Block

# 4

## MANAGING TALENT FOR BIG DATA ANALYTICS

UNIT 13

**Talent Management-I** 1-21

UNIT 14

**Talent Management-II** 22-42

**Ref. No. BDCA-SLM-IFHE – 112022B4**

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# BLOCK 4: MANAGING TALENT FOR BIG DATA ANALYTICS

A data scientist's significant role is to organize and analyze huge portions of data through custom-designed analytical software. This provides stakeholders with findings, to make informed business decisions. A data scientist has various roles and functions. More so working with big data, the data scientist can help build many predictive solutions.

Unit 13 – Big data analysis needs various professional talents, which cover: use of mathematics, sciences, and computer technology. *Talent Management-I* deals with, data scientist and their role in society, and at work, using math, science, and computer science, analytic talent and executive buy-in, developing decision sciences practices, the 90/10 rule and critical thinking.

Unit 14 – The organizational culture needs to be oriented towards use of analytics, allied analytics, and building talent force to institutionalize the practices. *Talent Management-II* covers, holistic view of analytics, creating decision science practices, creating a culture that nurtures decision sciences, setting up appropriate organizational structure for institutionalizing analytics. These two units will help the learner to be a very good business research analyst to play the similar role of data scientist at business decisions.

# Unit 13

# Talent Management-I

## Structure

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*"Data science is all about asking interesting questions based on the data you have—or often the data you don't have."*

- Sarah Jarvis, Director of Applied Machine Learning and Data Science at Secondmind

## 13.1 Introduction

Data scientists use math, science, computer science, and analytic talent and executive buy-in. They develop decision sciences practices using the 90/10 rule and critical thinking. They exhibit curiosity and communication, asking lots of questions, talking to people outside own comfort zones in the process.

In the previous unit, we have covered different business analytic techniques like visualizing data, 360 degrees modeling, get scrappy etc. In the unit we will be learning about data science and data scientists, analytic talent and decision science talent.

Big data and data science are gaining prominence in business. Companies are increasingly relying on data-driven decision making. Analysts project that data science would become a lucrative sector with large number of jobs created across the world. This demand for data scientists would steadily increase in the next ten years. McKinsey & Company, one of the leading global management consulting firms, has predicted a shortage of around 150,000 data scientists. This approximately represents 50% talent gap to meet the demand. Companies will experience a shortage of data scientists as demand is growing tremendously. Data science is not just about investing in systems and infrastructure. Hiring the right talent and retaining them hold the in adopting big data solutions. Knowledge and expertise in business, math as well as technology is required for data scientists to understand and address business challenges. As the business environment is dynamic, data scientists should be highly agile and flexible, to understand the situation quickly and gain requisite knowledge to address it. Success of adoption of data analytics depends on consumption of analytics and the buy-in from management and leadership.

## 13.2 Objectives

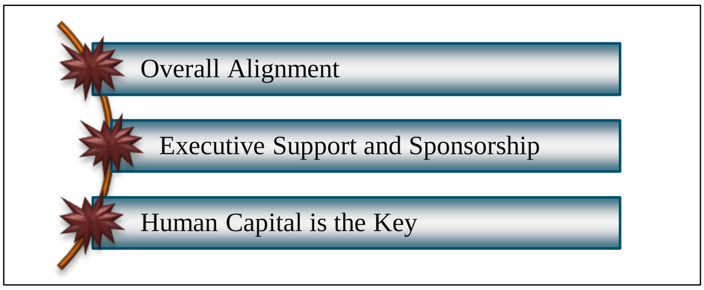
After going through this unit, you should be able to:

- Define data-driven decision science.
- Explain rise of data scientists.
- Types of decision making in business.
- Relate to skill set for data scientists.
- Discuss 90/10 rule for investments in human capital and systems.

## 13.3 Data Science Industry

Data science industry has been steadily growing with the emergence of new tools and technologies that are used to process huge volumes of data and produce results. Demand for the analysts embracing new skills and techniques has also grown over the past few years. The skill set & goals of analytics professionals and the needs of end consumers need to be aligned for this industry in order to thrive and emerge into a more relevant area for driving business or an organization. The three main important aspects to consider regarding data science in any business/organization are discussed below. (Refer Figure 13.1.)

**Figure 13.1: Aspects to Consider Regarding Data Science**




*Source: ICFAI Research Center*

- *Overall Alignment*: The overall business objectives and problems need to be identified and a proper road map for meeting the objectives and addressing the problems need to be prepared. Once the strategy is in place for achieving objectives and resolving problems, requisite tools, technologies, and people with appropriate skill-set can be brought in.
- *Executive Support and Sponsorship:* Leadership has to support fact-based and data-driven business analytics. This requires a lot of endorsement and encouragement for usage of data analytics for making crucial business decisions. This also requires socializing the insights and the value they bring to the business. It is not just adopting the sophisticated tools and technologies, but it is the implementable insights drawn from data that decide the value added to business as a result of embracing data analytics.
- *Human Capital is the Key:* Along with technology adoption, businesses have to invest wisely in building human capital, keeping the current as well as the long-term needs. This includes selecting the right talent and retention of talent. There is an increasing demand for business analysts who can quickly comprehend the new situations, adapt to them, learn and apply new techniques—be it math, tools or data driven methods.

Many analysts project a tremendous growth of data analytics, similar to that of IT sector. Many job opportunities would be available in this space, in the near future. Some of the emerging areas in data analytics are mentioned below. Data analytics requires aptitude for problem-solving and number crunching, in addition to being update with the latest tools and technologies are:

- ➢ Data Visualization (Charts, maps, figures, data matrices, heat maps, plots, etc., using Tableau, qlikview, MS Excel, SAS, R)
- ➢ Data Processing and Dash Boarding (SQL, NOSQL, SAS, R, VBA, Java, etc.)
- ➢ Data Storage and IT Systems (Infrastructure—servers, storage and integration of different data systems)
- ➢ Statistical Analysis (Testing the hypothesis, working on statistical techniques)
- ➢ Exploratory Analysis (Working on huge volumes of data to understand the trends in data. A specific business objective may not be there at the beginning of the analysis. However, this is used to mine the data so as to see any possible associations and trends that shed light on consumer buying habits or on particular operational processes of business)
- ➢ Machine Learning (Predictive modeling, artificial intelligence, etc.)

### 13.3.1 Creation and Consumption of Business Analytics

The presence of business analytics is growing immensely and companies are investing in it. However, the real question to be answered is whether someone in the organization is using the outputs generated and if there is any concrete business value generated from it. Hence, it is not just the support and creation but it is the consumption of analytics' outputs that is equally important. Companies should realize that they need to make the right set of investments in analytics space, recruit the right talent, and bridge the gap in investments and consumption of analytics. Companies in various sectors can leverage this and gain competitive advantage in data-driven decision-making.

**Example: Use of Data Science in the Travel Industry**

Data science had established as a crucial talent for the modern day analytic - based business decision organizations. Data science sprawled over strong verticals with close and highest customer centric activities like, Retail, Entertainment Industry, Travel Industry, Social media, Healthcare and Oil and gas.

Airbnb- San Francisco, a global travel giant was active in 97.5% of the globe. The data scientists focused on voice of customers to use as base data to offer personalized services, and achieved an excellent customer experience, through Search Ranking Algorithms. Airbnb shared 'local experiences' to customers and guests, 'listing quality score' to find a suitable residence using existing guest reviews.

Deep neural networks were built by taking guest's earlier stay and search algorithms, preferred host choices, earlier rankings, budgets, and users' needs. In this they were able to recommend best possible matches to customers.

'Natural language processing' developed using Convolutional neural networks, was used to analyze the various reviews through qualitative data.

Airbnb used predictive analytics to help their customers with competitive and optimal prices with locations closer to varied transport choices, excellent season, and comfortable amenities in the neighborhood of the recommended listing.

*Source: https://www.projectpro.io/article/data-science-case-studies-projects-with-examples-and-solutions/519#mcetoc_1fl8avrf2c July 2022, Accessed on 02/09/22*

## 13.4 Rise of the Data Scientist

Now that we have seen the data science industry and the emerging trends in that space, let us take a look at the people who are a part of this industry. By definition, data scientist is a person who has knowledge and skills to perform systematic and sophisticated analyses on data (be it structured or unstructured) and generates insights or identify potential strategic opportunities. The role of a data scientist has evolved from that of a business analyst role. Preparation for data scientist role involves training on computer applications, machine learning (predictive modeling), statistics, data-mining and mathematics.

Data scientists will not just focus on data-mining and processing but are also concerned with identification of a problem or business challenge. They will follow a holistic and comprehensive approach towards addressing that. So, data scientists need to have the business acumen to understand the challenge and use the data accordingly to address it. Data scientists will not just look at solving the problems in place but they also identify potential problems and address them. This, eventually, brings value to the organization.

Data scientist's role requires attention to details such as exploring the data and identifying trends, outliers and patterns. He then connects various pieces of information to comprehend them in the context of a specific business situation. Finally, he provides insights on addressing business challenges. One of the key differences in the role of a traditional data analyst and that of a data scientist is that the latter usually has to deal with disparate sources of data, integrate them, appropriately merge them and define the sources of truth for each important piece of information. The scope is not limited to simply collecting or reporting data in different formats, but involves understanding the data processing in the context of a business problem and looking at various types of data from different angles.

Data scientists usually have one or more of the following competencies apart from depending on their experience:

1. Statistical Analysis.
2. Data Mining.
3. Natural Language Processing.
4. Programming Skills on SAS, SQL, R, Python, etc.
5. Social Network Analysis.

Not every professional will have the knowledge on all of the above. However, it is commonly observed that they have at least one of the above skills in addition to basic domain knowledge.

**Example: Data Scientists could Raise to help Increase Airbnb's Valuation**

Airbnb had been using data science skills in all their business operations, like: product – finance – operations. Data science technology had a pivotal role in the witnessed growth of Airbnb. Data scientists raised to the occasion of need to develop unique data products, and adopting open-source technologies for Airbnb needs. Data scientists could convert the voice of customers through data by translating them to stories, for others to understand and respond rightly.

*Contd….*

Airbnb served 10 million requests, and processed one million queries a day. Airbnb focused on personalized services, and created perfect match to the guests and the hosts. Airbnb used the apt set of flexible and scalable data science techniques in their continued growth. The data science team at Airbnb used completely data science driven approach in arriving at decisions and recommendations which led to positive impact on customers.

Airbnb's Data Science team used A/B testing subjecting the visitors of their website to umpteen recommendations and ranking algorithms and correlate their actual ratings or reviews as they left to validate the effectiveness of the algorithms.

The major task areas for their data scientists included: Image Recognition and Analysis, Natural Language Processing, Predictive Modelling, Regression Analysis, Collaborative Filtering, Enhanced Search Features, providing help in Guiding Hosts to the Perfect Price, Driving Company Growth.

Airbnb matched guests looking for accommodation with hosts willing to rent in a given city. Guests, and Hosts could connect prior to decision finalization, and Airbnb would call it a success when the host accepted to accommodate the guest. Airbnb revenue rose to $25.5 billion as of June 2015.

*Source: https://www.projectpro.io/article/how-data-science-increased-airbnbs-valuation-to-25-5-bn/199 August 2022, Accessed on 12/09/22*

**Check Your Progress - 1**

1. What can be said about data science industry?
   a. Will see good growth in next few years
   b. Has become stagnant
   c. Is the best employer sector
   d. May decline in future
   e. Growth cannot be predicted
2. Domain knowledge and business knowledge are not required for data scientists as they deal with data regardless of sector/industry.
   a. True
   b. False
3. How is Data Visualization important?
   a. Is not required for data scientists
   b. Is limited to basic levels of data analyst
   c. Key aspect of data analysts to visualize data and understand it quickly

   d. Data scientists do not use this technique in recent times

   e. Do not fall under big data techniques

4. Which of the following is not among the general key areas where data scientists need to have good knowledge to excel in their profession?

   a. Business

   b. Math

   c. Communication skills

   d. Technology

   e. Hardware intricacies

5. What does data-driven decision science explain?

   a. Is not useful in operational decision making

   b. Will not be relevant for tactical decision making

   c. Will provide guidance for business decision making

   d. Has stagnated in terms of growth of its usage

   e. Is important for strategic decision making

## 13.5 Skills and Qualities of Data Scientists

We have seen the growth of the data science industry and the growing demand for data scientists. We will now look at the qualities and skills that recruiters usually look for, while hiring data scientists.

Below are the broad areas wherein data scientists should have sound knowledge:

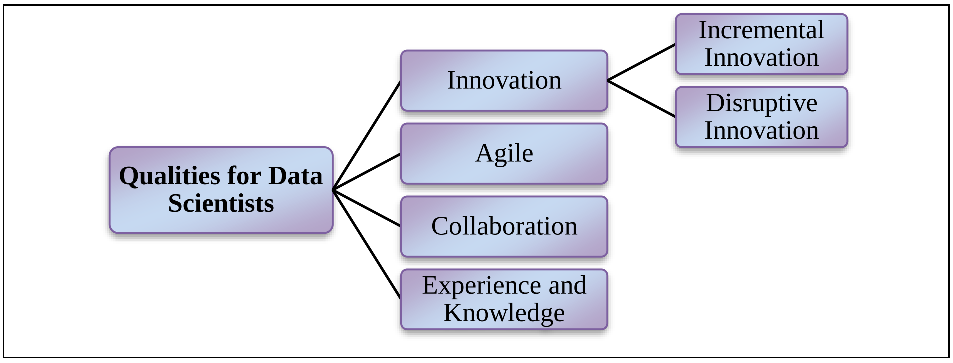
- Business (Understanding the business needs and challenges, ability to see the broader picture of data in the context of business situations).
- Mathematics (Dealing with data usually involves large data sets, merging those data sets and applying statistical techniques. This requires a good knowledge and aptitude for Mathematics and problem-solving).
- Technology (Data scientists need to be updated with new tools and technologies that are applied in business and data analytics).

### 13.5.1 Recruiting the Right Talent

As businesses are transforming rapidly, it is not just important to have domain knowledge and experience, but, data scientists should have the right talent to grasp new knowledge and acquire skills as needed. Understanding the business, having the right set of questions, inquisitive mind along with good skills of math and problem-solving are sufficient for one to start off as a data scientist.

Following are the qualities data scientists should have in order to excel in their profession (Refer Figure 13.2).

**Figure 13.2: Qualities for Data Scientists**




*Source: ICFAI Research Center*

- **Innovation:** As the market conditions are becoming more competitive and dynamic, analytics professionals need to innovate. Existing operations and data processing methodologies may not be relevant in the context of dynamic business situations and emerging technologies. Professionals need to revisit the methodologies and invent new techniques to address challenges. (For example, in exploratory data analysis, there will not be a specific objective to begin with. It requires the data scientists to sift the data, slice and dice it, view it from various aspects to comprehend it. Then they have to make analyses that are meaningful and useful for the company.) Innovation can be broadly classified into two types:
  - **Incremental Innovation:** This is usually associated with improving the existing processes and is not a radical innovation or a completely new thing. For daily operations and procedures, incremental innovation is the key to optimize them that will give cost savings to the organization.
  - **Disruptive Innovation:** This is a completely new or a different tool, product, service or technique. Disruptive innovation entirely changes the existing way of doing business or a part thereof.
- **Agile:** New challenges, new problems will come up frequently and data scientists need to be agile enough to quickly dive deep into those particular challenges, and gain the requisite skills and knowledge (pertaining to domain as well as data analyses techniques). This means the organizations need to be flexible to absorb new technology. Data scientists should be able to implement new processes.
- **Collaboration:** In general, MNCs have business units and verticals spread across geographies. More often, it entails data experts to collaborate across geographies and business units/verticals so as to understand and garner information from various sources, and then utilize it for analytics.

- **Experience and Knowledge:** While knowledge base could be increased by knowing new techniques and tools, experience is built over years of working on several projects of varying complexity. This enables the data professionals to face various challenges and complex situations. Therefore, they will gain experience on how and which techniques to use in such cases. Exhibit 13.1 shares examples of skill set for data scientists.

**Exhibit 13.1: Examples of Skill Set for Data Scientists**

Some of the specific examples of skill-set for data scientists are:

1. Fundamentals of data science
2. Statistics
3. Programming knowledge
4. Data manipulation and analysis
5. Data visualization
6. Machine learning
7. Deep learning
8. Big data
9. Software engineering
10. Model deployment
11. Communication skills
12. Storytelling skills
13. Structured thinking
14. Curiosity

*Source: https://www.analyticsvidhya.com/blog/2020/11/14-must-have-skills-to-become-a-data-scientist-with-resources/*

**Activity 13.1**

Look at the job description of data scientist jobs and roles in organizations from different sectors. What are the skills recruiters essentially look for? What are the key tools and packages (programming packages) they look for?

**Answer:**

### 13.5.2 Math, Science and Computer Applications

Big data is hard to comprehend from traditional data analytics methods. It is very difficult to manage such huge volumes of data, streamline it and process it in near real-time, to generate significant business value of companies and organizations.

Data scientists often have to apply a combination of skills involving deep math, science, as well as computer applications/programming, to analyze data and produce outputs and address problems. Data scientists can quickly learn and understand the business situation, and apply their expertise/knowledge in resolving them. By nature, data professionals are curious and investigating, often deep-diving into the data. They look out for patterns, aberrations in patterns, spot outliers, comprehend the trends and find out the rationale behind these.

Modeling has gained prominence in the recent past in data analytics stream. Modeling is a technique to create a data model for a particular process/information system by applying data analytics techniques. This is a systematic approach to create a data model that takes up inputs and the process is usually automated so as to generate outputs. This could vary from basic spreadsheet modeling to complex automated process that takes data from disparate systems, run the automated process, generate outputs and automatically disseminate output information to appropriate stakeholders. Data modelling is a kind of 'Formula Skelton' with fixed types of inputs. When input values vary the data model simply takes the new input values and put them in 'Formula Skeleton'. Outputs are then generated from the set of calculations/formulas or rules defined. This involves three steps: 1. The kind of programs/calculations/rules to be defined, 2. The exhaustive list of inputs that will be taken by this model and 3. The set of outputs generated and to whom they are communicated. Preparation of appropriate data model involves understanding of business problem, knowledge of deep math, technology to use and skills of programming or computer applications. In some cases, even the distribution of outputs is automated. It automatically sends them out to other data systems or distribute them to defined email lists.

**Example: Data Scientist at Amazon**

Amazon was among the top 3 companies in which Data Scientists aspire to work. At Amazon, data scientists dive into the big data, and bring out best business insights. One skill set was forecasting, pulling out strategic opportunities, and identifying implementable business insights. Technologies like: Tableau, data visualization, data warehousing expertise, were crucial for the data scientist. Second technology area was, research in 'natural language processing, deep learning'. Exposure and applying 'video recommendations, data analysis streaming, social networks' was highly desirable. Building large-scale simulations, research on optimization algorithms, were part of the role.

*Contd….*

On skills side, R, Stata, MATLAB, Python, SQL, C++, or Java, were of great use. Combining computing and math, and conducting statistical analysis was a major task. Another skill was use of techniques from 'supervised, unsupervised, semi-supervised and reinforcement learning' covering 'linear/logistic models, tree-based models, deep learning models, ensemble models, and Q-learning models. Another critical quality of data scientist was proven hands-on experience on machine learning, extracting data, data analysis, and excellent communication as analyst.

*Source: https://www.datatrained.com/post/amazon-data-scientist/ June 2022, Accessed on 02/09/22*

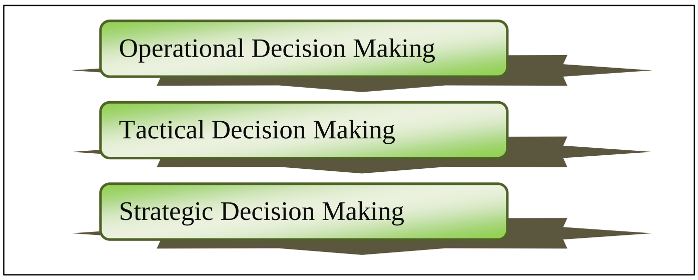
## 13.6 Critical Thinking

There are two aspects to embracing big data by organizations. One is investing in systems and infrastructure, while the other is people/talent. Big data is increasingly used to make processes streamlined, automate them and also to make tactical decisions that require little human intervention. In cases where the automated outputs cannot be used, human decision-making and interpretation of machine-generated outputs will come into picture. Usually, models provide insights on trends, patterns and anomalies. In the end, it is the humans who will need to interpret them appropriately and arrive at decisions. This is where the importance of data scientists and their expertise comes in. They will be the first set of people who will get to see the results and insights. It is crucial how they will present these results to the management. Management—together with data scientists—will finally make decisions based on the outputs generated.

According to Avinash Kaushik, digital marketing evangelist of Google, big data has definitely revolutionized the ways of marketing and advertising. New and more cost effective technology is being deployed as part of big data implementation in many companies. However, he lays emphasizes on the people or talent who will be involved in big data analysis. He has developed a "90/10" rule for technology and people. According to him, investments for big data initiatives should be approximately split in the ratio of 90 to 10 for human capital to infrastructure.

Decision-making by organizations can be broadly classified into 3 types as given below in Figure 13.3.

**Figure 13.3: Types of Decision Making by Organizations**




*Source: ICFAI Research Center*

- **Operational Decision Making:** These are at very basic level in terms of decision-making complexity. These are usually associated with daily operational processes. For example, number of units of a particular product to replenish in a supermarket.
- **Tactical Decision Making:** These are at mid-level complexity. Example for this is forecasting the number of units that may get sold for a new launch product in the next year.
- **Strategic Decision Making:** Very high level of complexity in terms of decision- making. Usually, the decision makers need to intervene and make these decisions. For example, a company entering into emerging markets with competitive pricing strategy.

In the digital marketing space, intelligent and smart systems are coming up that will automate tactical decision-making, and humans are less involved in this. Humans have to be involved more in strategic decision-making. This is at a broad level and requires more attention and human intervention. For example, the type of customers to be targeted in this quarter is more of a tactical decision, and this could be done automatically using the algorithms defined and inputs on customer universe, apart from various other parameters. However, whether to launch a particular product in a geography, whether to go for product extension, or do a redesigning of the existing service offerings, etc. are more of strategic decisions and require thinking beyond automation.

**Example: Critical Thinking as a Skill Need in Data Analytics**

Two cases needed ‘critical thinking’, to prevent “false positive” reporting using critical thinking to build confidence in CEOs for business analytics. The Brookings Institution identified an example of an assessment using risk by US judges, in finalizing bail and sentencing limits. The analytics could have generated inappropriate conclusions, with cumulative effects on specific groups and people of color, longer prison sentences, larger bails imposed. Because historic data would support, certain groups of people had been subjected to similar frequent, and tough sentencing. In another case, RAND Corporation found that, COVID-19 initial recommendations for social distancing depended upon data from smart thermometers. This act missed data, taking into account of certain strata people having their own thermometers. The IT and Analytics teams could check: whether the analytics was subjected to potential bias? Analytics were being applied to critical inclusive data, checking about missed data elements, etc. Analytics needed to be free from conventional thinking to solve uncommon and complex problems.

*Source: https://www.techrepublic.com/article/critical-thinking-must-have-skill-analytics/ April 2022, Accessed on 02/09/22*

| **Activity 13.2**<br><br>Pick up a company that has a dedicated analytics team and research about how their analytics help improve their products and services. |
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## 13.7 Analytic Talent and Implications for Executives and Management

Sometimes, analytics teams are left in silos in organizations which limit their scope of operation and influence on key strategic decision-making. Having an approach of setting up centralized analytics function often provides success for organizations implementing big data. Executives and management of organizations realize the importance of having the right analytic talent and they are focusing more on hiring and recruitment plans.

In recent times, one of the interesting opportunities is that various technological capabilities are available for companies to leverage them. This technology enables companies to access vast amount of information and data. But the question is—have the companies mastered how to integrate information from disparate sources and create relevant analysis in the given context.

In recent times, many companies are giving importance to big data. However, they still do not have a dedicated leadership team that takes the responsibility of analytics division to bridge the gap between the analytics function and strategic management. Many organizations do not have a dedicated position of 'Chief Analytics Officer' (CAO). This position is required especially in organizations that are making significant investments in big data and analytics. Even in the organizations that are planning to embrace big data solutions, it is ideal to have a CAO position so as to have smooth implementation of big data. He is the person who will liaise with various business units as well as vendors and suppliers, bring in new capabilities, tools, and techniques. Thus, it will be easy to identify potential opportunities such as new target markets, new segments and new clients. Exhibit 13.2 narrates the need for data scientists.

**Exhibit 13.2: Why to have Data Scientists?**

**How Data Scientist Can Add Value to Business**

Presented below are some action points for data scientists to add value to business.

1. **Empowering Management and Officers to Make Better Decisions**

   Experienced data scientist helps the organization's top management by ensuring that the staff maximize their analytics capabilities**.** He/she also adds value to the institution's data management and facilitates improved decision-making processes.

2. **Directing Actions Based on Trends—which in turn Help to Define Goals**

   A data scientist examines and explores the organization's data and recommends certain actions to help improve the institution's performance. He/she also helps to engage customers better and ultimately increase profitability.

3. **Challenging the Staff to Adopt the Best Practices and Focus on Issues That Matter**

   Responsibilities of a data scientist is to ensure that the staff is familiar and well-versed with the organization's analytics product.

4. **Identifying Opportunities**

   Data scientists question the existing processes and assumptions for the purpose of developing additional methods and analytical algorithms.

5. **Decision Making with Quantifiable, Data-driven Evidence**

   Data scientists create models using existing data that simulate a variety of potential actions for an organization to learn which path will bring the best business outcomes.

6. **Testing These Decisions**

   Data scientist is someone who can measure the key metrics that are related to important changes and quantify their success. Half of the battle involves making certain decisions and implementing those changes.

7. **Identification and Refining of Target Audiences**

   Data scientist has the ability to take existing data, that is not necessarily useful on its own, and combine it with other data points to generate useful insights that an organization can use to learn more about its customers and audience. With such derived knowledge, organizations can tailor services and products to customer groups, and help profit margins flourish.

*Contd….*

8. **Recruiting the Right Talent for the Organization**

   Data science specialists can work their way through all these resume's data points to find the most suited candidates for the organization. They achieve this by mining the vast amount of data that is already available, in-house processing of resumes and by conducting sophisticated aptitude tests and activities. Data science can thus help recruitment team to make speedier and more accurate selections.

*Source: https://www.simplilearn.com/why-and-how-data-science-matters-to-business-article, March 29, 2022, Accessed on 27/9/22*

**Example: Organization-Wide People Analytics**

Merck KGaA was a leader in healthcare, life science, and performance materials. The company was utilizing digitalization to drive innovation in people planning and management. They applied analytics for tasks like: planning workforce, managing the talent, etc. They focused and increased the use of data analytics to decide and drive decisions related to workforce. They brought uniformity by moving to globalized processes in data and definitions. The management team used analytics to change mindsets, which encouraged leaders to move to data-based decision making. Managers and HR colleagues could analyze many non-technical questions, leading to organization focus and management of people. Merck KGaA's combined Organization Development (OD) and People Analytics enabled managers to use real-time data and arrive at decisions using Visier. Visier helped their HR business partners also to transform into data-supported consultants, turning them as strategic advisors.

*Source: https://www.visier.com/blog/merck-kgaa-people-analytics-case-study/ case study, 2022, Accessed on 02/09/22*

## 13.8 Developing Decision Science Talent

Different organizations follow various methods to recruit the right talent. Some organizations look for innovative approaches. One of the notable examples for this is Mu Sigma, a leading big data solutions provider. This is a pure decision science company that works on math, technology, business and analytics. The conventional methods of recruitment did not work for this firm due to the robust requirements. They came up with an innovative idea of creating a university that produces the right talent for all its businesses.

Companies started realizing the importance of data-driven decision science and it is becoming a commonplace for almost any organization. Big data and analytics have remained a myth until recently. Companies like Mu Sigma, Dunnhumby, etc., have helped in producing analytics professionals and breaking this myth to a large extent. Adoption of decision science in daily decision-making has grown rapidly. But, for the organizations to successfully embrace analytics, it is important to institutionalize analytics (creating analytic talent, having scalable and sustainable processes and ensure consumption of analytics).

Realizing the importance of the growing demand for analytics professionals and talent, several universities have started offering analytics programs and even dedicated analytics degrees to tap this opportunity. As companies started leveraging analytics more and more, they are collaborating with universities to offer formal degree programs in analytics. Established organizations are augmenting the formal education with their corporate programs for analytics. This will provide real-time case studies and business context along with formal education programs.

Formal education programs tend to focus more on analytics techniques, tools, processing data, and applications. However, more holistic analytics programs are required. This focuses on challenges for decision-making in organizational context and will create programs for different roles that will together drive decision science. Data-driven decision science is a journey that requires the right talent across organizational levels. Programs and trainings to develop talent in decision science are still in a nascent stage and needs to evolve as a holistic approach towards creating the right talent. What essentially is required in these programs is an interdisciplinary approach towards problem solving and addressing the business challenges. As discussed earlier, these programs should have a strong foundation of math, business, technology, and problem-solving aspects. Real-time cases and corporate exposure gives the right mix of theoretical knowledge as well as the practical application of business analytics techniques.

**Example: Decision Science in Government agency**

A government agency intended to migrate from an Oracle-based system to SharePoint. VPI (a woman-owned strategic consulting and strengths-based solutions provider headquartered in Southern California) was given the requirements to help the situation, as a match management defined criteria to necessary employee needs, identify potential design elements fulfilling the need. VPI should also identify trouble areas to engage all generation employees, especially resistance coming from Gen X. The necessary development of decision science talent by VPI followed these steps:- Started with facilitating sessions on visioning with senior management, Conducted employee survey and assess expectations, Targeted on focus groups before process engineering and design, Understood the current usage of technology, Assessed the workforce motivations based and influenced by motivations of multigenerational workforce, Built action plans, Convened fortnightly meetings with people at varied levels implementing technology from each branch office, Updated senior management in weekly check-in meeting, Interviewed staff and conducted process engineering study, Designed blueprint, Designed and built SharePoint tool as per the given requirements

*Contd….*

and specifications of client, Maintained continuous communication with staff to arrive at enhanced understanding of the proposed activity on hand, Used webinars with troubleshooting training to staff, Created powerful reporting functionality. This led to upgraded technology in six months.

*Source: https://vpistrategies.com/case-studies/decision-science/ case study, 2022, Accessed on 02/09/22*

**Check Your Progress - 2**

6. What is 90/10 rule about?
   a. Revenues to investments made in company
   b. Investment in one business unit to other
   c. Investment in human capital to analytics infrastructure
   d. Investment in analytics infrastructure to human capital
   e. It means 90% of revenues are coming from 10% of our targets
7. What does consumption of analytics refer to?
   a. Communicating and utilizing outputs of analytics
   b. Resources consumed in analytics setup
   c. Financial constraints of adoption of analytics in a company
   d. Budgeting for analytics in the next financial year
   e. Creating analytic talent
8. Where does placing an order to replenish stock for the coming week falls under?
   a. Operational decision making
   b. Strategic business planning
   c. Collaborative planning
   d. Financial planning
   e. Budget allocation decisions
9. Human capital is not as important as having big data solutions and systems.
   a. True
   b. False
10. What are the traits of data scientists?
    a. Handle large data
    b. Manage structured data
    c. Store unstructured data
    d. Meticulous
    e. Innovative, collaborative and agile

11. Which of the following is true about implementing decision science team in an organization?
    a. It is always better to have this team built in-house
    b. It is always better to seek partnership with outside firms that are established in data analytics and decision science
    c. Organization should take a call on whether to build in-house team or to outsource this to a data science firm depending on various factors including requirement of team, expertise available, and flexibility of the organization to accommodate new team, etc.
    d. This team is not necessary in any organization and it must focus on its core business only
    e. Only mature organizations should have dedicated decision science team

## 13.9 Summary

- The data science industry is still at a nascent stage but is evolving at a faster pace.
- Companies and organizations have realized the importance of utilizing analytics for decision-making at operational, tactical as well as strategic level.
- While automation helps in daily operational as well as tactical decision-making, analytical solutions will hold key in driving strategic decision-making-too.
- The three key factors driving adoption of decision-science are: overall alignment of analytics team to the business objectives, executive support from leadership, and investment to recruit the right human capital.
- The 90/10 rule coined by Avinash Kaushik emphasizes the need to invest more in human capital rather than just having systems and infrastructure in place.
- With the rise of data analytics, the demand for data scientists has increased manifold. The key characteristics of data scientists include strong aptitude for mathematics, good domain & business knowledge, as well as knowledge of technology.
- As technology pertaining to business analytics continues to emerge, data scientists need to keep themselves updated with the latest tools and techniques available.
- As the demand for data scientists is increasing and jobs are created in this sector, formal education programs and courses are offered by various universities.
- Established and mature organizations are augmenting the training in data analytics.

## 13.10 Glossary

**90/10 Rule:** This rule was given by Avinash Kaushik; this explains the importance of human capital and investments made in this area, in comparison with investments made in systems and infrastructure.

**CAO:** Chief Analytics Officer; leadership position in an organization that heads all the analytics activities and works with data scientists as well as other business units, and collaborates with top management to make crucial decisions.

**Data Scientist:** Data professional is one who has knowledge and experience of handling large, structured as well as unstructured data and has good knowledge of math, business and technology. Data scientists are innovative, agile and collaborative, and are keen to identifying and addressing business challenges.

**Executive Buy-in:** Extent and degree to which executives and management in an organization are utilizing analytics outputs in decision making.

**Human Capital:** People who are part of an organization or company are termed as human capital.

**Sentiment Analysis:** Analyzing the social networking websites or social media so as to gauge the mood of the public or audiences on a particular topic.

## 13.11 Self-Assessment Test

1. Describe the typical role of a data scientist in an e-commerce company.
2. Mention the key characteristics of a data scientist and how they benefit him/her to excel in the profession.
3. Describe the 90/10 rule and support that argument in favor of this rule.
4. What do the terms consumption of analytics and executive buy-in refer to? Describe in detail.
5. Describe the importance of human capital in the data analytics industry.
6. Describe the latest trends in data scientist roles, mention some of the latest tools and technology used by data scientists.
7. Mention different types of decision making in any organization. What is the role of data scientists in each of these decision-making aspects? Illustrate each of these types with an example.

## 13.12 Suggested Readings/Reference Material

1. Maleh, Yassine. Shojafar, Mohammad. Alazab, Mamoun. Baddi, Youssef. Machine Intelligence and Big Data Analytics for Cybersecurity Applications (Studies in Computational Intelligence, 919) 1st ed. 2021 Edition.
2. Ahmed, Syed Thouheed. Basha, Syed Muzamil. Arumugam, Sanjeev Ram. Patil, Kiran Kumari. Big Data Analytics and Cloud Computing: A Beginner's Guide, 2021.

3. Saleem, Tausifa Jan. Chishti, Mohammad Ahsan. Big Data Analytics for Internet of Things 1st Edition, April 2021.

4. Jones, Herbert. Data Science: The Ultimate Guide to Data Analytics, Data Mining, Data Warehousing, Data Visualization, Regression Analysis, Database Querying, Big Data for Business and Machine Learning for Beginners Hardcover – 10 January 2020.

5. Maheshwari, Anil. Data Analytics Made Accessible: 2023 edition Kindle Edition.

6. Mayer-Schönberger, Viktor. Cukier, Kenneth. Big Data: A Revolution That Will Transform How We Live, Work, and Think Paperback – October 26, 2021.


## 13.13 Answers to Check Your Progress Questions

**1. (a) Will see good growth in next few years**

According to various predictions made, the data science industry is set to witness good growth in the coming years.

**2. (b) False**

Although data scientists deal with data analysis, having business knowledge will help them see the challenges and problems in overall business context and analyze data from various aspects.

**3. (c) Key aspect of data analysts to visualize data and understand it quickly**

Data visualization is a key aspect of data analytics. Visualizing data in graphs, charts, heat maps, scatter plots, etc., gives a good idea of how data is distributed; trends and patterns in data.

**4. (e) Hardware Intricacies**

Knowledge of hardware intricacies is not a general key area to focus for a data scientist.

**5. (c) Will provide guidance for business decision making**

Data science will provide base and guidance to informed decision making for business or organizations.

**6. (c) Investment in human capital to analytics infrastructure**

90/10 rule is about the ratio of investments in human capital to analytics infrastructure.

**7. (a) Communicating and utilizing outputs of analytics**

Consumption of analytics refers to how the outputs of analytics are being utilized.

**8. (a) Operational decision making**

Operational decision making (Replenishing stock for a particular product for coming week is much of an operational decision that can be based on sales expected in next week).

**9. (b) False**

Human capital is important apart from just systems and infrastructure. In fact 90/10 rule emphasizes and attributes more importance to human capital.

**10. (e) Innovative, collaborative and agile**

Data scientists should be innovative, agile and collaborative.

**11. (c)** Organization should take a call on whether to build in-house team or to outsource this to a data science firm depending on various factors including requirement of team, expertise available and flexibility of the organization to accommodate new team, etc.

# Unit 14

# Talent Management-II

## Structure

14.1 Introduction

14.2 Objective

14.3 Holistic View of Analytics

14.4 Different Types of Analytics

14.5 Creating Decision Science Talent

14.6 Hiring Decision Science Talent

14.7 Organization Culture to Nurture Decision Science Talent

14.8 Organizational Structure and Institutionalizing Analytics

14.9 Organizational Structure Based on Analytics

14.10 Summary

14.11 Glossary

14.12 Self-Assessment Test

14.13 Suggested Readings/Reference Material

14.14 Answers to Check Your Progress Questions

*"Data scientist: The person who is better at explaining the business implications of analytical results than any scientist, and better at the analytical science than any MBA."*

- Dr. Jennifer Priestley, Professor of Statistics and Data Science at Kennesaw State University

## 14.1 Introduction

Data science is the upcoming technology trend with portfolio of technology and skills. The technology areas covered include statistical analysis and computing, machine learning, mathematical programming and deep learning. These skills are used for processing large data sets, data visualization, and data wrangling.

In the previous unit, we learnt about data scientists and their role in society. We also learnt about their work, using math, science and computer Science. We studied about the 90/10 Rule, critical thinking, analytic talent and executive buy-in and developing decision sciences practices. In the present unit, we will be learning about different types of analytics and how it is made use of in the organization in various ways. We will also get acquainted with decision science talent.

Data-driven decision science, as a business area, is growing rapidly and so is the demand for decision science talent. Decision science requires a holistic approach to analytics. Descriptive analytics, predictive analytics and prescriptive analytics are the broad categories of analytics. Organizations should choose the right mix of these for addressing challenges and for decision making based on their business requirement and need. Data scientists or data professionals form the key to analytics stream in any organization. Having decision science talent is not a one-time affair. It requires continuous efforts to hire suitable talents with particular professional traits, train them, motivate them and nurture e them. Organizations have the flexibility to follow centralized or a de-centralized models of analytics structure. Nevertheless, it is not uncommon that a few organizations follow federated model which brings in the advantages of both centralized and de-centralized ones. Adopting analytics at an organizational level is not just about investing in analytics, infrastructure and human capital. It is about how the organization structures itself, the kind of framework or model it follows based on its vision & culture, and the way it motivates and nurtures its talent.

## 14.2 Objectives

After going through this unit, you should be able to:

- Outline holistic view of analytics.
- Explain the 4 different types of analytics.
- Express creating talent for decision science.
- Infer hiring decision science talent.
- State professional traits for data professionals.
- Relate to types of organizational structure based on analytics.
- Give examples of some of the best practices for nurturing decision science talent.
- Identify institutionalizing analytics.

## 14.3 Holistic View of Analytics

As plenty of data is being produced, companies cannot afford to ignore the value they bring; especially, if competitors are using data to make decisions. Once the required data is identified and collected, the analysis is to be performed. This involves deciding on the kind of analytics that needs to be performed, where to begin and how the analysis of data can be related to the business. Data-driven decision science includes wide variety of techniques to look at data from various perspectives and to have a holistic approach to address challenges. Organizations require a systematic framework to approach analytics-based problem-solving. Each of these types is used to generate a particular type of output that is relevant to a particular time frame.

**Example: Predictive Analytics benefitting the human life**

WABC in New York City had been using the AccuWeather and predictive analytics, along with Data Science service for around fifty years. AccuWeather was the best tool for high temperature forecasts. The Weather Channel was found accurate for low temperature forecasts. AccuWeather forecasts were more localized up to individual addresses, and provided detailed forecasts specific to location and time and could provide predictions for 3 months globally. With accessible and highly reliable weather forecast predictive analytics, a large transportation company used to plan and ensure the safety of their transports. Another example was that of sports arenas and team facility owners taking advantage of historical weather data for better business models, on fan attendance and operations of arenas.

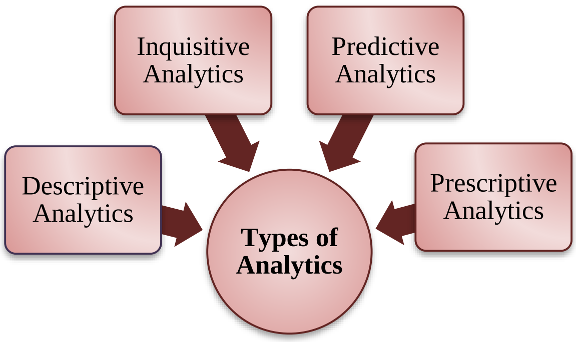
A national grid energy used to assess impactful events like, floods and severe winds as the ground was saturated. As predicted trees would topple over or bring down power lines. Historical weather data could help with tactical and strategic decision-making and activate disaster recovery plans.

*Source: https://www.dataversity.net/case-study-predictive-analytics-and-data-science-keep-an-eye-on-the-weather/ August 2021, Accessed on 03/09/22*

## 14.4 Different Types of Analytics

Given below, in Figure 14.1, is a list of various types of analytics used.

**Figure 14.1: Different Types of Analytics**




*Source: ICFAI Research Center*

- *Descriptive Analytics:* This deals with the data of the past and answers the question 'what has happened to business in the past?' This question will be answered taking past data into account and analyzing it from various angles and presenting the trends and patterns. As the name suggests, this is used to describe the historical information related to business. This includes MIS, dashboards and various other tools to observe past data. Some of the analyses include summarizing data at different levels, presenting the contribution of various geographies and ascertaining the growth rates.

Example of Descriptive Analytics

Let us take the example of a retail store. Assuming that it has been 6 months since the store opened in a new area, the management wants to perform descriptive analytics. Some of the possible metrics for this analytics would be Sales (by volume as well as by value) in past 6 months with respect to product category, peak hours sales, sales when discounts were offered, profit margin from each product and customer satisfaction scores.

- *Inquisitive Analytics*: This is a kind of extension of descriptive analytics. While descriptive analysis answers what happened in the past, inquisitive analytics tries to answer why it has happened like that? What are the possible reasons for such situations, trends, patterns, or anomalies that occurred? In a way this amounts to investigating into possible reasons for past events. Reasons are essential to be found as we can strategize in future what to continue and what things to stop in order for the business to succeed. For example, by analyzing the past data, if it were found that customers are not choosing our product over the competitor products because of quality issues, the company can take this insight and work on quality to overcome the challenge and increase the sales of its own product. Hypotheses are formed and by analyzing data, the hypotheses gets either validated or rejected. In this manner, conclusions will be drawn on possible reasons for historical events.

  Example of Inquisitive Analytics

  In the above example of a retail store, a company can investigate into low customer satisfaction scores. Possible reasons could be long waiting times/queues, product stock not available sometimes, home delivery not available, etc.

- *Predictive Analytics:* This has become very vital for organizations to base their decisions. Predictive modelling, as the name suggests, tries to predict the future. This could be the likelihood of occurrence of a particular event, forecasting revenues or predicting consumer behavior. Predictive analytics as a technical field has evolved in the recent times with the advancements in artificial intelligence. Organizations are more interested in this area to have the outcomes generated as a base for their decisions. Predictive modelling has evolved into a lucrative job opportunity for many data scientists. This analytics is to answer "What would happen?"

  Example of Predictive Analytics

  In the above example of retail store, the company can use predictive modelling to estimate the peak hours demand/footfalls, estimate the demand for top products and plan for sufficient supply, etc.

- *Prescriptive Analytics:* This analytics provides an insight into what should be done in the future. Optimization and simulation techniques are generally used to look at various possible scenarios and look at the most likely scenario.

This enables the companies to chalk out a proper plan of action for the coming quarters or business cycles. As the name suggests, this analytics is used to prescribe something for business. Some action points could be arrived at, by the end of this analytics. In general, this could be termed as the most comprehensive form of analytics as it encompasses other forms indirectly, unless the organization is completely new. To advise something for future also requires an understanding of existing or past situation, inquiry into possible reasons for failure or success, prediction of future outcomes and evaluation of various scenarios.

Example of Prescriptive Analytics

In the above example of retail store, now that the company has the past data, reasons for low customer satisfaction can be studied. Besides, insights on events of future based on predictive modelling are possible. It can have prescriptive analytics which look at various scenarios of maintaining staff at appropriate times (to meet peak hours demand), to maintain supply of products (dealing with vendors) and when & how much discounts to be offered (to boost up sales), etc. Prescriptive analytics give proper direction and recommend actions for the organization.

It is not absolutely necessary that companies need to follow this sequence of analytics; but, they need to have the right mix when addressing any problem or challenge. This framework allows organizations to have a holistic approach for problem-solving, gives them perspectives from the past and plans for the future.

Exhibit 14.1 presents various types of analytics.

**Exhibit 14.1: Different Types of Analytics**

**Shell's inventory management – A predictive strategy of spare parts**

Handling the failures of drilling machines was a major challenge for Shell - a multinational oil and gas company. The firm deployed a centralized analytics platform to bring down costs and save time on repairs.

Shell pooled data from different vendors and analyzed it, to predict the likely failure of nearly 3,000 different oil drilling machines parts across various locations. The analytics platform was linked to Shell's spare parts inventory system to manage them (spares).

The centralized analytical platform informed which parts to be kept in stock and where the parts should be located. This helped Shell save millions on inventory and reduced the need to move parts. Shell's repair times were reduced as the analytical platform ensured that the right parts are available in right locations at the right time.

*Source: https://www.datameer.com/blog/three-analytics-success-stories/, January 20, 2020, Accessed on 27/9/22*

**Example: Prescriptive Analytics in Consumer-Packaged Goods (CPG)**

A leading 'Pet Food Brand' CPG company, took the help of World Quant Predictive (WQP) to optimize advertising spend. Using a mix of first-party client data and third-party data, indicators like unemployment, inflation, pandemic patterns, house price index, population mobility, pet ownership trends, and analytics were arrived at.

This data used high velocity, automated ETL workflow, and checked for freshness of the data sources. The hyper-predictive models computed the incremental impact of the designed factors, and created optimization engines. These engines had the best values, with constraints involving factors for KPIs maximization.

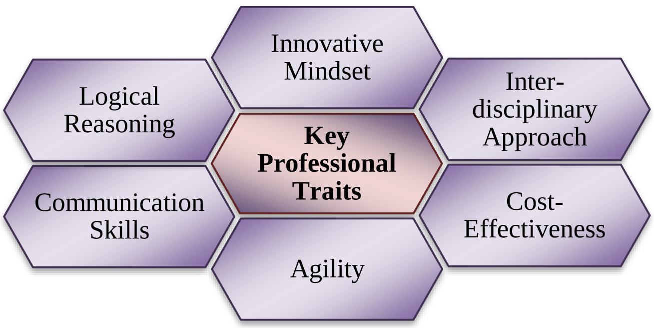
WQP created an Interactive Prescriptive Analytics with visual workflow for their customers for prediction, simulation and optimization, variety of constraints, and "what if" scenarios. The workflows supported the habits of the user-personas. These new analytical approaches improved the marketing effectiveness of Pet Food Brand

*Source: https://consumergoods.com/case-study-interactive-prescriptive-analytics?from=gate February 2022, Accessed on 03/09/2022*

## 14.5 Creating Decision Science Talent

New jobs are being created heavily in the data-driven decision science sector. Companies can use big data and analytics solutions to enable data-driven decision making. However, one of the constraints of this sector seems to be the shortage of the right talent. Analysts have predicted a talent shortage of around 150,000 in the decision science sector. Gartner, a leading market research firm, has estimated that millions of jobs are created globally in the decision science sector. Data scientists require knowledge and skills from various disciplines and on various fields so as to handle the business challenges efficiently. It is a combination of key values, traits and skills that are required for decision science talent to excel in their profession. Some of the key professional traits required for decision science are (Figure 14.2):

**Figure 14.2: Key Professional Traits**




*Source: ICFAI Research Center*

- *Innovative Mindset*: Innovative mindset means aptitude to think from different perspectives and bring in new methodology, process or product that adds value to business. Though data scientists use same set of computations for automation, the codes they take are fresh each time. Thus they think differently every time and generate output accordingly. Innovative mindset is required to present the available data in a different perspective. The data scientists distribute the aggregate data into small subsets as per requirement. Innovation thus results in simplification of a process.
- *Inter-disciplinary Approach*: Knowledge of various disciplines helps data professionals analyze data quicker and enables them to solve it effectively. Good knowledge of math, business and technology is required for a data professional. While business knowledge helps to understand the context/situation to grasp what exactly is required, knowledge of math is required to formulate approaches for problem-solving. Once the algorithm is defined, appropriate technology or tool is selected that works best for the given situation.
- *Cost-Effectiveness*: Data professionals need to have an understanding of the tools and technology to be used, and how to leverage them across business units and franchises, to have cost-effective solutions. Sustainable enterprise solutions and problem-solving approaches are to be followed.
- *Agility:* Continuous transformation is the key in the context of dynamic business environment and data professionals need to be agile enough to cope with this and apply their expertise to understand the complex business environment and address the challenges.
- *Communication Skills:* Data scientists need to have good communication skills to interact with various stakeholders and gather the required information. This becomes more important when these professionals scale up the career ladder and have to partner with clients, besides driving consumption of analytics.
- *Logical Reasoning*: Apart from knowledge, decision science talent needs to have aptitude for math and should have logical thinking approach to address business challenges in the right manner. Often, complete and accurate data may not be available or the required granularity of data is not available. In such cases, data professionals need to think of logical approach for estimation of final outcomes.

**Example: The Driving Mindsets of Innovation at Google**

Google was widely identified with its strong analytics culture and innovation. In the baseball analogy, innovation was steered by creating "more at-bats per unit of time and money than anyone else".

*Contd….*

Google encouraged and rewarded trying out and risk-taking ("at bats"), in the areas like: core product, tech businesses, sales divisions, and support functions. The results at Google stressed the importance of driving organization to opportunities for successful innovation. The practices of profitable driving involved governing the company with focus of innovation.

Organizations needed to give priority to innovation efforts, orienting response to customer, and fund to address market forces. Vision with action mindsets were major focus at Google and were highly recognized. They were well prepared and also made necessary innovation changes, to adopt change focus across their business functions and drove maximum impact. The behaviors that helped Google to successfully implement changes suitable to the innovation ideas included: "adaptability, passion, and intuition'.

*Source: https://www.accenture.com/_acnmedia/PDF-169/Accenture-Innovation-Unleashed-Final.pdf 2021, Accessed on 03/09/22*

**Activity 14.1**

Assume you are a recruiter for a decision science firm for entry level associates. What traits will you essentially look for in the candidates (and why?) so as to ensure you extract the best talent from the applicants.

**Check Your Progress - 1**

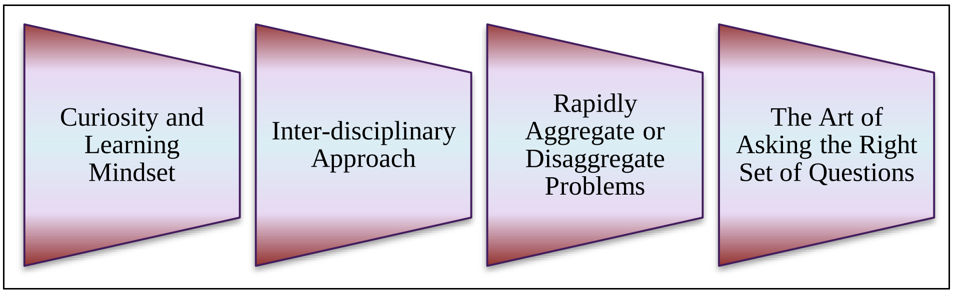
1. Descriptive analytics answers/affirms the following:
   a. What may happen in the future
   b. Describes the likelihood of occurrence of events in future
   c. What happened in the past
   d. Action items to deal with future goals
   e. Possible reasons for various situations
2. Assume you are a bank manager with responsibility to classify the individuals in the customer universe into possible defaulters or the ones who repay, if offered a loan. Which type of analytics will you use for this?
   a. Inquisitive analytics
   b. Descriptive analytics
   c. Subjective analytics
   d. Predictive analytics
   e. Analytics cannot be used for this case

3. Due to which of the following reasons did the company's market share decline in last quarter?
    a. Falls under prescriptive analytics
    b. Comes under descriptive analytics
    c. Falls under predictive modeling
    d. Can be classified under inquisitive analytics
    e. Analytics need not be used on past data
4. Providing advice based on analytics for future time period comes under which of the following?
    a. Predictive analytics
    b. Prescriptive analytics
    c. Forecasting
    d. Inquisitive analytics
5. Descriptive analytics Which of the following statements is true?
    a. Currently, there is excess supply of decision science talent in market
    b. The decision science sector has reached stagnation and is set to decline in the coming years
    c. The decision science sector is growing at a good pace and there are good job opportunities in the near future
    d. Decision science is only a part time work for any company as it needs to focus on its core business
    e. Decision science talent does not require an interdisciplinary approach

## 14.6 Hiring Decision Science Talent

Now that we have seen some of the professional traits that decision science talent possesses in general, let us take a look at what exactly companies look for in candidates while hiring for data-driven decision science roles. Given below is a list of qualities that companies look out for in applicants (Refer Figure 14.3).

**Figure 14.3: List of Qualities in Applicants**




*Source: ICFAI Research Center*

- *Curiosity and Learning Mindset:* Addressing business challenges often involves working in uncertain conditions and unfamiliar situations. So, this entails the data professionals to be curious to find out the requisite information, analyze the data from various perspectives and bring in new ways of looking at data. Although there may be a particular objective while beginning with data analysis, it is often seen that once the data is looked at in different ways, many more insights are drawn. So, the data scientists must be curious to extract as much information as possible from the given data. They should have willingness to learn new things and work in uncertain and unfamiliar situations.

- *Inter-disciplinary Approach:* Candidates will be looked for their approach towards problem-solving. Usually, ideal candidates do not jump directly into solutions but look into the problem at hand from different perspectives. They gather all the required information and then approach towards it with the right mix of technology, algorithms and process flow. As the data professionals move up the career ladder, the required skill set changes significantly. At the basic level, it is all about data and analysis; but, when one grows up in the organization, the focus shifts towards more mature skills such as client relationships, setting up the overall objectives of analysis, broad level guidance and approach and people management.

- *Rapidly Aggregate or Disaggregate Problems:* Sometimes, the problems become simple when they are broken down (disaggregated) into small pieces or sub-problems. Solving each of these tasks could well help in addressing the overall problem at hand. Breaking down into multiple analytical tasks can also help in sharing the work in the team. So, data scientists need to have clear understanding of a given problem, and they should be able to break it down into small and meaningful parts. Similarly, sometimes, it becomes hard to comprehend or get a complete picture of the small sub-problems at hand. In such cases, aggregating them and looking at them together will help the organization address them in the right perspective.

- *The Art of Asking the Right Set of Questions:* Often, it is found that one must ask the right set of questions in order to understand the problem in its entirety. Usually, we get pieces of information from various business units and stakeholders. This information may or may not be complete. So the data scientist should be skillful to ask the right questions to extract the requisite information and use it wisely. Also, while solving the problem, the data scientist should ask the right set of questions to probe and investigate the matter thoroughly.

**Example: Building Curiosity and Inquisitive Mindset**

Malaysia Airlines passenger Flight (MH17) from Amsterdam to Kuala Lumpur, was shot down in 2014. Bellingcat; a pool of researchers, investigators, and journalists; worked with analytics on combined 'open source and social media data', inspired by 'inquisitive and curious mindset 'and uncovered evidence of the Russians involvement. Bellingcat, got a break through, using discovered videos and photos, and identified the Russian military involvement. Curiosity to explore and inquisitive mind were natural human traits. Curiosity was the most attributed human characteristic, surpassing the AI-powered machines, which were trained to continuously-learn and adapt.

The five-dimensions of curiosity were: "Deprivation sensitivity, Joyous exploration, Social, Stress tolerance and Thrill seeking ". Great data scientists, instead of thinking outside the box, would redefine the box. They would explore, discover, blend new ways, new variables leading to better performance predictors. Curiosity needed to be encouraged, results needed to be integrated to business operations to flourish. Design Thinking was key to ensuring encouragement to curiosity, and inquisitive mindset. Design Thinking guided that "diverge to converge" would be most powerful ideation concept. Improving business decisions in constantly changing business world emphasized a culture of 'continuous exploring, learning, and adapting'

*Source: https://www.datasciencecentral.com/curiosity-and-inquisitive-mindset-keys-to-data-science-and-life/ August 2021, Accessed on 03/09/22*

## 14.7 Organization Culture to Nurture Decision Science Talent

If an organization is into decision science, it has to realize that developing and nurturing talent is not a one-time effort, but a continuous process. Recruitment, training, as well as appraisals should be in line with the objectives and culture of the organization. People are the most valuable asset and they must be utilized for competitive advantage. For example, two companies which are into the same business may have enough money to invest in big data solutions. However, if one of the companies has a better way of managing people in terms of hiring, training and motivating them, it may get competitive advantage and perform better. Organizations must use human capital to leverage analytics solutions and drive growth.

## 14.8 Organizational Structure and Institutionalizing Analytics

We have seen the importance of analytics for organizational decision making and the increasing use of data-driven decision science by companies and organizations for various purposes. We will now see in this section what it takes to establish a successful decision science team and how organization structure should be maintained so as to maximize the usage of analytics' outputs.

Many organizations are focusing on the analytics solutions suite and the people to manage it. However, it is even more important to have the right organizational structure in place. The power of analytics solutions can be fully leveraged only when there is collaboration among various teams, business units, business verticals and geographies. Generation as well as consumption of analytics is important. Leadership should acknowledge and endorse the analytics solutions and decision making, based on analytics outputs.

Hence, any organization should focus on following areas while institutionalizing analytics:

- Collaboration across enterprise.
- Support from leadership for consumption of analytics.
- Best practices in the sector (what competitors are doing).
- Budget and financials.

Organization structure needs to be set up taking into account the following factors:

- Mission and Vision of the organization.
- Culture of the organization.
- Overall organizational objectives and goals.
- Change management.

**Example: Institutionalization in Governance Scenario**

Germany had focused on institutionalizing governmental data analysis, to take advantage of rising artificial intelligence, their own efforts on digitalization. They built data labs in every ministry, integrated these to the network of existed ministry data teams, statistical departments, agencies providing technical services, and research institutes. Few other steps envisaged by Germany include: Identify chief evaluation officers and bring in corporate data-driven evidence into policymaking. Build talent pool of data scientists as part of fulfillment of long-term talent needs. Enhance use of data by government employees. Build comprehensive plans, to create accountability, avoid redundancy. In 2021they recommended for hiring a Chief Data Scientist, followed by a data lab in every ministry and the Chancellery.

German governance could start from the Organization for Economic Cooperation and Development (OECD) categorization of governance as, ‘anticipation and planning, service delivery, evaluation and monitoring context’. It had established monitoring systems using ‘program evaluation, statistics, and open data’. They were recommended to relate data from non-governmental agencies like: civil society, academia, private business sector.

*Contd….*

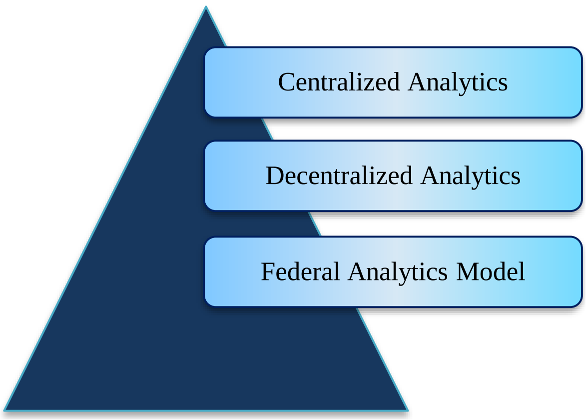
The major areas where German governance could apply analytics and institutionalize include: *Anticipatory Governance (use* of data to forecast the future of the policy related information), *Data-driven service delivery, Monitoring and evaluation* and *Non-governmental factors: Civil society, academia, and the private sector*. Germany was strong at data analytics, AI etc., ranks fifth or sixth in AI publications, and called for 100 new AI professorships. The programs focused on the overlap between data and social sciences to add value to governance.

*Source: https://www.brookings.edu/research/institutionalizing-data-analysis-in-german-federal-governance/ March 2022, Accessed on 03/09/22*

## 14.9 Organizational Structure Based on Analytics

Usually, the vast majority of organizational structures fall into one of the categories described below in Figure 14.4.

**Figure 14.4: Categories of Organizational Structures**




*Source: ICFAI Research Center*

❖ *Centralized Analytics:* In this type of organizational structure, all the ownership, decision-making power and responsibility of analytics lie with the centralized analytics team. There will be single analytics team spanning across the enterprise, catering to the needs of all business units.

Advantages:

- Faster decision making.
- Economies of scale.
- Integrated infrastructure for analytics.
- Separate cost center and budget.
- Collaboration, coordination and planning across functions and lines.

Disadvantages:

- Agility is less as the analytics team is bundled together that caters to all business units. The team is not tailored to meet the requirements of each business unit. In case a particular business unit is restructured, it will take a lot of time to meet the requirement.
- Flexibility to meet ad-hoc demands and requirements from a specific geography or business unit will be less.

❖ *Decentralized Analytics:* Individual analytics teams catering to business units or geographies are set up in this type of organizational structure. Each team has its own data infrastructure as well as analytics team.

Advantages:

- Agility to quickly address any changes in business units such as restructuring, downsizing, etc.
- Flexibility to meet individual business unit/geography demands.

Disadvantages:

- Different business units may choose different tools and technologies.
- Economy of scale is not achieved.
- Not cost effective.
- No centralized decision making on purchase of analytics suite.
- Only short-term focus.

Exhibit 14.2 presents financial planning transformation.

**Exhibit 14.2: Financial Planning Transformation for a Leading Specialty Retailer**

Mu Sigma is a leading decision-science firm. It analyzes data and skilled data of the clients and makes improvements in processes. Mu Sigma assisted a leading retailer to remodel its financial planning process (FPP) at its outlets with an agile feedback-driven process. The transformation entailed in linking capability development of people along with processes, and platforms.

**Problem**

The financial planning of the client was revamped in 2008. But the business had grown considerably in the later days. Hence the processes too became more complex, rigid and analytical.

The client was looking for its current financial planning to be broken into monthly and weekly cycles in order to improve their performance and achieve the set goals.

*Contd….*

**Approach**

Mu Sigma made a thorough study and identified the process gaps. It scrapped the obsolete processes and brought new ones the operation was called "Create Destruction". They organized a series of design thinking workshops on "Art of Problem Solving" for the heads of various departments lime merchandizing, supply chain, and store planning departments. This gave insights to department wise financial planning needs.

**System**

With the inputs from the workshop and also based on its own assessment Mu Sigma gave a final shape to the Financial Planning Process (FPP) of its client. The highlight was the use of latest technologies like machine learning and analytics.

- The existing systems were revamped with algorithm enabled analytical modules.
- Real-time transparency was achieved across as there was synchronous planning.
- Prototypes were enabled to check the adaptability of each process to the changing business needs.

**The Result**

The process of conversion took two-year to be completed. The value additions were meant to minimize operational risk. Other benefits include:

- Annual process cycle time reduced considerably (from 42 weeks to 15 weeks or 65%).
- Human intervention reduced from 23000 to 9000 man-hours-80% p.a.).
- Decision making became totally transparent and feedback driven.

*Source: https://www.mu-sigma.com/our-musings/case-studies/transforming-financial-planning-through-creative-destruction, February 28, 2020, Accessed on 27/9/22*

❖ *Federal Analytics Model:* This type of organizational structure is a mix of both centralized and decentralized models. While each line or function is given flexibility to have an analytics team, at a broad level these teams need to adhere to the policies and guidelines set by the centralized decision-making team. This model brings in the advantages of decentralized model without losing centralized control in the degree of mix of centralized and decentralized models, and it varies from model to model.

**Example: Analytics and People at KGaA**

Merck KGaA, Darmstadt, Germany was into 'healthcare, life science, and performance materials'. With the consultation from Visier, they could develop people, analytics at KGaA, and moved to advanced analytics. Till 2011, talent processes like: 'recruiting, performance, compensation, and succession planning' at KGaA, were more localized and lacked uniformity with associated analytics. With association with Visier in 2016 they had established evidence-based decision making. KGaA managers had access to Visier, which helped them to build network of people, analytics ambassadors and technical champions. This synergy helped the people in analytics team to ascertain new approaches, and share with HR community. The ambassadors could go deep into various questions freeing up resources for advanced analytics, and making advanced analytics accessible to complete user population.

The analytics ambassadors helped rest of the teams to take evidence-based decisions, and build knowledge champions. The people analytics team enabled HR business partners, to be more confident at analytics, including development items available in their learning platform. Merck KGaA in parallel increased people analytics capability to fulfill a goal of analytics to improve employee experience. Activity to support advanced analytics was often time-consuming, and was very time expensive. Visier helped them in Data collection, and data cleaning at faster pace. From a new organization they acquired, they picked up all the patents, used network analysis to locate the most influential scientists in search of future leaders for Merck KGaA. Later Merck KGaA team embarked to augment targeted employee profiles, through Natural Language Processing (NLP).

*Source: https://www.visier.com/customer-stories/merck-kgaa/, 2022 case study, Accessed on 03/09/22*

**Activity 14.2**

Assume that you are recruited at senior management level to lead a company as analytics head. What all factors will you consider before implementing a particular type of organizational structure (centralized, decentralized or federated).

**Check Your Progress - 2**

6. Which of the following is not a professional trait required for data professionals (although it may be good to have and sometimes it may help)?
   a. Good communication skills
   b. Agility and flexibility
   c. Inter disciplinary approach
   d. Knowledge of sciences
   e. Logical reasoning
7. Which of the following is a common organization structure for analytics set up?
   a. Centralized model
   b. Matrix model
   c. Cumulative model
   d. Three dimensional model
   e. Hub and spoke model
8. Developing decision science talent is a one-time affair.
   a. True
   b. False
9. Which of the following statements is true?
   a. Centralized analytics model is used widely as it has no disadvantages in any case
   b. Decentralized analytics does not fit in large organizations
   c. Federated analytics has only advantages in any case as it combines both centralized and decentralized models
   d. Any analytics model may have both advantages and disadvantages to some extent
   e. Decentralized model often brings economies of scale compared to centralized model
10. Which of the following statements is true?
   a. Organizations should always take experienced professionals so that no risk is involved in this process.
   b. Organizations should always look out for cheaper talent, as personnel costs become a big chunk of operational costs for company.
   c. Organizations should have to be careful, and have a proper plan for hiring, motivating and training decision science talent.
   d. Organizations should always recruit inexperienced professionals and train them in required manner.
   e. There need not be any particular plan while hiring decision science talent.

## 14.10 Summary

- Organizations need to have a holistic view of analytics and find out the right mix of analytics for its business requirement.
- Descriptive analytics deals with the historical or current data, analyzes it to find out the key metrics, trends, patterns, outliers and summary of information that data contains. Essentially, descriptive analytics answers the question, “What happened to our business in the past?”
- The second type of analytics is inquisitive analytics that deals with knowing why a particular event or pattern has occurred. Inquiring and investigating into the business events or trends forms inquisitive analytics.
- The third type of analytics, predictive analytics, deals with forecasting the future business events and related metrics. Predictive modeling uses techniques to predict and answer the question, “What will happen in the future?”
- Prescriptive analytics is used to advise business on the action items for the coming cycles.
- Some of the professional traits required for data professionals are innovative mindset, agility, cost effectiveness and interdisciplinary approach.
- Developing decision science talent and nurturing it, forms the key for building robust human capital. It is the human capital that leverages the analytics infrastructure for bringing in competitive advantage.
- Institutionalizing analytics is an important aspect for adopting analytics.
- Three main models governing this are—centralized model, decentralized model, and federated model. As both centralized and decentralized have their own advantages and disadvantages, organizations tend to follow a federated one, which is a mix of both models.

## 14.11 Glossary

**Centralized Analytics:** A single centralized team will own all the decisions pertaining to decision science in a company. This single team will cater to all business functions and geographies.

**Decentralized Analytics:** Individual business functions will have a separate analytics teams. Each analytics team will have the freedom to make its own decisions, and caters only to a particular business unit or geography.

**Descriptive Analytics:** A type of analytics that uses current or historical data to summarize the information, present various views and perspectives, plot trends, patterns, outliers, etc.

**Federated Model of Analytics:** It is a mixed model of analytics framework in organizations. It is a combination of both centralized and decentralized ones.

**Inquisitive Analytics:** Type of analytics that inquires and investigates into historical and current, trends and patterns, and tries to find out the reasons behind them.

**Interdisciplinary Approach:** Using knowledge of various disciplines while approaching a problem. Knowledge of business, math and technology is usually preferred for data professionals.

**Nurturing Talent:** Grooming employees using training programs, motivating them, and giving them the right experience and opportunities is called nurturing talent in the context of organization.

**Predictive Analytics:** Branch of analytics that deals with predicting the future outcomes/likelihood of events related to business and market.

**Prescriptive Analytics:** Type of analytics that is used to advise organizations on future course of action, and how they need to proceed. In general, the most optimized scenario based on overall goals of business becomes the objective of the future.

## 14.12 Self-Assessment Test

1. What does holistic view of analytics mean? Describe this in detail.
2. Describe in detail the four different types of analytics that are used by organizations. Provide an example for each of these types.
3. Mention any four professional traits of decision science talent that you feel are relevant and necessary.
4. How do organizations develop and nurture decision science talent? Mention some of the best practices followed by companies.
5. Describe the various types of organizational frameworks for institutionalizing analytics. Mention the advantages and disadvantages of each model.
6. Describe the roles and skills of decision science talent in the order of organizational hierarchy (Basic/Entry level, Mid-manager level and Senior management level).
7. Describe the 'Interdisciplinary' approach of data professionals.

## 14.13 Suggested Readings/Reference Material

1. Maleh, Yassine. Shojafar, Mohammad. Alazab, Mamoun. Baddi, Youssef. Machine Intelligence and Big Data Analytics for Cybersecurity Applications (Studies in Computational Intelligence, 919) 1st ed. 2021 Edition.
2. Ahmed, Syed Thouheed. Basha, Syed Muzamil. Arumugam, Sanjeev Ram. Patil, Kiran Kumari. Big Data Analytics and Cloud Computing: A Beginner's Guide, 2021.
3. Saleem, Tausifa Jan. Chishti, Mohammad Ahsan. Big Data Analytics for Internet of Things 1st Edition, April 2021.

4. Jones, Herbert. Data Science: The Ultimate Guide to Data Analytics, Data Mining, Data Warehousing, Data Visualization, Regression Analysis, Database Querying, Big Data for Business and Machine Learning for Beginners Hardcover – 10 January 2020.
5. Maheshwari, Anil. Data Analytics Made Accessible: 2023 edition Kindle Edition
6. Mayer-Schönberger, Viktor. Cukier, Kenneth. Big Data: A Revolution That Will Transform How We Live, Work, and Think Paperback – October 26, 2021.


## 14.14 Answers to Check Your Progress Questions

**1. (c) What happened in the past**

Descriptive analytics answers the question "What happened in the past?" It involves working on present and past data, and extracting insights from them.

**2. (d) Predictive analytics**

Predictive Analytics is used to classify customers into likely defaulters or those who repay promptly.

**3. (d) Can be classified under inquisitive analytics**

Working on data for last quarter and finding out the reasons behind it falls under inquisitive analytics.

**4. (b) Prescriptive analytics**

Prescriptive analytics is used to advise business on the future course of action.

**5. (c) The decision science sector is growing at a good pace and there are good job opportunities in the near future.**

The decision science sector is growing at a good pace and there are good job opportunities in the near future (predictions from analytics and by consulting firms support this).

**6. (d) Knowledge of sciences**

Knowledge of sciences is a not a 'Must to have' trait but a 'good to have' one for data professionals.

**7. (a) Centralized model**

Centralized model is a common analytics structure seen in many organizations.

**8. (b) False**

Developing decision science talent is not a onetime affair, but a continuous process of training and nurturing talent.

9. (d) **Any analytics model may have both advantages and disadvantages to some extent**

   No single model has only advantages, but any model will have, to some extent, both advantages and disadvantages in it.

10. (c) **Organizations should have to be careful and have a proper plan for hiring, motivating and training decision science talent.**

# Big Data, Cloud and Analytics

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