intelligence (BI) is an umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance.” ⁴

BI efforts often involve smaller data than other data science disciplines, and a greater mix of qualitative and quantitative assessment approaches in order to perform self-assessments. Sounds complicated, but we already have significant guideposts at our disposal: data science tradecraft principles and existing intelligence community analytic tradecraft standards.

Data Science Tradecraft

Although data science tradecraft is not currently codified by a single authoritative entity, its practitioners generally agree that data science is a team sport that supports a blending of various analytic approaches. Table 1 provides one way to characterize the major themes. In short: know the overall goals, know the data, be flexible in your approach, careful in your assumptions, and holistic in your analysis.

Table 1: Data science tradecraft principles ⁵	
Data is a strategic asset	Need an organizationally focused mindset
Systematic process for knowledge extraction	Need clear and distinct stages (data model foundations, building, and iteration)
Sleeping with the data	Need data evangelists who are data literate, creative, and understand the value of the data
Embracing uncertainty	Data is a decision enabler, not a silver bullet
Business context	Need to define the business problem, and use analytics to solve it

A key part of any data science skillset involves an enterprise mindset, meaning knowing if you have the right data for your goals, and knowing how to ask the right questions to get to your enterprise goals. ⁶ For BI, how we store, structure, and clean business data impacts our ability to manipulate it for trend discovery. How we understand the source and content of the business data we’ve gathered impacts our success in querying it. How we relate trends within numerical and categorical descriptions of business data impacts how we answer the business questions. Having the right variety of team members and managers in place to understand the data, execute the appropriate analysis techniques, and adjust business planning impacts the success of the overall business outcomes.

Analytic Tradecraft

The nine tradecraft standards identified by ODNI (Table 2) have impacts for the analysis of business data as well as the analysis of intelligence information.

Table 2: ODNI Analytic Tradecraft principles ²	
(1) Sourcing	Properly describes quality and credibility of underlying sources, data, and methodologies
(2) Uncertainty	Properly express and explains uncertainties associated with major analytic judgments
(3) Underlying assumptions	Properly distinguishes between underlying intelligence information and analysts' assumptions and judgments
(4) Alternatives	Incorporates analysis of alternatives
(5) Relevance	Demonstrates consumer relevance and address implications
(6) Logic	Uses clear and logical argumentation
(7) Consistency	Explains change to or consistency of analytic judgements
(8) Accuracy	Makes accurate judgements and assessments
(9) Visualization	Incorporates effective visual information

How well we identify bias, relevancy, and accuracy of the business data we've gathered impacts our assessment of success toward the intelligence outcome. How well we include situational information outside the business' control (politics, financial pressures, crisis demands) impacts how well we adjust (course or expectations) for goal success. How well we identify assumptions about the data or our business goals can impact data collection, analysis, and presentation. Last but not least, how we visualize raw and analyzed business data can impact perception of mission success, and therefore the direction of future mission goals.

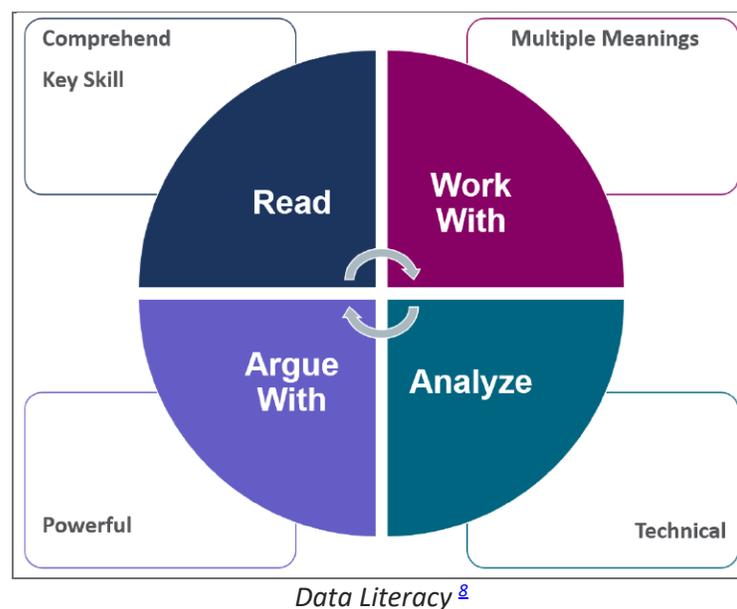
Making the Connections: Data Literacy

In many cases within industry and government, self-assessments of mission success are already performed at broad strategic levels and also granularly at individual program levels. However, the manner and focus of those self-assessments can differ greatly, causing disconnects in the outcome equation. For example, specific program efforts with single-customer or single-topic goals often have a great level of detail regarding outcomes. At the higher echelons, strategic

corporate assessments can consolidate interdependent goals of multiple mission topics, but often without as many direct ties to specific outcomes on the front lines.

The key, of course, is to foster better connections across these levels. But for the intelligence community it won't be through cookie cutter metrics drills, or any one method defined in a professional paper. We must instead grow the ability of our professionals within each mission domain to understand the data and innovate the appropriate connections. This means increasing the level of data literacy throughout workforces and into the executive core.

Data literacy does not necessarily mean having a data science degree. One community definition simply explains that data literacy is “the ability to read, work with, analyze, and argue with the data.” [8](#)



We can break this down further: successful connections of business value between organizational levels depend on the data and the people.

The Data

For BI, we find the most valuable business data in collected metadata and through calculated key performance indicators (KPIs). Data literacy illuminates a broader understanding of terms like “data” and “calculated”; these terms often come with a hard numerical bias that limits innovative approaches for business self-assessment. Consider instead terms like “information” or “evidence” and “translation” or “evaluation”, and more data sources (collected or calculated) will be considered for analysis and comparison.

For example, companies in industries such as finance and manufacturing run on monetizable KPIs – standardized units, easy to count, connect, compare, and translate into “success”. KPIs for intelligence mission success are not typically generated or translated across organizational levels with the same ease. At individual program levels the business value can be based on discrete numerical values, but the translation to overall mission goals may require qualitative binning that also includes many caveats. Or more accurately, there can be a series of ever-broadening qualitative binning translations to higher management levels.

The People

Alongside this expanded concept of data, proper evaluation of enterprise mission success depends greatly on the ability of its professionals to guide the collection and translation of performance criteria that matters. Specifically, we need:

- a common expectation of providing and being asked to provide connections (vs a common specific method)
- interdisciplinary teams at multiple organizational layers that combine intelligence analysis, data science, corporate resource awareness

Intelligence analysts and resource management professionals abound. So do data science skills and tools. The future of our business self-assessments lie in multi-disciplinary teams of people who understand the mission domains (intelligence topic areas), business support domains (like collections, analytic output/production, finance, human resources, etc.), IT enabling functions (infrastructure, business analysis tools), and data tradecraft (data engineers, data owners, data visualization specialists, etc.). Translations of data into business value can include unstructured data and the business questions can rely heavily on qualitative interpretation. That interpretation needs to be driven by the mission domains and tempered with applicable tradecraft. Empowered with corporate vision and a common expectation of translating assessments upchain, those interdisciplinary teams facilitate the best basis for business value.

Conclusion

Actively planning for outcomes is not a new concept; the basis of formal program management is setting major goals, creating the right teams, working objectives in stages, adjusting to unforeseen events, and producing results. Why do we overlook the parallels of these middle steps when we attempt to judge the progress or success of our intelligence missions? We

don't expect miracles without focused effort in disciplines like intelligence analysis, resource management, and functional support enablers. Intelligence analysis has defined priorities, and we invest in multi-disciplinary teams and apply analytic tradecraft to discrete intelligence topics. For traditional resource management there are given goals and objectives for which we actively track and analyze financial spend rates, personnel fill rates, and contract execution rates for possible course changes. For technical enabling functions we prioritize software licenses, reduce functional duplication, and incorporate data science and tradecraft for big data. Plus, in all these disciplines there is an expectation to translate outcomes across organizational levels and upchain for executive decision making.

Furthermore, why do these disciplines remain largely separate? Business intelligence – in our case, the self-assessment of intelligence mission success – needs them all. Business self-assessment is just another team sport that requires rules, coaches, and right mix of people to play in order to win. The true high velocity outcomes in Naval intelligence's future will come from an improved cross-pollination of these disciplines and associated tradecrafts, and more mature expectations throughout all levels to provide an evidentiary basis for any business outcome assessment.

¹ Sidney Harris, "Then a Miracle Occurs", The New Yorker, <https://www.newyorker.com/cartoons>.

² "A Design for Maintaining Maritime Superiority, Version 2.0," Chief of Naval Operations, December 2018, https://www.navy.mil/navydata/people/cno/Richardson/Resource/Design_2.0.pdf.

³ Carl Anderson, "Creating a Data-Driven Organization", O'Reilly publishing, August 2015, <https://www.oreilly.com/library/view/creating-a-data-driven/9781491916902/ch01.html>.

⁴ Gartner IT Glossary, "Business Intelligence {BI}", <https://www.gartner.com/it-glossary/business-intelligence-bi/>.

⁵ Pradeep Menon, "Data Science Simplified Part 1: Principles and Process", Becoming Human: Artificial Intelligence Magazine, July 2017, <https://becominghuman.ai/data-science-simplified-principles-and-process-b06304d63308>.

⁶ Dominik Haitz, "The Third Wave Data Scientist", KD Nuggets, May 2019, <https://www.kdnuggets.com/2019/05/third-wave-data-scientist.html>.

⁷ Intelligence Community Directive 203, "Analytic Standards", Office of the Director of National Intelligence, January 2015, <https://www.dni.gov/files/documents/ICD/ICD%20203%20Analytic%20Standards.pdf>.

⁸ "A Culture of Data Literacy", Qlik, 2019, <https://qcc.qlik.com/course/view.php?id=723>