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Overdue Diligence: Questioning the Promise, Not the Premise, of Analytics

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Abstract:

The number of emerging business technologies and the possibilities about the impact they will have on business performance seem endless. Naturally, all companies want more competitiveness and profitability. Thus, if new technology such as big data analytics can deliver superior performance, we might ask why they should not invest in data scientists, algorithms, and excellence centers. However, Gartner (2017) has reported that over 85 percent of big data analytics projects fail. A recent McKinsey survey found that only eight percent of respondent organizations have been able to scale analytics beyond limited and isolated cases (Fleming et al., 2018). We conducted a root cause analysis to examine why so many analytics projects fail. We discovered that we could group the reasons why these projects fail into at least six categories: data causes, modeling causes, tools causes, talent causes, management causes, and culture causes.

Keywords: Analytics, Due Diligence, Big Data, Root Causes, Failures, Data Modeling, Analytics Tools, Talent, Management, Corporate Culture, Frameworks, Checklists.

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1 Introduction

The number of emerging business technologies and the possibilities about the impact they will have on business performance seem endless. Naturally, all companies want more competitiveness and profitability. Thus, if new technology such as big data analytics can deliver superior performance, we might ask why they should not invest in data scientists, algorithms, and excellence centers. However, Gartner (2017) has reported that over 85 percent of big data analytics projects fail. A recent McKinsey survey found that only eight percent of respondents have been able to scale analytics beyond limited and isolated cases (Fleming, Fountaine, Henke, & Saleh, 2018). O'Neill (2019) lists some recent reports that describe analytics failures:

- July, 2019: VentureBeat AI reports 87 percent of data science projects never make it into production
- January, 2019: NewVantage survey reports 77 percent of businesses report that "business adoption" of big data and AI initiatives continues to represent a big challenge for business. That means three-fourths of the software being built is apparently collecting dust.
- January, 2019: Gartner says 80 percent of analytics insights will not deliver business outcomes through 2022 and 80 percent of AI projects will "remain alchemy, run by wizards" through 2020.

Not surprisingly, boards demand that management demonstrate meaningful and sustainable returns on costly data analytics investments.

We have spent our careers in and around technology, performance measurement, and management in the public and private sectors (and from academia consulting for large and small public and private companies). We have learned that organizations always find it challenging to adopt technology despite exciting case studies, exotic short courses, seminars, and whole conferences devoted to such technology. However, despite adoption challenges, the IDC has reported that investments in big data analytics will exceed US$203B in 2020 up from US$130B in 2016 (Vesset et al., 2018). Statistica (2019) has predicted investments in big data analytics will top US$260B by 2022. With the possible exception of investments in artificial intelligence (AI), we have never seen a gap as wide between investments and failures as we see in big data analytics. While companies pursue the opportunity to leverage big data analytics to improve competitiveness and profitability, overeagerness, inflated expectations, and even fear to adopt analytics and related technologies as quickly as possible often drive them to do so no matter how much such technologies cost (Bean & Davenport, 2019; Andriole, 2018).

2 Why So Much Failure?

A good old-fashioned root cause analysis explains why so many analytics projects fail. Root cause analyses often help one identify and describe why systems and processes fail[1]. A root cause refers to a factor whose removal would prevent adverse events (e.g., failed analytics projects) from occurring. While various root cause methods, tools, and techniques exist, we defaulted to a fishbone diagram, the most popular root cause analysis technique (see Figure 1)[2].

Rather than brainstorm about why analytics projects fail, we decided to examine "analytics failures research". In conducting such an analysis, we identified more than 26 practitioner articles that have examined why analytics projects fail (Henrion, 2019; McShea, Oakley, & Mazzei, 2016a, 2016b; NewVantage Partners, 2017; Asay, 2017; Fleming et al., 2018; Ruzicka, 2017; Kesari, 2019; Gray, 2019; Mittal & Mittal, 2018; Cordoba, 2014; Singh, 2017; Axryd, 2019; van Vulpen, 2017; Bruce, 2019; Schrage, 2014; Remington, 2018).

From inspecting the reasons why analytics projects fail, we found that we could group them into six categories: data causes, modeling causes, tools causes, talent causes, management causes, and culture causes. The bold causes in Figure 1 identify the most threatening causes in each category. But our

[1] Researchers and practitioners frequently use root cause analyses to identify why systems and processes fail (see https://www.6sigma.us/etc/root-cause-analysis-for-beginners/ and https://asq.org/quality-resources/root-cause-analysis for more information about root cause analyses and their range of their applications).
[2] Such methods, tools, and techniques include fishbone diagrams, "five whys", flowcharts, Pareto charts, and scatter diagrams.

analysis also revealed that not all categories are created equal. Among the six, the bottom three (talent, management and culture) are the most threatening.

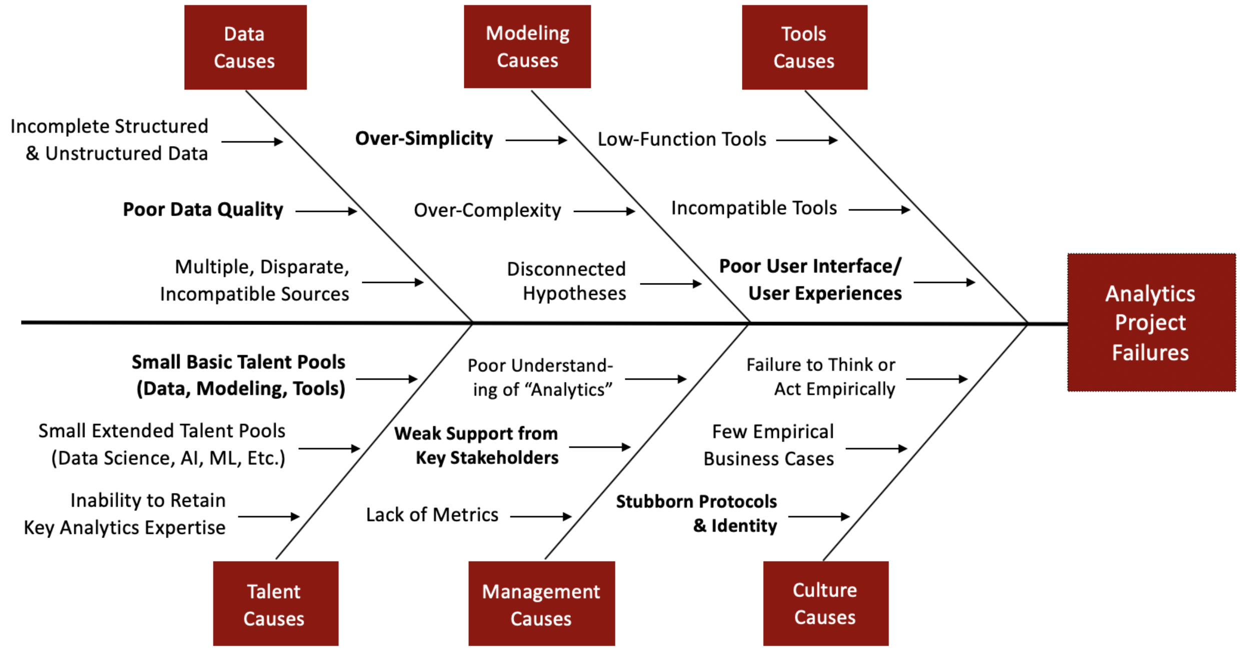

Figure 1. Root Causes for Why Analytics Projects Fail

3 Data, Modeling, and Tools Problems

The problems surrounding data, modeling, and tools have existed for decades: clean, comprehensive, validated data has always been expensive to collect, challenging to integrate, and confusing to interpret. Analytics places data squarely in the requirements crosshairs: without good data, analytics does not work. For instance, Ghosh (2021) states: "widespread harm can be caused by bad data in data analytics, where anything from the wrong medical diagnosis to incorrect interpretation of stock history can cause service providers to close shops or face lawsuits". In investigating analytics failures research, we found that many factors can lead to inaccurate and poor-quality data, such as poor standardization in a company; inconsistent data-collection methods, tools, and techniques; the fact that data changes over time; inconsistent data governance; and insufficient repeatable, validated processes to assess data quality (i.e., its accuracy, veracity, and timeliness).

Additional data problems include the unavailability and inaccessibility of high-quality structured and unstructured data. For example, if a pharmaceutical company wants to predict when consumers will stop taking a specific medication, it needs accurate, timely structured data about sales, customer contact, pricing, competitive products, and so on *and* unstructured data about what consumers are saying about the medication on social media. Without both this structured and unstructured data, the predictive model will fail. Similarly, sneaker manufacturers need access to structured and unstructured data from everywhere, such as enterprise resource planning (ERP) and customer relationship management (CRM) systems, Instagram, Facebook, and Twitter (and countless influencer blog sites). Analytics relies on a specific set of structured and unstructured data analytics capabilities, such as 1) the ability to collect hundreds of millions of data snippets daily; the 2) ability to classify, index, and store hundreds of millions of data points in real time; 3), the ability to use lexical, semantic, and statistical data filters; the 4) ability to use machine learning (ML) techniques to continuously improve data filters; the 5) ability to extract applications; 6) the ability to author and publisher information; and 7) the ability to augment everything with statistical models and AI.

Modeling should enable derivative analytics. The wider and deeper the context in which an organization interprets data, the more inferences it can make based on that data. In the social media analytics world, for example, since conversations have a multi-dimensional nature in that multiple simultaneous conversations occur continuously, organizations can parse conversational trajectories and purposes in numerous ways. The challenge here involves understanding what passes as focused versus unfocused discussion on different websites since they can differ in this regard and no rules about what individuals can or cannot post, tweet, or blog exist. The ability to explore these alternative analytics paths and discover connections, meaning, and purpose represent one among many modeling challenges that organizations face.

In order to exploit whatever data is available, modeling must be creative. Organizations face questions such as about what variables and relationships determine behavior; what integrating data will show; what descriptive, explanatory, and predictive variables explain the greatest variance in models' behavior. If an organization wants to understand why sales for its popular products/services have fallen, it needs to identify the right variables. Models should illuminate old and new relationships. Data-driven models will search for new variables, relationships, and models that describe, explain, and predict behavior. One cannot easily develop and test models partly due to data problems but also due to the complexity around even descriptive modeling. Explanatory and predictive modeling involves more complexity and requires more variables, more data, and more relationship calculations. Managers and executives love to ask questions such as "what happened?" and "what's happening?", but they crave answers to questions such as "what's going to happen next?" and "what should we do about it?". When properly conducted, modeling helps answer such questions with some empirical quantitative confidence.

Organizations also face challenges in selecting the right tools. For starters, they cannot select the "best" tool without assessing and profiling their data and modeling capabilities and objectives. Tools should also satisfy an organization's unique analytical requirements, such as real-time analytics, applications integration, and shareable dashboards. After that matching, well-qualified and well-motivated vendors need to support the tools. Organizations must run pilot tests before acquiring and developing tools. They must negotiate appropriate service level agreements (SLAs), which have become increasingly complex in the cloud computing area. They also need to train analysts.

4 Talent, Management, and Culture Problems

From examining analytics failures research, we found that failures in the so-called soft side of analytics—that is, talent, management, and culture—predict that BDA projects will fail more significantly than failures in data, modeling, and tools.

Talent, management, and culture problems naturally relate to one another, but each has unique properties that can undermine success and, worse, compound one another's failings. By their nature, organizations comprise people who manage (often complex) processes to customer markets. Any business model requires access to talent (especially highly skilled labor) in competitive labor markets. As companies hire such talent to fulfill their rising expectations about the impact analytics can have on business performance, available data scientists and data base managers shrink in number (Walker, 2017). The market for data scientists with business acumen or experienced business professionals with credible data science abilities is fierce (few in today's marketplace have sufficient skills at the nexus of business acumen, technological skill, and data science). Consulting firms offer premium compensation for the best and brightest analytics talent, which exacerbates the competition for key talent.

Even with qualified talent on board, corporate managers face considerable challenges integrating analytics into existing business processes and administrative functions. These obstacles have their roots in incentives, incompetence, and—yes—ignorance. Organizations must make bold choices about the responsibility for managing the analytics teams and demonstrate strong support from key stakeholders. For instance, they need to decide whether to integrate analytics teams across functions, whether they accept their work products as input to key business decisions, whether analytics resides under a particular "horizontal" or "vertical" C-suite executive's supervision (i.e., CTO, CFO, COO, etc.), and whether they should sell analytics' value across an organization or just in silos.

Whether analytics succeeds or fails depends greatly on management's expectations and capability to use the new, usually costly resource. Organizations expect analytics to help make them smarter about who they are, what they do, and how they increase profitability. Optimistically, they expect such benefits from hard and soft data, from qualitative and quantitative analyses, and from the ability to describe, explain, predict, and even prescribe behavior in real time.

However, we do not know whether analytics provides truly profound, counterintuitive, and strategic insights as so many promise, or do such insights simply validate routine decisions. Data scientists in some organizations offer intuitive findings such as advising a grocery retailer that cereal buyers frequently purchase milk and informing a distributor that high volume customers make shipping more efficient. Business acumen about the salient questions that challenge a business must motivate meaningful queries, and resulting findings must be translated into actionable items to enhance business performance.

Organizational challenges in aligning information and decision support systems with strategic issues have been longstanding as El Sherif and El Sawy (1988) illustrate in their seminal study about the Egyptian Cabinet. Mismanaging analytics can result in disengaged business leaders and resentful data managers who perceive technologists with a solution seeking a problem. In other organizations, analytics outputs add to the deluge of indecipherable monthly reports and meetings built on detailing data yet offer little insight and action. Worse, many organizations cannot easily distinguish between traditional "business intelligence" and "business reporting". As McKinsey argues (Fleming et al., 2018), executives often face difficulty in distinguishing the two because they do not solidly understand "the difference between traditional analytics (that is, business intelligence and reporting) and advanced analytics (powerful predictive and prescriptive tools such as machine learning)".

Organizations also cannot ignore the measurement and monetization problems connected to significant investments in analytics. Return on investment (ROI) measures the business impact that assesses costs versus benefit. Total cost of ownership (TCO) drives ROI and represents the overall cost that an organization faces in purchasing and licensing analytics tools. When compared to the largest enterprise technology projects such as ERP, CRM and systems management projects, analytics projects are inexpensive. But, given the significantly high rate at which they fail, they actually cost far more than projects intended to keep the trains running (versus projects that make them go a little further and faster). In earnings environments with slim margins, organizations must watch carefully if analytics improves or impairs profitability as escalating fixed costs often do. Declining profitability, especially in highly visible organizations, creates even more pressure and incentives to manage cost, especially with active boards insisting on substantive outcomes.

Even if an organization can find and install the right tools, manage data, model properly, hire good people, and lead with aligned incentives, a resistant corporate culture to change represents the greatest barrier that imperils analytics. Data analytics, if implemented as advertised, impales the essence of most organizations: their culture. Organizations constitute socio-political (and often dysfunctional in their collective neurosis) beings. Analytics demands empiricism, debate, and comfort while challenging orthodoxy—attributes commonly associated with disruptive mavericks, not the masses. Analytics done right expects an organization to have the fortitude to face quantitative-empirical reality and act accordingly. Analytics requires a culture of accountability and identifiable decisions rather than the typical corporate morass of decisions that committees, teams (often just groups reluctantly getting along to get ahead), and bureaucracy defer and dilute. Much research has shown that managers make notoriously poor decisions, that they make even worse decisions in groups, and that biases, heuristics, overconfidence, and escalations in commitment easily distract them (Sowell, 1980; Cosier & Schwenk, 1990; Russo & Shoemaker, 1992; Lehrer, 2009; Kahneman, 2011; Kochenderfer, 2015). Culture also defines the protocols around decision making, planning, investing, compensating, hiring and firing, and other activities that usually stubbornly resist modification or replacement. These protocols comprise corporate identity and help resist any attempt to change the predominant "ways of working" even when faced with the opportunities that analytics presents.

Thus, analytics necessitates lots of challenges and lots of failures. (A cottage industry that tracks analytics project failures has actually already begun to emerge.) However, analytics also has great promise. We believe there are due diligence questions that can improve the probability that big data analytics projects will succeed, though the steps can be complicated.

4.1 Analytics Best Efforts

No board member or C-suite executive ever wants to hear the words: "we should have done our due diligence". Organizations often bypass the due diligence that data analytics requires due to promises about what could go right rather than unnerving questions about what could go wrong.

Table 1 presents a path toward least damages. It is as much a corporate mirror as it is a due diligence checklist. It is a diagnostic tool that lists organizational ailments[3], symptoms, and diagnostic questions. It provides a chance to diagnose a company's chances for analytics success or understand why analytics projects failed.

The table contains lots of questions that have complex answers. Tepid, negative, incomplete, or ambiguous answers will yield failed analytics projects. Affirmative answers increase the likelihood that they will succeed. Failure rates today suggest that most companies lack the sufficient preparation to leverage analytics projects or programs and that most companies—based on results—would have a difficult time defending their analytics investments.

Table 1. Analytics Diagnostics

Ailments	Symptoms and related root causes	Diagnostic questions
Absentia	• Lack of accessible, quality structured and unstructured data • Inability to model causal and non-causal variables • Confusion about the most cost-effective analysis and display tools **Root causes:** data, modeling, and tools	• Does leadership and management understand the data necessary to achieve verifiable analytics? • Will leadership and management invest in the means to acquire, clean, and distribute data across the organization? • Has the organization modeled costs as part of a sound business case? • Can the organization model old, new, alternative, and disruptive hypotheses about behavior and performance? If not, does it have the resources to increase its capability to do so? • Does the organization have the ability to objectively assess the cost effectiveness and performance quality of off-the-shelf analytics tools?
Inertia	Lack of common purpose/reliance across the C-suite Overreliance on or underuse of analytics outputs Inadequate staffing and/or poor clarity about data scientists' roles/authority **Root causes**: data, modeling, tools, talent, management, and culture	• Can the leadership and management team cite specific ways that data analytics will change the business model, not internal reporting, in some way? • Will leaders clearly articulate specific plans to utilize data analytics to face business realities and take action, as necessary? • Are stakeholders ready and willing to challenge their corporate cultures even if it means confronting the most stubborn protocols? • In how much time will using data analytics streamline (or increase) key decision and approval processes?
Fantasia	Illusion of operational control Organization uses analytics with a transactional and not a transformational focus Overhead and administrative bloat without meaningful business results **Root causes**: data, management and culture	• If the organization meets its operating plan for the next three years, will the plan remain strategically relevant at that time? • Does the organization have a clear and compelling vision for how data analytics will increase business acumen across all management levels? • Can leaders credibly estimate analytics program implementation and execution feasibility? • Can employees articulate how analytics results will drive business value while citing specific examples and measurable expectations that will scale?
Myopia	• Mired in minutiae: much activity, increased internal reporting, little action/accomplishment • Short-term incentives override strategic action • Lack of strategic clarity **Root causes**: talent, management and culture	• Will the changes that the organization anticipates from data analytics be substantive, meaningful, and lasting? • Will reliance on data analytics result in more of a transformational or transactional focus. What implications will the resulting focus have for overall business risk? • Can the organization define, reduce, and/or mitigate risk? • What is the likelihood that short-term performance incentives will override willingness to address analytics results in a courageous manner?

[3] Adapted from Shulman (1999), one can apply and extend common educational maladies to human failings and frailties in the corporate workplace.

Table 1. Analytics Diagnostics

Amnesia	• Fundamental lack of understanding of industry/company economics • Ignorance of company history/lessons from past successes and failures • Lack of commitment and connection to balance sheet stewardship, cash flow, and business growth **Root causes***:* talent, management and culture	• Do decision makers have the credible insight, experience, and leadership ability to articulate and execute strategy, manage risk, and measure results? • Do leaders ask questions that reflect the competitive marketplace, customer needs, value chain requirements, and strategic plan (and perhaps in that order)? • How much money has the organization invested in data analytics overall, and what accountability measures has it implemented to monitor whether revenue growth, margin improvement, expense control, or financial flexibility will offset such cash outflow?

5 Is Failure Inevitable?

In this paper, we assume that organizations can—with considerable expense and management—find, clean, and validate data. We also assume that organizations can select the right tools even though they will face challenges in doing so. While organizations typically find modeling more challenging, it will not likely completely derail an analytics project (again, if organizations make the right investments). The real problems lie elsewhere. We found that the complexities that organizations face in analytics lies in the lack of talent, management, and—most significantly—culture. As unsatisfying as the answer might be, the probability that analytics projects will succeed directly depends on a company's ability to look objectively into its own diagnostic mirror, recruit the best talent, manage with creativity and insight, and change its corporate culture enough to appreciate and leverage quantitative-empirical operational strategic decision making and planning. Note that we provide guidance in Table 1: answers to the questions do not constitute a solid "go" (or "no go") outcome. Rather, practitioners should treat the questions as diligence questions that they should ask and answer to the best of their ability in the same way as they would for any important decision. Even if practitioners answer "yes" to all questions, such confidence may be fleeting or unsubstantiated, which demonstrates need for executive and managerial vigilance.

Corporate culture is historically impenetrable, which explains why prospects for high-payoff analytics investments remain low. But the situation will not stay that way forever. Competition and leadership attrition will combine to evolve stubborn cultures to be more objective, open ones where the huge gap between analytics investment and failure will shrink. But not tomorrow or even the next day—it will take some time, courage, and (overdue) diligence.

References

Andriole, S. J. (2018). Implement first, ask questions later (or not at all). *MIT Sloan Management Review*, *59*(3), 1-5.

Asay, M. (2017). 85% of big data projects fail. TechRepublic, *11*, 1-5.

Axryd, S. (2019). Why 85% of big data projects fail. Digital News Asia. Retrieved from https://www.digitalnewsasia.com/insights/why-85-big-data-projects-fail

Bean, R., & Davenport, T. H. (2019). Companies are failing in their efforts to become data-driven. *Harvard Business Review.* Retrieved from https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven

Bruce, P. (2019). 5 Key reasons why analytics projects fail. *Elder Research*. Retrieved from https://www.elderresearch.com/blog/5-key-reasons-why-analytics-projects-fail/

Cordoba, A. (2014). Three reasons reporting and analytics projects fail and how to avoid the pitfalls. *SAS*. Retrieved from https://www.sas.com/fi_fi/insights/articles/analytics/three-reasons-reporting-and-analytics-projects-fail-and-how-to-avoid-the-pitfalls.html

Cosier, R. A., & Schwenk, C. R. (1990). Agreement and thinking alike: Ingredients for poor decisions. *Academy of Management Perspectives*, *4*(1), 69-74.

El Sherif, H., & El Sawy, O. A. (1988). Issue-based decision support systems for the Egyptian cabinet. *MIS Quarterly*, *12*(4), 551-569.

Fleming, O., Fountaine, T., Henke, N., & Saleh, T. (2018). Ten red flags signaling your analytics program will fail. *McKinsey*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/ten-red-flags-signaling-your-analytics-program-will-fail

Ghosh, P. (2021). How is bad data is crippling your data analytics? *Dataversity*. Retrieved from https://www.dataversity.net/bad-data-crippling-data-analytics/#

Gray, D. (2019). 10 reasons why analytics & data science projects fail. *Caserta*. Retrieved from https://caserta.com/data-blog/reasons-why-data-projects-fail/

Henrion, M. (2019). Why most dig data analytics projects fail. *ORMS Today*. Retrieved from https://pubsonline.informs.org/do/10.1287/orms.2019.06.08/full/

Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Farrar, Straus and Giroux.

Kesari, G. (2019). 5 reasons analytics projects fail. *The Enterprisers Project*. Retrieved from https://enterprisersproject.com/article/2019/10/why-analytics-projects-fail-5-reasons

Kochenderfer, M. J. (2015). *Decision making under uncertainty*. Cambridge, MA: MIT Press.

Lehrer, J. (2009). *How we decide.* New York, NY: Houghton-Mifflin Harcourt.

McShea, C., Oakley, D., & Mazzei, C. (2016a). How CEOs can keep their analytics programs from being a waste of time. *Harvard Business Review*. Retrieved from https://hbr.org/2016/07/how-ceos-can-keep-their-analytics-programs-from-being-a-waste-of-time

McShea, C., Oakley, D., & Mazzei, C. (2016b). The reason so many analytics efforts fall short. *Harvard Business Review.* Retrieved from https://hbr.org/2016/08/the-reason-so-many-analytics-efforts-fall-short

Mittal, D., & Mittal, S. (2018). 7 reasons why analytics projects fail. *NextGen Invent Corporation*. Retrieved from https://www.nextgeninvent.com/7-reasons-why-analytics-projects-fail/

NewVantage Partners. (2017). *Big data executive survey.*

O'Neill, B. T. (2019). Failure rates for analytics, AI and big data projects = 85%. *Designing for Analytics.* Retrieved from https://designingforanalytics.com/resources/failure-rates-for-analytics-bi-iot-and-big-data-projects-85-yikes/

Remington, S. (2018). How to avoid analytics failures: 10 factors for analytical success from research and practice. *Minerra*. Retrieved from https://www.minerra.net/articles/how-to-avoid-analytics-failure-10-factors-for-analytics-success-from-research-and-practice/

Ruzicka, W. (2017). 8 reasons why so many analytics projects fail. *DZone*. Retrieved from https://dzone.com/articles/8-reasons-why-so-many-analytics-projects-fail

Russo, J. E., & Schoemaker, P. J. H. (1992). Managing Overconfidence. *Sloan Management Review*, *33*(2), 7-17.

Schrage, M. (2014). Learn from your analytics failures. *Harvard Business Review.* Retrieved from https://hbr.org/2014/09/learn-from-your-analytics-failures

Shulman, L. (1999). Taking learning seriously. *Change: The Magazine of Higher Learning*, *31*(4), 10-17.

Singh, P. (2017). 10 reasons why big data and analytics projects fail. *Analytics India Magazine*. Retrieved from https://analyticsindiamag.com/10-reasons-big-data-analytics-projects-fail/

Statistica. (2019). *Revenue from big data and business analytics worldwide from 2015 to 2022.* Retrieved from https://www.statista.com/statistics/551501/worldwide-big-data-business-analytics-revenue/

Sowell, T. (1980). *Knowledge & decisions* (vol. 10). New York, NY: Basic Books.

van Vulpen, E. (2017). 5 reasons why HR analytics projects fail. *AIHR Analytics*. Retrieved from https://www.aihr.com/blog/reasons-hr-analytics-projects-fail/

Vesset, D., Gopal, C., Olofson, C. W., Schubmehl, D., Bond, S., & Fleming, M. (2018). Worldwide big data and analytics software forecast, 2018–2022. *IDC*.

Walker, J. (2017). Big data strategies disappoint with 85 percent failure rate. *Digital Journal*. Retrieved from http://www.globalbigdataconference.com/news/141982/big-data-strategies-disappoint-with-85-percent-failure-rate.html

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